Downward nominal wage rigidity in the United States*

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Abstract

This paper uses two nationally representative household surveys, the Current Population Survey (1979-2017) and the Survey of Income and Program Participation (1984-2013), to establish the existence and cyclical pattern of downward nominal wage rigidity in the United States. The distribution of individual workers' year-over-year changes in nominal hourly wages has a large spike at zero and is asymmetric, with many more raises than cuts. The distribution also exhibits a notable cyclical pattern: the share of workers with no wage changes, which accounts for the spike at zero, has greater countercyclical fluctuations compared to the share of workers with wage cuts. This finding, which is novel in the literature, suggests that downward nominal wage rigidity exists, with potentially important implications for fluctuations in employment. Finally, this paper compares heterogeneous agent models with five alternative wage-setting schemes—perfectly flexible, Calvo, long-term contracts, menu costs, and downward nominal wage rigidity—and shows that only the model with downward nominal wage rigidity is consistent with the empirical findings regarding the shape and cyclicality of the wage change distribution.

JEL classification: E24, E32, J30.

Keywords: Downward nominal wage rigidity, Countercylical, Employment

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1 Introduction

Downward nominal wage rigidity (DNWR) is the resistance of nominal wages to adjusting downwards. While the existence of DNWR has been arguably established in the literature,[1] it remains controversial whether DNWR could have consequences for employment. Recent studies have theorized that DNWR led to massive unemployment in peripheral Europe and in the United States during the Great Recession (Schmitt-Grohé and Uribe (2016); Schmitt-Grohé and Uribe (2017)). During periods of high inflation, real wages can fall even when nominal wages cannot adjust downwards. However, because inflation stayed low during the Great Recession, it is believed that DNWR also prevented real wages from falling, resulting in greater unemployment. However, empirical evidence on the relationship between DNWR, inflation, and employment is still lacking.

This paper uses two nationally representative household surveys in the US, the Current Population Survey (CPS, 1979 - 2017) and the Survey of Income and Program Participation (SIPP, 1984 - 2013), to determine if the empirical patterns of wage change distributions of individual workers are consistent with theories of wage rigidities and their impact on employment. While a number of other studies have investigated this relationship, their findings are contradictory, making the role of DNWR during recessions a controversial topic.[2] To shed light on this discussion, I examine the cyclical properties of the nominal wage change distribution in relation to employment and inflation. I show that the empirical patterns are not only consistent with theories of DNWR, but also that among five heterogeneous-agent models with different wage-setting schemes, only the model with DNWR is able to match all the empirical patterns.

The CPS and the SIPP provide a number of advantages for the present analysis. First, the panel structure of both data sets allows one to measure individual year-over-year hourly wage growth rates, thus accounting for level differences in individual-specific wages. In addition, both data sets contain population weights, which allow for the aggregation of data to the national level. The two data sets are also complementary. The CPS, unlike the SIPP, is composed of rotating panels, allowing one to study a long time series over the entire period of data containing multiple recessions. On the other hand, the SIPP contains an employer ID for each job of each respondent, allowing one to compare the wage change distributions of job stayers versus that of job switchers.

As the first step of the analysis, I examine the nominal wage change distribution for each year from 1979 to 2017 for the nation as a whole. Consistent with the findings of previous authors, I find that each year's distribution has a large spike at zero. That is, a large share of workers do not experience wage changes in any given year. Furthermore, these distributions are distinctively asymmetric; nominal wages changes are composed of many fewer wage cuts than raises. An analysis for each state confirms that the general shape of wage change distributions holds not

[1] Kahn (1997); Card and Hyslop (1997); Lebow, Sacks, and Anne (2003); Daly, Hobijn, and Lucking (2012); Barattieri, Basu, and Gottschalk (2014); Daly and Hobijn (2014); Elsby, Shin, and Solon (2016); Fallick, Lettau, and Wascher (2016)

[2] Daly and Hobijn (2014) argue that the DNWR is more binding in the recession, however Elsby, Shin, and Solon (2016) argue that the DNWR does not respond to the business cycle.

only at the national level but also at the state level.

While it is apparent that nominal wages are more often moving upwards than downwards, this empirical fact alone is not compelling evidence of the existence of DNWR, as it could be due to other factors such as labor productivity growth or inflation. Hence, I examine how the wage change distribution changes over business cycles, and whether these changes are related to employment and inflation in the ways consistent with DNWR.

My analysis mainly focuses on three statistics from the nominal wage change distribution: the share of workers with no wage changes (which corresponds to the spike at zero), the share with cuts, and the share with raises. The theory of DNWR suggests that DNWR would have little effect on employment during periods of high inflation, but could adversely affect employment during periods of low information. Indeed, I find that the three statistics have statistically significant relationships with employment only when controlling for inflation. In particular, the size of the spike at zero has a negative correlation with employment when controlling for inflation. This is consistent with the prediction that years in when DWNR is more binding, as indicated by the greater share of workers with no wage changes, employment decreases more. This finding is also consistent with that of Daly and Hobijn (2014), who focus on a period of relatively low inflation, namely the years 1986 – 2014, and find that the fraction of workers with no wage changes appears countercyclical.

I document a novel empirical finding namely that in a recession the share of workers with no wage changes has greater countercyclical fluctuations compared to the share of workers with wage cuts. With DN WR, because the movement of wages is restricted downwards, it is plausible that the share of workers wage cuts would vary little over time, while the share of workers with no wage changes would fluctuate more along the business cycle.

With the national level data, I first show that, unsurprisingly, both employment and the share of workers with raises decline during recessions: a one percentage point decline in employment is associated with a 0.9 percentage point decline in the share of workers with raises, controlling for inflation. Mechanically, this decline in the share of workers with raises corresponds to the sum of the increases in the share of workers with no wage changes and in the share with wage cuts. I then examine which of these two shares shows a larger co-movement with employment, controlling for inflation. I find that a one percentage point decline in employment is associated with a 0.67 percentage point increase in the share of workers with no wage changes and a 0.33 percentage point increase of workers with a wage cut. That is, as employment falls during recessions, the share of workers with no wage changes increases a lot more than the share of workers with wage cuts.

This pattern I identify at the national level across time also holds in the cross-sectional analysis of the data at the state level: controlling for state and time fixed effects, declines in state-level employment still show greater association with the increase in the share of workers with no wage changes compared to that of workers with wage cuts.

At first sight, this appears to contradict the recent finding by Beraja, Hurst, and Ospina (2016), which shows a positive correlation between state-level changes in nominal wages and employment during the Great Recession. Based on this finding, these authors argue wages were fairly flexible, as lower employment growth was associated with lower wage growth. However, also using the state-level data for the time period, I show that lower employment growth was also associated with larger increases in the share of workers with no wage changes. That is, in the states with low employment growth, the overall nominal wage growth may be lower due to declines in the share of workers with raises, but the distribution of wage changes contains a substantial increase in the size of the spike at zero. I therefore argue that Beraja, Hurst, and Ospina (2016)'s finding is still consistent with DNWR. I therefore conclude, contrary to Beraja, Hurst, and Ospina (2016) that nominal wages were fairly rigid.

My empirical analysis suggests that the shape and cyclical properties of the nominal wage change distribution are consistent with DNWR. The findings are established using both the CPS and the SIPP data, at the national as well as at the state level, and provide comparisons between job stayers and job switchers. In summary, my empirical analysis presents three stylized facts about inflation, employment, and the nominal wage change distribution. Namely, controlling for inflation, the share of workers with zero wage changes increases as employment falls, the share of workers with wage cuts also increases as employment falls, and most importantly, the relative change in the former is nearly twice as large as that of the latter.

In the last section, I examine whether models with other wage-setting schemes are able to match these stylized facts.I build heterogeneous agent models with 5 different wage setting ¬schemes widely discussed in the literature—perfectly flexible, Calvo, long-term contracts, menu costs, and DNWR. The models feature not only idiosyncratic uncertainty but also aggregate uncertainty. Using numerical methods, I characterize the year-over-year wage change distributions implied by each model and study how they change with aggregate employment.

I find that, except for the perfectly flexible model, all the other models can predict a stationary wage change distribution that has a spike at zero. However, the time-dependent models—Calvo and long-term contracts—fail to generate the countercyclical movement of the spike since they predict that the size of the spike would stay constant over the business cycle. On the other hand, the state-dependent models—both menu costs and DNWR—can generate the countercyclical spike at zero. However, according to the menu cost model, as employment declines, the share of workers with wage cuts changes more than the share of workers with no wage changes, which contradicts the last stylized fact. Thus, among these models, only the model with DNWR is able to generate all these key empirical patterns observed in the data.

The remainder of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the data sets: the CPS and the SIPP. Section 4 discusses the shape of nominal year-over-year hourly wage change distributions. Section 5 examines the cyclical properties of the nominal wage change distribution: as employment declines, the share of workers with no wage changes increases more than the share with wage cuts. The state-level analysis of this finding is presented in section 6. Section 7 builds heterogeneous agent models with 5 alternative wage setting schemes, equipped with both aggregate and idiosyncratic shocks. Section 8 compares numerical predictions from 5 those wage setting schemes to the empirical findings. Section 9 concludes and discusses future work.

2 Related Literature

This paper is related to a various branches of the empirical literature on nominal wage rigidity. An early literature uses individual level panel data for the period of high inflation, 1970-1993 and documents a relationship between nominal wage change distributions and inflation rather than a relationship between moments of nominal wage change distribution and employment. Kahn (1997) using data from the Panel Study of Income Dynamics (PSID) from 1970 to 1988 shows that nominal wage change distributions are asymmetric with a spike at zero. However, this author could not find a statistically significant relationship between the share of workers with no wage change, the spike at zero, and employment. My interpretation is that this is because in her sample period, the average inflation was 6.1 percent per year. Card and Hyslop (1997) use both PSID and CPS data from 1979 to 1993, a period during which the average inflation rate was about 5.3 percent per year. They conclude that inflation can grease the wheels of the labor market by showing that the share of workers with no wage change is significantly negatively correlated with the inflation rate: fewer workers experience rigid wages when inflation is high. Like Kahn (1997), these authors could not find a statistically significant relationship between the spike at zero and employment.

A recent paper by Daly and Hobijn (2014) studies the period of low inflation, 1986 - 2014, when the average inflation was 2.7%. They find that the spike at zero is countercyclical: the share of workers with no wage changes increases when employment declines. The spike at zero from Daly and Hobijn (2014) is available from Wage Rigidity Meter, published by Federal Reserve Bank of San Francisco.[3] In contrasts to Daly and Hobijn (2014), Elsby, Shin, and Solon (2016) argue that the spike at zero is acyclical since 1998. Elsby, Shin, and Solon (2016) use CPS data with bi-annual job-tenure supplements from 1980 to 2017. They show that the spike at zero has increased since 1998. They argue that the increase in the spike at zero is secular rather than cyclical in nature and is the consequence of a secular decline in inflation.

Different from Elsby et al. (2016), I find that the spike at zero is countercyclical using the longest time period of the sample, 1979-2012, controlling for inflation. Furthermore, I investigate not only the cyclicality of the spike at zero but also the cyclicality of the fraction of workers with wage cuts, which gives a better understanding of the cyclicality of nominal wage change distribution and is crucial to

In the previous literature mentioned earlier, a zero wage change is defined as an exact change of zero, that is, a worker has to report the exact same hourly wage rate in interviews one year apart. Reported wages suffer from measurement error, which can over- or understate the size of

[3]The Wage Rigidity Meter shows the percentage of workers with no wage change within the subgroups of the labor force by type of pay, education, and industry using the CPS, which is available from here.

the spike at zero wage changes. Barattieri, Basu, and Gottschalk (2014) use SIPP panel data for the period 1996 to 2000 to estimate the constant frequency of no wage change taking into account measurement error. They argue that correcting for measurement error leads to a larger estimate of the size of the spike at zero and a decline in the estimate of the share of workers experiencing a wage cut.

Furthermore, Fallick, Lettau, and Wascher (2016) use data from the Employment Cost Index for the period 1982 to 2014. This BLS survey includes information on the annual costs for specific job descriptions and the annual hours that workers are supposed to work (contracted hours) to obtain their annual compensation. One advantage of employer-reported wage data is that they are free of measurement errors as they are recorded systematically. A disadvantage of this data is that it does not allow for controlling for individual fixed effect since the base unit of observation is a job rather than an individual. They find mixed results on the amount of downward nominal wage rigidity during the Great Recession, and they conclude that they cannot reject the hypothesis that the labor market distress during the Great Recession lowered nominal wage rigidity.

Unlike the previous studies mentioned thus far, Beraja, Hurst, and Ospina (2016) use state variations of wages and employment to argue that wages were fairly flexible during the Great Recession. They use nominal wage data from the 2007-2010 American Community Survey (ACS), which does not have a panel structure. To avoid composition bias, they used the residual wages, taking out variations of wages depending on observable worker characteristics. They argue that wages were fairly flexible based on their finding of a positive correlation between state-level changes in nominal wages and employment during the Great Recession. However, as shown in detail in section 6.2, this paper shows their finding still can be consistent with the existence of DNWR by showing the negative association between state-level changes in the spike at zero and employment.

Kurmann and McEntarfer (2017) uses data of Washington state from Longitudinal Employer-Household Dynamics and they argue that the increased incidence of wage cuts during the downturn suggest that DNWR may not be a binding constraint. However, this paper shows there is more increase in the spike at zero compared to the share of workers with wage cuts.

My paper is also related to the more theoretical literature on nominal wage rigidity. Schmitt-Grohé and Uribe (2016) build a representative agent model with DNWR: nominal wages cannot be lowered by more than a fixed fraction. This model predicts the spike at that fixed negative wage growth rate in the recession and no spike in the boom. Although it is discrete, it implies that DNWR is more binding during the recession.

Fagan and Messina (2009) use a heterogeneous agent model with DNWR and show that the implied stationary wage change distribution is similar to the empirical nominal wage change distribution: a spike at zero and fewer wage cuts than wage increases. Their model has only idiosyncratic shocks. To generate the stationary distribution similar to the empirical distribution, they impose 3 different menu-costs: one for raise, one for cuts, and one for wage growth rate being less than inflation.

Daly and Hobijn (2014) build a heterogeneous agent model with either perfectly flexible wage setting or DNWR, and they compare the stationary distribution implied by perfectly flexible wage model and DNWR. After a one-time negative aggregate shock, they also find the spike at zero increases. However, they do not mention the share of wage cuts but instead focusing on the spike at zero. Mineyama (2018) presents a heterogeneous agent model with DNWR, equipped with both idiosyncratic and aggregate shock. The model by Mineyama (2018) generates the countercyclical spike at zero; however, this paper does not fully explore changes in nominal wage change distribution. Mineyama (2018) argues that DNWR is helpful to explain the observed flattening of the Philips curve in the Great Recession.

3 Data

This paper uses two nationally representative household panel data sets, the CPS and the SIPP, in the United States, which have individual level wage data. It is important to use disaggregated data to avoid the composition bias embedded in aggregate time series of wages. Solon, Barsky, and Parker (1994) show that the composition of employed workers changes over the business cycle, which gives more weights to low-skilled workers during booms than recessions. Because the wages of low-skilled workers tend to lower than the wage of high-skilled workers, such cyclical changes in the composition of worker can lead the result that aggregate wages fail to fall in recessions, spuriously suggesting wage rigidity To avoid the composition bias, the present paper uses panel data.

3.1 Current Population Survey

The Current Population Survey[4] (CPS) is jointly collected by the United States Census Bureau and the Bureau of Labor Statistics (BLS). The purpose of this survey is mainly to construct nationally representative labor force related statistics such as unemployment rates and median weekly earnings in the United States. Almost 60,000 households are interviewed monthly. The sample period starts 1979 and ends in 2017.

The CPS has the special sampling design. Each household in the sample will be asked about their labor force status 8 times but not in a continuous way. After the first four months of the interview, households are out of the sample for 8 months and will be interviewed 4 times again for the following 4 months. Table 1 shows the sampling design of the CPS. Among the 8 interviews, only when households are in the Outgoing Rotation Group (Earner Study) - the fourth and eighth interview of the survey - do they respond to earnings related questions: usual earnings, hours worked last week, union coverage, and so on. Thus, each individual in the survey reports wages at most two times in a year apart, in the month in sample (MIS) in 4 and 8.

Knowing the special sampling design of the CPS, the monthly CPS could be exploited as panel data. However, CPS microdata does not provide with unique individual identifiers within the

[4]CPS monthly micro-data are available from http://www.nber.org/data/cps_basic.html .

Table 1: CPS sampling design

Calendar Month	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4
Month in Sample (MIS)	1	2	3	4		——— Break ———							5	6	7	8
Labor force status	✓	✓	✓	✓									✓	✓	✓	✓
Outgoing Roation group				✓												✓

Notes. This table is from Daly, Hobijn, and Wiles (2011)

households. Instead, Integrated Public Use Microdata Series - CPS (IPUMS-CPS)[5] provides unique individual identifiers to link individuals across monthly CPS based on Drew, Flood, and Warren (2014).[6] To take advantage of the longitudinal features of the CPS data, this paper uses unique individual identifiers from IPUMS-CPS.

The main objective of this paper is hourly workers who directly report hourly pay rates both in the previous year and the current year.[7] For non-hourly workers, hourly wages can be obtained by dividing the usual weekly earnings by the usual hours worked per week. However, the imputed hourly rate for salaried workers in this manner can be excessively volatile, as it is sensitive to any reporting errors on the number of hours worked, which is known as division bias. To remove errors caused by imputing the hourly pay rate, the main results are shown only for hourly-rated workers. In the United States, about 58% of workers are hourly-rated in 2014.[8] Workers paid hourly both in the previous and the current year represent about 50% of all wage and salary workers.

Wages, the most important variable in this paper, are often imputed in the CPS. On average, 34% of the hourly wages of hourly paid workers have been imputed since 1996.[9] Bollinger and Hirsch (2006) show that including imputed wages may cause the match bias due to imperfect matching. Therefore, it is essential to exclude imputed wages. Although IPUMS-CPS provides individually linked CPS data, the IPUMS-CPS does not provide allocation flags for wage variables, indicating whether wage variables are imputed or not. Therefore, I merge the IPUMS-CPS data with the monthly CPS, merged with the Outgoing Rotation Group. In this way, this paper exploits the longitudinal feature of the CPS after excluding imputed wages.

One disadvantage of the CPS is hard to define job stayers and job switchers. Although the CPS provides the variable to inform whether the respondent is employed by the same employer from the last month since 1994, this variable is missing in the MIS5 after 8 months break of the interview.

[5]IPUMS-CPS data are available from .https://cps.ipums.org/cps/.

[6]Based on a method suggested by Madrian and Lefgren (1999) for matching the monthly CPS by exploiting differential basic demographic features within the households such as age, gender, race, and education level.

[7]When respondents are in the Outgoing Rotation Group (MIS4 or MIS8), they report their earnings in the easiest way: hourly, weekly, annually, or some other basis. Those who reported that the easiest way to report their wage is hourly are considered as hourly workers. While some workers report the easiest way to report their earnings is not hourly, they could have been rated as hourly. Therefore, for those who indicated that the easiest way to report their wages is some other way than hourly, they are asked again whether they are paid hourly basis and if so, their hourly pay rate.

[8]https://www.bls.gov/opub/reports/minimum-wage/archive/characteristics-of-minimum-wage-workers-2014.pdf.

[9]Table A1 in the appendix shows the imputation ratio for usual weekly earning and hourly wage.

Thus, it is difficult to define job stayers in the CPS. For example, if the respondent has switched job during the 8 month break period, say in the calendar month 5, and stayed the same job since then, he/she would respond to be employed by the same employer for MIS6-8. This respondent is likely to be identified as job stayers from MIS4 to MIS8, although he/she is job switchers. Therefore, this paper does not distinguish job stayers from job switchers for the empirical analysis using the CPS.

This paper considers only workers above the age of 16. Self-employed workers and workers whose earnings are top-coded or imputed are also dropped. The average number of observations is 15,418 per year. The time series number of observations is available in the appendix table A2.

3.2 Survey of Income and Program Participation

The SIPP [10] is a U.S. household survey conducted by the U.S. Census Bureau. Each panel consists of approximately 14,000 to 52,000 households, and the interview is conducted every 4 months over 3 or 4 years. Longitudinal weights provided by the SIPP are used to adjust this sample nationally representative. This paper uses thirteen panels: 1984, 1985, 1986, 1987, 1988, 1990, 1991, 1992, 1993, 1996, 2001, 2004, and 2008. The sample period is from 1984 to 2012.

The main objective is annual hourly wage growth rate for hourly paid workers. Although monthly wages for each worker are available from the SIPP [11], this paper studies the annual hourly wage growth rate since the hazard of a nominal wage change is highest at 12 months after a wage change (Barattieri, Basu, and Gottschalk (2014)). Similar to the CPS, this paper focuses on hourly paid workers who report the hourly rate directly to the survey, in order to eliminate errors from the imputation of the hourly pay rate for salaried workers.[12]

There are advantages of using the SIPP. First, the SIPP provides unique individual identifiers so we can match individuals across waves without additional process. Second, the SIPP keeps track of movers, while the address-based CPS does not follow movers in the sample. Third, the SIPP provides the unique and consistent job IDs across waves for each job that the respondent had, whereas the CPS does not offer them. Since job IDs are allocated based on respondent's employer information in the SIPP, I define job stayers as employer stayers.[13] One disadvantage of SIPP data is that the time series data is discontinuous because of gaps between the panels. Thus, state-level analysis is more reliable than the aggregate time series analysis in the SIPP.

The average number of observations in the SIPP is 13,937 per year, which is smaller but

[10] Data can be downloaded from http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html .

[11] Each individual is required to provide monthly wages for the prior 4 months at the time of the interview; therefore, monthly wages are available. However, due to seam bias, this paper uses wages only from the reference month.

[12] The SIPP uses a specific questionnaire to ask whether survey respondents are paid by the hour for the main jobs. For workers who are paid by the hour, the SIPP questions for the regular hourly pay rate at that job from the specific employer.

[13] After the major revision of survey design in 1996, if the respondent was not employed for the entire 4 months for the reference period of the interview, then job ID will be renewed at the next interview. Thus, even if this respondent works for the same employer after the jobless spell, the job ID can be different. This issue is raised by Fujita and Moscarini (2017) and I corrected this problem using the method followed by Fujita and Moscarini (2017). For the panel 1990 - 1993, I used the revised job IDs.

comparable to the CPS sample size.[14] In the SIPP, 55% of workers are hourly rated. On average, 71% of them are job stayers. The time series number of observation is available from the table A11 and the number of job stayers and job switchers are available from the table A12 in the appendix.

4 Asymmetric nominal wage change distribution

This section shows that year-over-year nominal hourly wage change distribution is highly asymmetric: a significant fraction of workers experience exact zero wage change and there are fewer wage cuts than raises for the entire sample period , using two independently collected US nationally representative panel data: the CPS and the SIPP, consistent with previous literature (Kahn (1997); Card and Hyslop (1997); Lebow, Sacks, and Anne (2003); Barattieri, Basu, and Gottschalk (2014); Elsby, Shin, and Solon (2016); Fallick, Lettau, and Wascher (2016)).

4.1 Nominal wage change distribution: CPS

Nominal hourly wage change distribution is highly asymmetric. Figure 1 shows the distribution of log nominal hourly wage differences of individual hourly paid workers from 2009 to 2010. There is an apparent spike at zero, which is shown in red, defined as the percentage of hourly paid workers whose annual hourly wage growth rate is exactly zero. Different from the red bin, the size of the blue bin is 0.02. The very last bin on the right includes all the hourly paid workers whose wage growth rate is greater than 0.5. Similarly, the bin on the very left includes all the hourly paid workers whose hourly wage growth rate is less than - 0.5. Not only an apparent spike at zero, but we could also observe fewer wage cuts compared to raises from nominal hourly wage change distribution in 2010. Especially, in a close range around zero, there is a sudden drop in density left to the spike compared to the right to the spike.

The asymmetric wage change distribution with the spike at exact zero in figure 1 suggests the existence of DNWR. In 2010, the unemployment rate was the highest 9.7% after the onset of the Great Recession, and the inflation rate was 1.6%. Even with massive excessive labor supply in the economy, 21.1% of the hourly paid workers experienced zero wage change from 2009 to 2010. The median hourly wage growth rate is 1.7%, suggesting that more than half of the hourly paid workers had nominal raises higher than the inflation rate. In total, 54.2% of hourly paid workers had raises and 24.6% of the hourly paid workers had wage cuts in 2010. In the absence of wage rigidity, we could imagine smooth nominal wage change distribution around the zero. However, instead, we can observe a sudden drop in the density from left to the zero compared to right to the zero and bunching at zero in 2010. Kahn (1997) interpreted that the spike at zero considered as “pile-up” of workers otherwise had negative wage changes. Similarly, Card and Hyslop (1997) described that the part of spike at zero is from “swept-up” of workers who might otherwise had nominal wage cuts. Therefore, this shape of distribution is consistent with DNWR.

[14]The original sample size of the CPS is much larger than that of the SIP; however, the CPS collects only 2 wage data for individual for the whole interview. Therefore, the sample size of the SIPP is comparable to that of the CPS.

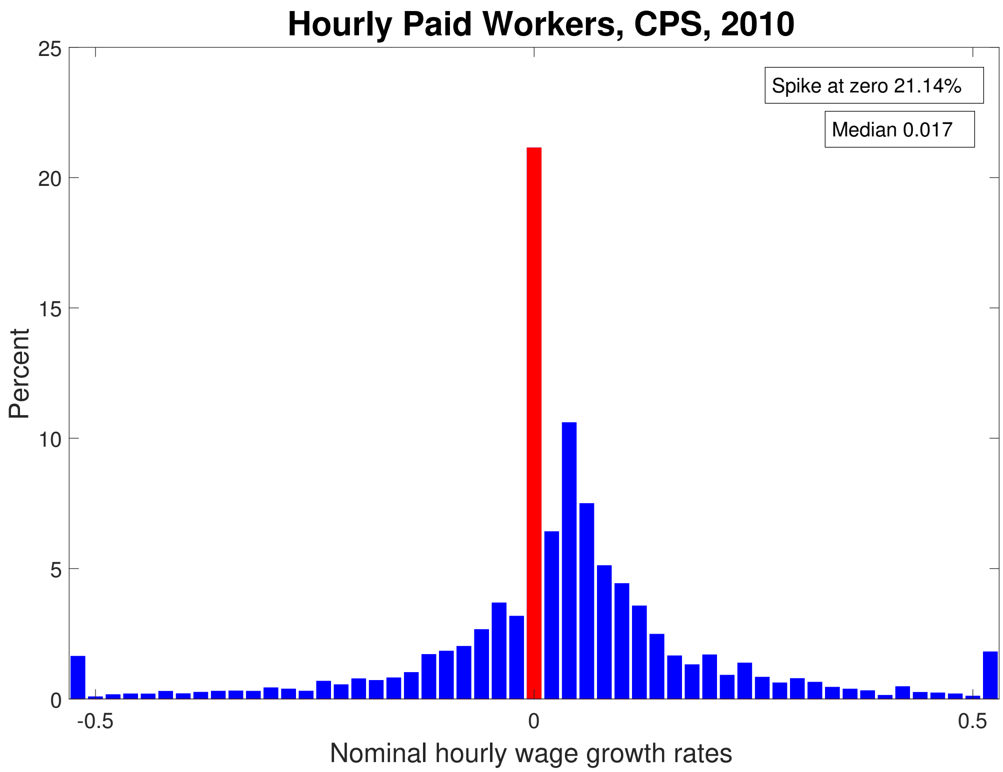


Figure 1: Year-over-year nominal hourly wage growth rates in 2010

Data source: CPS and author's calculation. The bin size is 0.02. The red bin shows the spike at zero, which represents the percentage of workers whose year-over-year nominal hourly wage growth rate is exactly zero from 2009 to 2010. The bin to the right of the exactly zero wage change represents the percentage of workers whose log nominal hourly wage differences is strictly greater than zero and lower than 0.02 and so on. The bin on the very right includes all the workers whose log nominal hourly wage differences are greater than 0.5, and the bin on the very left includes all the workers whose hourly wage growth rates are less than -0.5.

Nominal hourly wage change distribution is asymmetric for the entire sample period 1979 - 2017 in the CPS. Figure A1 and A2 in the appendix show the distribution of individual workers' year-over-year log nominal hourly wage differences from 1979 to 2017. Similar to the nominal hourly wage change distribution in 2010, there are an apparent spike at zero and many more raises than wage cuts. This shows nominal wage change distributions are consistent with DNWR for the entire sample period: 1979 - 2017.

To further exploit cyclical properties of nominal wage change distribution, I construct three statistics: the spike at zero - the fraction of workers with no wage change, the fraction of workers with wage cuts, and the fraction of workers with raises. Table 2 shows the sample average of the spike at zero and the share of workers with wage cuts and raises from 1979 - 2017. On average 15% of hourly workers had exact zero year-over-year hourly wage change, 21% of them had wage cuts, and 64% of them had raises. Excluding minimum wage workers[15] has a marginal effect on

[15]Workers with lower than state minimum wages are dropped. Vaghul and Zipperer (2016) document monthly state-level minimum wage from 1973 to 2016. To extend the data set to 2017, I use https://www.dol.gov/whd/state/stateMinWageHis.htm..

the sample average of the spike at zero and fractions of wage cuts and raises.

Table 2: Descriptive statistics by worker charcteristic, CPS

	% of all workers	% of hourly workers	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
Hourly paid workers			15.25	21.13	63.63
Exc. Minimum wage workers			15.10	20.64	64.26
Male	52.17	49.25	15.17	22.15	62.69
Female	47.83	50.75	15.32	20.09	64.59
16 <= age <40	47.39	53.13	13.95	20.83	65.22
40 <= age <64	49.01	42.98	15.94	21.68	62.38
White	84.48	85.13	15.36	20.57	64.07
Non-white	15.52	14.87	14.62	24.39	60.99
High School or less	44.24	58.50	15.75	21.49	62.76
College or more	55.76	41.50	14.46	20.65	64.88

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). This table shows the sample average of spike at zero and the fraction of workers with wage cuts and raises over time by worker characteristics.

Nominal hourly wage change distribution does not show significant heterogeneity across worker characteristics. The table 2 shows descriptive statistics by worker characteristics. As this paper focuses only on hourly workers, there is sample selection: female workers, young workers, less educated workers are over-represented. However, the sample average of the spike at zero, the share of workers with wage cuts and raises are similar across workers characteristics.

Table 3: Nominal hourly wage change distribution, CPS, by hourly wage quartiles

Hourly wage Quartiles	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
25th below	20.85	31.70	47.45
25th to Med	15.48	20.77	63.75
Med to 75th	13.29	18.09	68.62
75th and above	12.83	16.65	70.52

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). This table shows the sample average of the spike at zero and the fraction of workers with wage cuts and raises over time by hourly wage quartiles.

On the contrary, nominal hourly wage change distribution shows heterogeneity across the level of hourly wage and industry. The table 3 shows the sample average of the spike at zero, the share of wage cuts and raises by hourly wage quartiles. Workers in lower hourly wage quartile tend to show a higher spike at zero and share of wage cuts. Workers in higher hourly wage quartile are likely to have more raises. Similarly, table A3 displays the sample average of the spike at zero, the share of wage cuts and raises by 2 digit NAICS industry code, sorted by the sample average of the spike at zero. The sample average of the spike at zero varies from 11% to 23%. The biggest industry in terms of the fraction of hourly workers is the manufacturing industry, and its sample

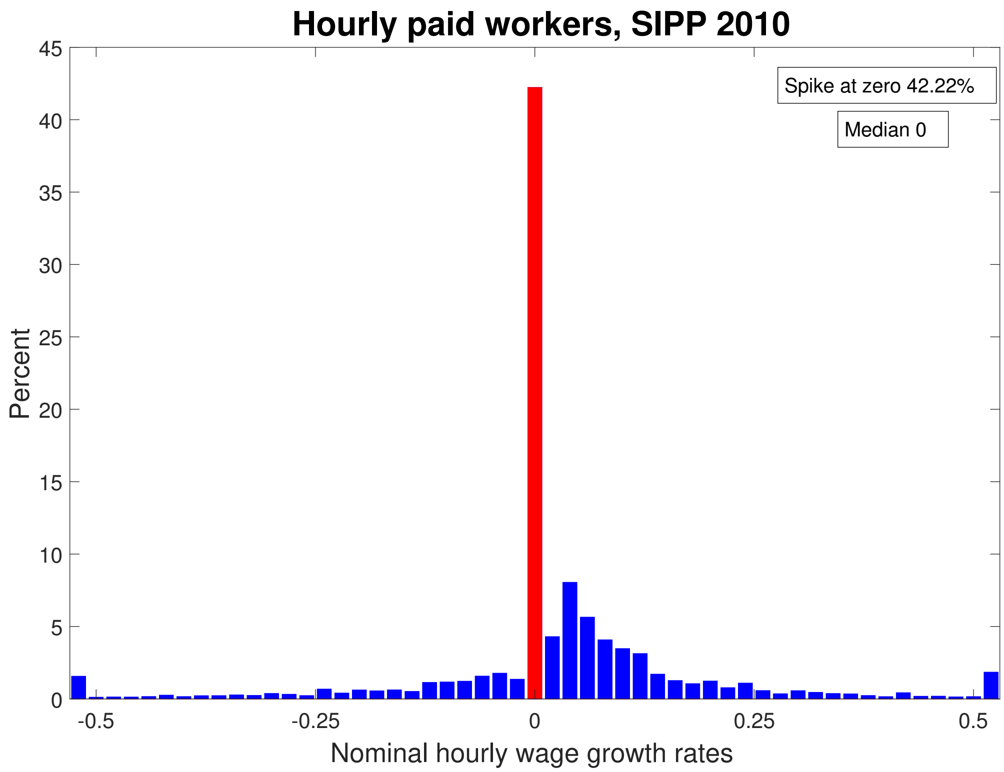


Figure 2: Nominal hourly wage growth rates distribution in 2010

Data source : SIPP. The red bin shows the spike at zero, which represents the percentage of workers whose hourly wage growth rate is exactly zero from 2009 to 2010. Other than red bin, bin size is 0.02. The bin on the very right includes all the workers whose hourly wage growth rates are greater than 0.5, and the bin on the very left includes all the workers whose hourly wage growth rates are less than -0.5.

average of the spike at zero is around 14%, comparable to the national average.

4.2 Nominal wage change distribution: SIPP

Figure 2 shows the distribution of individual workers' log nominal hourly wage differences from 2009 to 2010 using the SIPP. Similar to the figure 1, the spike at zero, which is colored in red, shows the percentage of hourly workers whose year-over-year nominal hourly wage growth rate is exactly zero. Figure 2 again shows asymmetry: the significant spike at zero and fewer wage cuts compared to wage raises. Furthermore, nominal hourly wage change distribution for hourly workers is asymmetric for the entire sample period from 1984 to 2013 (except 1990, 1996, 2001, 2004, and 2008)[16]. Figure A3 in the appendix shows nominal hourly wage change distribution for the entire sample period in the SIPP. We can clearly see that the significant spike at zero and many more wage raises compared to wage cuts for every year. Asymmetric nominal hourly wage change distribution itself is consistent with DNWR.

Nominal hourly wage change distribution does not show heterogeneity across worker characteristics.

[16]The SIPP has a gap between each panel so that there is a discontinuity in aggregate time series data.

Table 4 shows the average spike at zero and the fraction of workers with wage cuts and raises by worker characteristics over the sample period. Excluding minimum wage workers do not affect the sample average of the spike at zero and the share of wage cuts and raises. Furthermore, it does not show heterogeneity across gender, the level education, race, and union coverage.

Table 4: Descriptive statistics by worker characteristics, SIPP

	% fo hourly workers	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
Hourly paid workers		24.00	17.42	58.58
Exc. Minimum wage workers		23.99	16.68	59.33
Job stayers	71.08	28.89	12.32	58.79
Job switchers	28.92	12.52	29.86	57.62
Male	49.31	24.45	18.25	57.30
Female	50.69	23.58	16.59	59.83
White	83.27	23.92	17.00	59.08
Non-white	16.73	24.31	19.62	56.07
High School or less	54.92	25.19	17.51	57.30
College or more	45.08	22.54	17.30	60.15
No union coverage	89.55	25.02	14.75	60.24
Union coverage	10.45	24.39	16.14	59.47

Data source: SIPP and author's calculation. Sample Period: 1984-2013 (except 1990, 1996, 2001, 2004, 2008). This table shows the average of size of peak and the fraction of workers with wage cuts and raises over time by worker characteristics.

Nominal wages are more downwardly rigid for job stayers than job switchers.[17] Table 4 shows the spike at zero for job stayers is higher than the spike at zero for job switchers whereas the fraction of wage cuts for job stayers is lower than the fraction of wage cuts for job switchers. We can also observe more dispersed nominal hourly wage change distribution in 2010 for job switchers than job stayers from the figure 3. The figure 3 displays nominal hourly wage change distribution in 2010 for job stayers (left) and job switchers (right). Both nominal hourly wage change distribution displays the significant spike at zero, although the spike at zero for job stayers is much higher than the spike at zero fro job switchers.[18] Compared to job stayers, nominal hourly wage change distribution is more dispersed for job switchers. Also the median size of wage growth rates for job switchers are much larger than that for job stayers, which is shown at the table 5. This is consistent with Bils (1985) and Shin (1994), arguing that wages are more flexible for job switchers than job stayers. Nominal hourly wage change distribution for job stayers and job switchers for the entire sample period is available from the figure A4 and A5.

Even if we include job switchers, nominal hourly wage change distribution for all hourly workers in figure 2 shows asymmetry: the significant spike at zero and fewer wage cuts than

[17]Hourly workers who reported working for different employer this year from the last year, regardless of jobless spell between employer switching.

[18]Table A13 in the appendix shows the sample average of the spike at zero and share of wage cuts and raises by reasons why hourly workers switched their employer over the sample period.

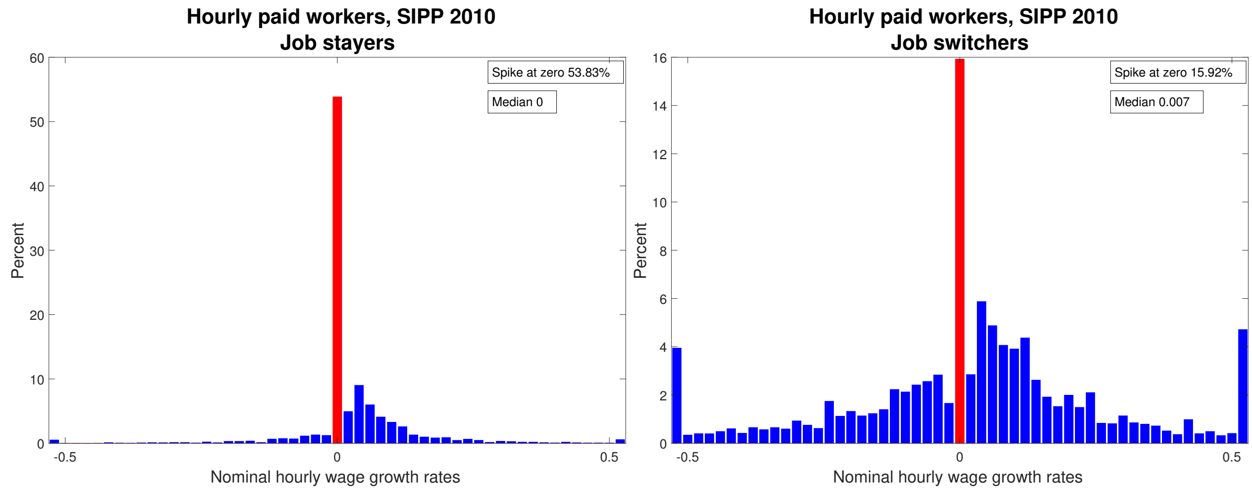


Figure 3: Nominal hourly wage distribution in 2010: job stayers vs. job switchers

Data source: SIPP. The left figure shows nominal hourly wage change distribution for job stayers and the right figure is for job switchers. The red bin shows the spike at zero, which represents the percentage of workers whose hourly wage growth rate is precisely zero from 2009 to 2010. Other than the red bin, bin size is 0.02.

raise. This is because only about 29% of hourly workers are job switchers in the SIPP. Nominal hourly wage change distribution using the CPS is also for all hourly workers including both job stayers and job switchers and we still observe the asymmetry and a spike at zero.

Table 5: Median size of wage change, SIPP

	Median size of ΔW given $\Delta W < 0$	Median size of ΔW given $\Delta W > 0$
Job stayers	-7.07	6.76
Job switchers	-16.29	16.20

Source: SIPP and author's calculation. Sample Period: 1984-2013 (except 1990, 1996, 2001, 2004, 2008).

Similar to the CPS, workers from lower hourly wage quartile are likely to have higher spike at zero and wage cuts. This is true for both job stayers and job switchers, shown in the table 6.

5 The aggregate cyclicality of nominal wage change distribution

This section shows the cyclicality of nominal wage change distribution. Although it is obvious that there are more raise than cuts in nominal wage change distribution, this empirical fact alone would be week evidence of the existence of DNWR, as it could be due to growth in productivity or inflation. Thus, this paper analyzes how nominal wage change distribution changes along the business cycle.

To address the cyclicality of nominal wage change distribution, this paper constructs three aggregate time series: the spike at zero, defined as the percentage of hourly workers whose year-

Table 6: The spike at zero, fraction of wage cuts and raises (%), SIPP, by hourly wage quartiles

	Hourly wage Quartiles	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
Job-stayer	25th below	36.11	15.45	48.44
	25th to Median	28.11	11.21	60.68
	Med to 75th	25.83	11.33	62.84
	75th and above	24.86	11.10	64.04
Job-switcher	25th below	18.11	45.20	36.69
	25th to Med	11.71	29.69	58.60
	Med to 75th	9.53	23.08	67.39
	75th and above	9.77	19.42	70.81

Data source: SIPP and author's calculation. Sample Period: 1984-2013 (except 1990, 1996, 2001, 2004, 2008). This table shows the sample average of the spike at zero and the fraction of workers with wage cuts and raises over time by hourly wage quartiles.

over-year nominal wage growth rate is precisely zero, the fraction of workers with wage cuts and raises. The section shows the increase in the spike at zero is higher than the increase in the fraction of wage cuts when employment declines using the CPS (section 5.1) and the SIPP (section 5.2), which is consistent with the existence of DNWR.

5.1 Aggregate analysis: CPS

Nominal hourly wage change distribution can be summarized into three statistics: the spike at zero and the fraction of workers with wage cuts and raises. The number of observation and three aggregate time series - the spike at zero and shares of wage cuts and raises - for each year are available from the table A2 in the appendix.

To explore cyclicality, let's think about the following 3 regression equations :

$$\begin{aligned} \text{[Spike at zero]}_t &= \alpha_s + \beta_s(1-e_t) + \epsilon_{st} \\ \text{[Fraction of wage cuts]}_t &= \alpha_n + \beta_n(1-e_t) + \epsilon_{nt} \\ \text{[Fraction of raises]}_t &= \alpha_p + \beta_p(1-e_t) + \epsilon_{pt} \end{aligned} \tag{1}$$

, where e_t is the employment to population ratio. Adding above three equations will give us

$$1 = \alpha_s + \alpha_n + \alpha_p + (\beta_s + \beta_n + \beta_p)(1-e_t) + \epsilon_{st} + \epsilon_{nt} + \epsilon_{pt}$$

, followed by the definition of probability density function. Since the left hand side of equation is constant, we know that

$$\beta_s + \beta_n + \beta_p \equiv 0.$$

Thus, a decrease in the fraction of workers with raises by β_p can be decomposed into two: either an increase in the spike at zero by β_s or an increase in the share of workers with wage cuts by β_n.

This framework allows capturing changes in nominal wage change distribution more extensively, compared to the previous literature - exploring the only cyclicality of the spike at zero. Card and

Hyslop (1997) use the sample period of high inflation from 1979 to 1993 and conclude that the spike at zero is negatively correlated with inflation: inflation can grease the wheels of the labor market. Daly and Hobijn (2014) use the sample period of low inflation from 1986 to 2014 and argue that the spike at zero is positively related to the unemployment rate. Different from the previous literature, this paper explores cyclicality of the spike at zero as well as the fraction of workers with wage cuts and raises.

Self reported hourly wages have measurement error (Bound and Krueger (1991)); however, measurement error on the dependent variables would not bias the coefficient estimates. For hourly wages, we can expect largely two types of measurement errors. First, when respondents report their hourly wage, it may be possible to report their true wage plus error. This type of measurement error would understate the wage rigidity, the spike at zero. Second, workers can report rounded hourly wages and this would overstate the spike at zero. However, as long as measurement error does not vary with employment, measurement error on dependent variables would not add the bias to the coefficient estimates.

Table 7: The spike at zero, the fraction of wage cuts, and raises along the business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero $\Delta W = 0$	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$
1-Epop ratio	0.433	0.200	-0.632	0.616***	0.305*	-0.921***
	(0.299)	(0.221)	(0.498)	(0.161)	(0.156)	(0.281)
Inflation rate				-1.181***	-0.674***	1.855***
				(0.122)	(0.145)	(0.218)
				0.617/0.920 = 0.67		
Observations	37	37	37	37	37	37
Adjusted R^2	0.0419	-0.00492	0.0313	0.727	0.331	0.703

Standard errors in parentheses

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Data source : CPS and author's calculation. Sample Period: 1979-2017 (except 1995). Inflation rate is calculated from CPI-U.

When inflation varies a lot during the sample period, we cannot find the statistically significant relationship with changes in the nominal wage change distribution and employment. First three columns of table 7 shows regression results based on the regression equation (1) and coefficients are not statistically significant. This is because the sample period includes the period of high inflation. When inflation is high, nominal wage rigidity has a limited impact on the real wage rigidity compared to the period of low inflation. Hence, we have to control the level of inflation, which determines real wage growth rates from nominal wage growth rates.

The spike at zero moves countercyclically, controlling for the inflation. We can find the statistically significant relationship between the spike at zero and employment, once we control inflation. From the column (4) of the table 7, we can see that the spike at zero is negatively correlated with employment and inflation. The spike at zero decreases when inflation increases, consistent with

Kahn (1997); Card and Hyslop (1997). Controlling inflation, the spike at zero increases when the employment declines, which is consistent with Daly and Hobijn (2014).

The spike at zero shows greater countercyclical fluctuations compared to the share of workers with wage cuts. Instead of exploring cyclicality of the spike at zero only, let's explore the cyclicality of three statistics together, controlling inflation. Now we can find the statistically significant relationship between nominal hourly wage change distribution and employment along the business cycle, column (4) - (6) from the table 7. When there is a decline in the employment by 1 percentage point, the fraction of workers with raises declines by 0.9 percentage points. Among 0.9 percentage points, 0.6 percentage points of them experience zero wage change and the other 0.3 percentage of them experience wage cuts. In other words, whenever there is a decrease in employment, among workers not having raises, 67% of them experience zero wage change, downwardly rigid wages. When employment declines, yes, there is an increase in workers having wage cut. However, the increase in the spike at zero is higher than the increase in the fraction of wage cuts; the increase in workers with downwardly rigid wages is higher than the increase in workers having wage cuts. Similarly, when employment inclines, there is more decrease in the spike at zero than the decrease in the workers with wage cuts. Hence, we can conclude that the spike at zero exhibits the greater countercyclicality compared to workers with wage cuts, which is consistent with DNWR.

Table 8: The spike at zero, the fraction of wage cuts and raises along the business cycle

	(1) Spike at zero	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$
1-Epop	0.624***	0.280*	-0.904***
	(0.159)	(0.156)	(0.274)
$(\text{1-Epop})_t \cdot \mathbb{I}(\Delta(\text{1-Epop})_t > 0)$	-0.00792	0.0235	-0.0156
	(0.0170)	(0.0203)	(0.0271)
Inflation rate	-1.175***	-0.691***	1.866***
	(0.115)	(0.143)	(0.227)
Observations	37	37	37
Adjusted R^2	0.721	0.341	0.697

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: CPS and author's calculation. Sample Period: 1979-2017

There is no asymmetric response of nominal hourly wage change distribution to employment. Consider the specification, taking into account an asymmetric response of nominal wage change distribution to the employment, meaning that the response to the declining employment is different from the response to inclining employment. From the regression specification (2), γ captures asymmetric response to declining employment. However, from table 8, we can see γ is not statistically different from zero, implying that there is no asymmetric response of nominal wage change distribution to employment.

$$\begin{aligned}
\text{[Spike at zero]}_t &= \alpha_1 + \beta_1(1-e_t) + \gamma_1(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t)>0] + \epsilon_{1t} \\
\text{[Fraction of wage cuts]}_t &= \alpha_2 + \beta_2(1-e_t) + \gamma_2(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t)>0] + \epsilon_{2t} \\
\text{[Fraction of raises]}_t &= \alpha_3 + \beta_3(1-e_t) + \gamma_3(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t)>0] + \epsilon_{3t}
\end{aligned} \tag{2}$$

Primary results are robust to nominal hourly wage change distribution for salaried workers. For salaried workers, we can calculate the hourly wage as dividing the usual weekly earning by the usual weekly hours worked.[19] Table 9 shows regression results using imputed hourly wages for salaried workers. We can still see that the spike at zero is negatively related with inflation and employment, and the spike at zero fluctuates more than the fraction of workers with wage cuts.

Table 9: Regression results using imputed hourly wages for salaried workers

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero $\Delta W = 0$	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$
1-Epop	0.429***	-0.0646	-0.364	0.471***	0.0535	-0.524**
	(0.0805)	(0.240)	(0.308)	(0.0539)	(0.165)	(0.196)
Inflation rate				-0.278***	-0.782***	1.060***
				(0.0322)	(0.122)	(0.132)
				0.472/0.524 = 0.9		
Observations	36	36	36	36	36	36
Adjusted R^2	0.416	-0.0269	0.0224	0.656	0.430	0.601

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1994, 1995). Inflation rate is calculated from CPI-U. Hourly rate is calculated from usual weekly earning/usual hours worked per week.

The main result is robust to groups of hourly workers based on worker characteristics - gender, age, race, education. Robustness results are available from the appendix A.2.

5.2 Aggregate analysis: SIPP

To analyze the cyclicality of nominal wage change distribution using the SIPP, this paper creates three aggregate time series using the SIPP for both job stayers and job switchers. Table A11 in the appendix shows the spike at zero and the fraction of wage cuts and raises for each year and table A12 shows three time series data for both job stayers and job switchers.

Consider regression specification (1) to explore the cyclicality of three data series. Different from the CPS, the SIPP does not have rotating panel and there are discontinuities between panels.

[19] This imputed hourly wage can be more volatile than the actual hourly wage due to measurement error in hours worked for salaried workers.

To control heterogeneity coming from different panels, panel fixed effects are included.[20] The table 10 shows regression results based on (1), first three columns include all hourly workers and the column (4) ~ (6) are for hourly job stayers, and the last three columns are for hourly job switchers.

Table 10: The spike at zero, the fraction of wage cuts and raises - job statyers vs. job switchers, SIPP

	All hourly paid workers			Job stayers			Job switchers		
	(1) Spike at zero	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$	(7) Spike at zero	(8) Fraction of $\Delta W < 0$	(9) Fraction of $\Delta W > 0$
1 - Epop	1.794***	-0.437	-1.357***	2.186***	-0.369	-1.817***	1.234*	-0.383	-0.851
	(0.386)	(0.270)	(0.438)	(0.720)	(0.353)	(0.550)	(0.590)	(0.629)	(0.678)
Inflation	0.0405	-0.753***	0.713*	0.288	-0.856***	0.568	-0.218	-0.677	0.895*
	(0.312)	(0.213)	(0.391)	(0.357)	(0.220)	(0.447)	(0.351)	(0.574)	(0.499)
Panel Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	1.794/1.357=1.32			2.186/1.817=1.20			1.234/0.851 = 1.45		
Observations	24	24	24	24	24	24	24	24	24
Adjusted R^2	0.982	0.762	0.970	0.985	0.877	0.975	0.644	0.567	0.810

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source : SIPP and author's calculation. Sample Period : 1984-2013 (except 1990, 1996, 2001, 2004, 2008).

The results from first three columns of the table 10 show that the spike at zero increases when employment declines and the spike at zero fluctuates more than the fraction of wage cuts, which is consistent of the existence of DNWR and results using the CPS.

Then, is the countercyclicality of the spike at zero mostly coming from job stayers? Yes, the spike at zero of job stayers responds to the employment more than the spike at zero of job switchers. However, the spike at zero of job switchers also increases when employment declines. Nominal wages are more rigid for job stayers than job switchers, as the average spike at zero of job stayers is higher than the average spike at zero from job switchers. It is not true that the cyclical property only comes from job stayers. Even job switchers show greater countercyclicality of the spike at zero compared to the fraction of wage cuts.

5.3 Comparisons to the previous literature: CPS

The figure 4 compares the spike at zero from the previous literature using the CPS and the one that I constructed. When I construct the spike at zero from nominal wage change distribution, I include all hourly workers including both job stayers and job switchers. One major difference of this paper from previous literature using the CPS is that it focuses on the spike at zero among job stayers only.

Card and Hyslop (1997) use the CPS of sample period from 1979-1993 to construct the share of workers with no wage change among hourly paid job stayers. Elsby, Shin, and Solon (2016) use the CPS from 1980 - 2012 and job tenure supplements to construct the share of workers with no

[20] Overall, 5 panel fixed effects are included. One for every panel before 1996 panel and dummies for 1996, 2001, 2004, and 2008 panel. There are 24 observations but 8 regressor.

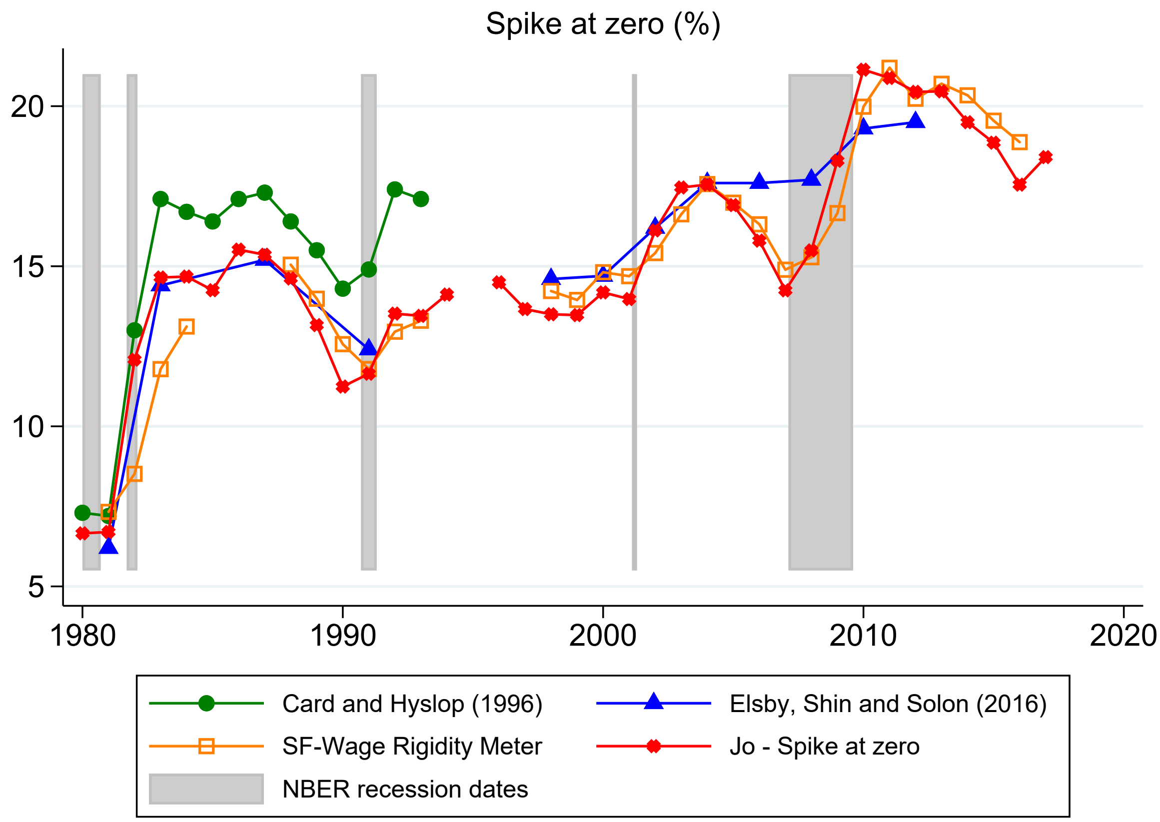


Figure 4: Comparisons of the spike at zero from the previous literature

Notes: Card and Hyslop (1996) - Data: CPS, Sample Period: 1979 - 1993, Job stayers only
Elsby, Shin and Solon (2016) - Data: CPS, Sample Period: 1980 - 2012 (biannual), Job stayers only
SF Wage Rigidity Meter - Data: CPS, Sample Period: 1980 - 2017, Job stayers only
Jo (2018) - Data: CPS, Sample Period: 1980 - 2017, Both job stayers and job switchers

wage change among hourly paid workers whose job tenure is more than one year. San Francisco Fed publishes Wage Rigidity Meter using the CPS from 1980 to 2017 with some gaps, which tells the fraction of works with a zero wage change among workers who have not changed their jobs.

Based on the description, the spike at zero from Card and Hyslop (1997), Elsby, Shin, and Solon (2016), and Wage Rigidity Meter should be the same; however, this is not the case. Although they are highly correlated with each other, there are differences in the level of the spike at zero. The spike at zero by Card and Hyslop (1997) is higher than the one from Elsby, Shin, and Solon (2016) and Wage Rigidity Meter. Instead, the spike at zero from Elsby, Shin, and Solon (2016) and Wage Rigidity Meter closely follows the spike at zero that I constructed, which includes both job stayers and job switchers in the CPS. However, we know that the spike at zero for job stayers is higher than the spike at zero for job switchers from the SIPP. This may imply that the spike at zero from Elsby, Shin, and Solon (2016) the Wage Rigidity Meter do not solely come from job stayers.

6 The state-level cyclicality of nominal wage change distribution

Using cross-regional data allows more observations to test the hypothesis. To explore cyclicality of nominal hourly wage change distribution across US states, this paper constructs the state level spike at zero, share of wage cuts and raises. This helps to provide different interpretation from the recent papers using the state-level variations, Beraja, Hurst, and Ospina (2016) and Kurmann and McEntarfer (2017). Beraja, Hurst, and Ospina (2016) argue that wages are fairly flexible using cross-state variations of nominal wage growth rates and employment growth. Kurmann and McEntarfer (2017) showed the increased incidence of wage cuts during the downturn suggest that DNWR may not be a binding constraint using the data from Washington state. This section shows that state-level changes in nominal wage change distribution are still consistent with the existence of DNWR.

6.1 State-level analysis: CPS

This paper constructs three statistics - the spike at zero, the fraction of wage cuts and raises- and employment for 50 states from 1979 to 2017 except 1985, 1986, 1995, and 1996.[21]

Similar to the regression equation (1) in the aggregate analysis, we can think of the following state level regression equations:

$$\begin{aligned} \text{[Spike at zero]}_{it} &= \alpha_{i,s} + \gamma_{t,s} + \beta_s(1 - e_{st}) + \epsilon_{1st} \\ \text{[Fraction of wage cuts]}_{it} &= \alpha_{i,n} + \gamma_{t,n} + \beta_n(1 - e_{st}) + \epsilon_{2st} \\ \text{[Fraction of raises]}_{it} &= \alpha_{i,p} + \gamma_{t,p} + \beta_p(1 - e_{st}) + \epsilon_{3st} \end{aligned} \tag{3}$$

, where $\alpha_{i,s}$, $\alpha_{i,n}$, and $\alpha_{i,p}$ are state fixed effects and $\gamma_{t,s}$, $\gamma_{t,n}$, and $\gamma_{t,p}$ are time fixed effects. State fixed effects control state specific differential time trends. Time fixed effects control common factors across states in each point of time such as aggregate shocks including monetary policy shocks and aggregate inflation.

The increase in the spike at zero is higher than the increase in the fraction of workers with wage cuts when the employment declines in a state. Table 11 shows the regression results using the regression specification (1), exploiting state-level variation. A 1 percentage point decrease in the employment in one state lowers the fraction of workers with raises by 0.67 percentage points. Out of 0.67 percentage points, the spike at zero decreases by 0.38 percentage points and the fraction of workers with wage cuts decreases by about 0.29 percentage points, which makes 57% of hourly workers experiencing no wage change among workers not having raises when employment declines. The higher responsiveness of the spike at zero compared to the fraction of workers with wage cuts in state-level variations implies that then state-level cyclical variations in nominal wage change distribution is still consistent with DNWR.

However, the excess responsiveness of the spike at zero using cross-state variation is smaller than the aggregate evidence. This is because time fixed effects absorb all aggregate variations and

[21] 4 years are droped due to small sampe size.

Table 11: The spike at zero, the fraction of wage cuts and raises across states

	(1)	(2)	(3)
	Spike at zero	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
1 - Epop	0.383***	0.292***	-0.675***
	(0.0792)	(0.0642)	(0.0865)
State fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
	0.383/0.674 = 0.57		
Observations	1700	1700	1700
Adjusted R^2	0.606	0.537	0.712

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: CPS and author's calculation. Sample Period: 1980-2017 (except 1985, 1986, 1995, and 1996 due to small sample sizes). The sample consists of 50 states over 34 years.

we are exploiting only differential variations from its state average and aggregate average, which allows variations are within-states only.

6.2 State-level analysis during recessions: CPS

Then, were wages fairly flexible during the Great Recession? According to Beraja, Hurst, and Ospina (2016), nominal wage growth rates were strongly and positively correlated with the employment growth rates across states during the Great Recession, which is shown in the left panel of figure 6. The left panel of figure 6 plots the percentage change of median nominal wage growth rates from 2007 to 2010 against the percentage change in employment for each state.[22] It shows that a state with a higher drop in employment has a lower wage growth rates. Thus, they conclude that wages were fairly flexible since nominal wage growth rates were responding to changes in employment. However, we can see that the increase in the spike at zero is negatively correlated with the employment growth rates across states during the Great Recession in the right panel of figure 6. In other words , a state with a higher drop in employment had a higher increase in the spike at zero; more workers experienced downwardly rigid wages for those states with more drop in employment.

To explore how nominal wage growth distribution changes across states from 2007 to 2010

[22]The left panel of figure 6 is replicated figure 3 of of Beraja et al. (2016). They compute the composition adjusted average nominal wage for each state every year using the ACS from 2007 - 2010, as the ACS does not have a panel structure. The sample consists of men between the ages of 21 and 55 with a strong attachment to the labor market only.

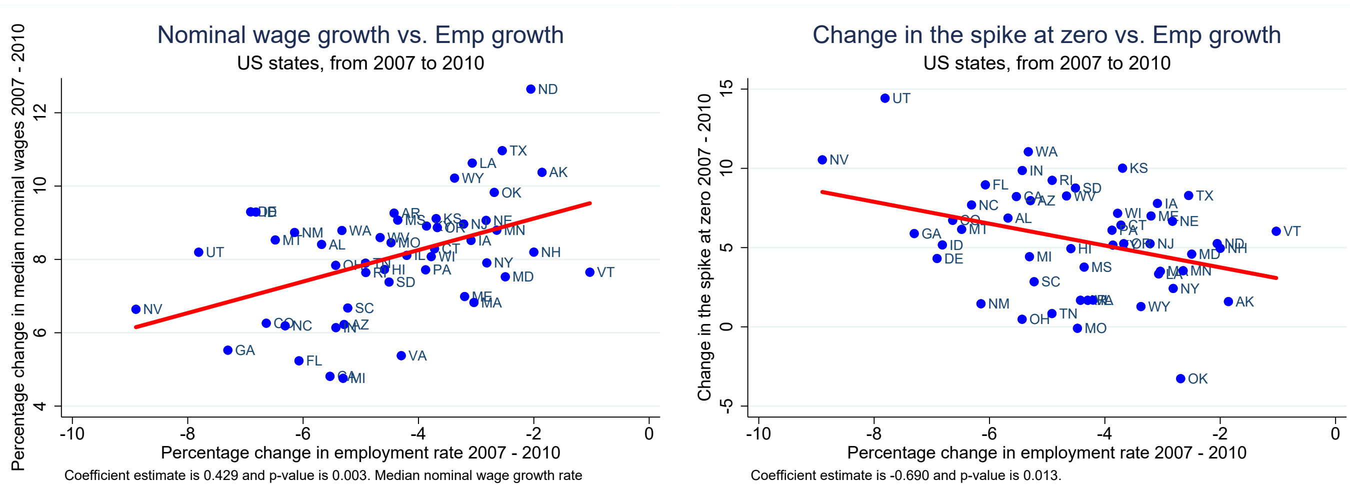


Figure 5: Nominal wage growth and changes in the spike at zero vs. employment growth from 2007 to 2010

Data source: CPS and author's calcuation. The left panel shows the median nominal wage growth and employment growth rates from 2007 to 2010 across states. The right panel shows the change in the spike at zero and employment growth from 2007 to 2010 across states.

during the Great Recession, consider following regression equations:

$$\begin{aligned}
\Delta[\text{Spike at zero}]_{it} &= \alpha_s + \beta_s \Delta(1 - e_{st}) + \epsilon_{s,it} \\
\Delta[\text{Fraction of wage cuts}]_{it} &= \alpha_n + \beta_n \Delta(1 - e_{st}) + \epsilon_{n,it} \\
\Delta[\text{Fraction of raises}]_{it} &= \alpha_p + \beta_p \Delta(1 - e_{st}) + \epsilon_{p,it} \\
\ln W_{i2010} - \ln W_{i2007} &= \alpha + \beta \Delta(1 - e_{st}) + \epsilon_{it}
\end{aligned} . \tag{4}$$

Table 12 shows regression results based on (4). A 1 percentage decrease in employment in a state leads to a decrease in the fraction of raises by 0.9 percentage points. Out of 0.9 percentage points, there was an increase in the spike at zero by 0.7 percentage points and increase in the fraction of wage cuts by 0.2 percentage points. As 7 out of 9 workers had no wage change when there is a decrease in the employment in a state, we can still see that the responsiveness of the spike at zero is higher than the responsiveness of wage cuts.

Yet still, the empirical result is compatible with Beraja, Hurst, and Ospina (2016)'s empirical finding: the positive correlation with nominal wage growth rates and changes in employment from the last column of table 12. This is possible because a state with more decline in employment is likely to have a higher share of wage cuts, leading to more drop in nominal wage growth rates. Thus, I argue that the finding by Beraja et al. (2016) is still consistent with the existence of DNWR.

The left panel of figure 6 is often called as the nominal wage Phillips curve. Galí (2010) shows that the wage Phillips curve is steeper if the degree of wage rigidity is smaller in the New Keynesian model. In the case of full wage flexibility, the nominal wage Phillips curve should be

Table 12: Change in nominal wage distribution from 2007 to 2010 across states

	(1) Change in Spike at zero $\Delta W = 0$	(2) Change in Fraction of $\Delta W < 0$	(3) Change in Fraction of $\Delta W > 0$	(4) $\ln \frac{W_{s2010}}{W_{s2007}}$
Percentage change in the employment	-0.690** (0.269)	-0.215 (0.321)	0.904** (0.397)	0.429*** (0.136)
		0.690/0.904 = 0.76		
Observations	50	50	50	50
Adjusted R^2	0.103	-0.0103	0.0695	0.186

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Data source: CPS and author's calculation. Sample Period: 2007 - 2010.

vertical. From the fact that the curve is not vertical, we can conclude that there exists wage rigidity. To further argue changes in the degree of wage rigidity, we should explore changes in the slope of the nominal wage Phillips curve.

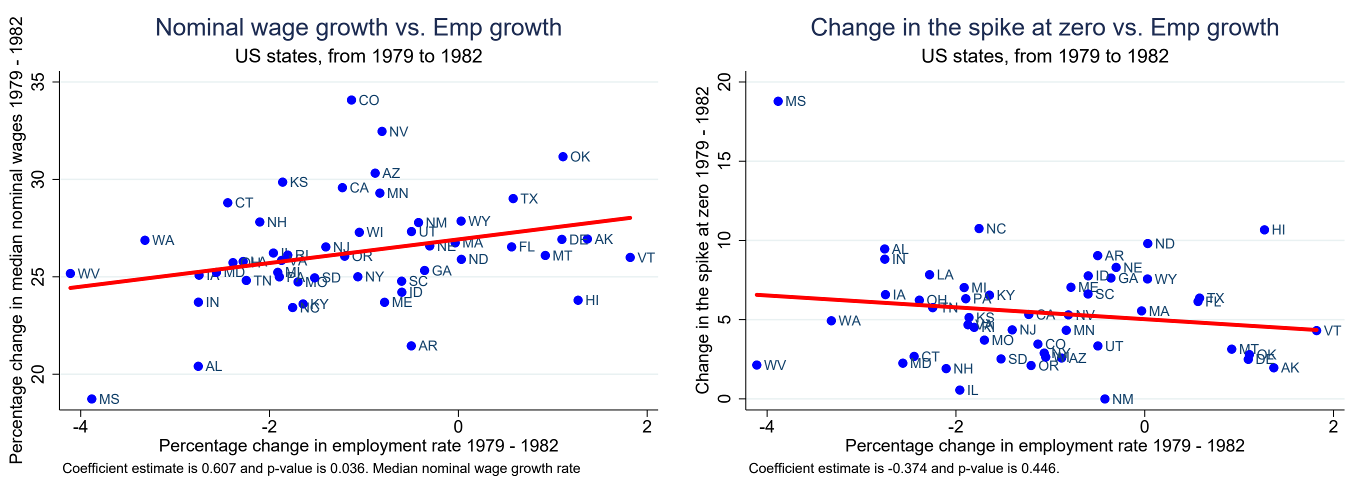


Figure 6: Nominal wage growth and changes in the spike at zero vs. employment growth from 1979 - 1982

Data source: CPS and author's calcuation. The left panel shows the median nominal wage growth and employment growth rates from 1979 to 1982 across states. The left panel shows the change in the spike at zero and employment growth from 1979 to 1982 across states.

6.3 State-level evidence: SIPP

The table 13 shows regression results based on the equation (3) using the SIPP. First three columns include all hourly workers, the next three columns include only job stayers, and the last three columns are for job switchers.

For hourly workers, the decrease in the employment by 1 percentage point in one state leads to the decrease in the fraction of workers with raises by 0.5 percentage points. Out of 0.5 percentage point, 0.4 experience no wage change, which is 80% of them. We can still find the increase in the spike at zero is higher than the increase in the fraction of wage cuts when employment declines, which is consistent with the existence of DNWR. Both job stayers and job switchers show higher responsiveness of the spike at zero compared the fraction of wage cuts, consistent with the existence of DNWR. This again shows that not job stayers is not the sole one deriving the main results, but also hourly wages for job switchers behave in a consistent way of the existence of DNWR.

Table 13: The spike at zero, the fraction of wage cuts and raises - job-statyers vs. job-switchers across states, SIPP

	All hourly paid workers			Job stayers			Job switchers		
	(1) Spike at zero	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$	(7) Spike at zero	(8) Fraction of $\Delta W < 0$	(9) Fraction of $\Delta W > 0$
1 - Epop	0.407***	0.0989	-0.506***	0.489***	0.121	-0.610***	0.348***	0.124	-0.471**
	(0.101)	(0.0767)	(0.111)	(0.123)	(0.0789)	(0.121)	(0.101)	(0.176)	(0.182)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	0.407/0.506=0.80			0.489/0.610=0.80			0.348/0.471= 0.74		
Observations	855	855	855	855	855	855	855	855	855
Adjusted R^2	0.842	0.341	0.783	0.871	0.499	0.814	0.171	0.0608	0.148

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: SIPP and author's calculation. Several small states are dropped due to small sample sizes. Overall 43 states. 36 states for 21 years. 7 states for 20 years.

7 Model

This section builds a heterogeneous agent model with both idiosyncratic and aggregate shock, imposing 5 different wage setting schemes - perfectly flexible, Calvo, long-term contracts, menu-costs, and downward wage rigidity model. Firm uses aggregate labor to produce output and provides labor demand function. Households supply heterogeneous labor in terms of idiosyncratic labor productivity, and they set the nominal wage subject to labor demand and a wage setting constraint. The basic set up of the model is from Erceg, Henderson, and Levin (2000). Daly and Hobijn (2014); Mineyama (2018) introduced heterogeneous disutility of labor supply, and Fagan and Messina (2009) introduced idiosyncratic labor productivity shocks on the basis of Erceg, Henderson, and Levin (2000). The basic wage setting mechanism of heterogeneous labor in this paper is from Fagan and Messina (2009).

7.1 Firm

There is a representative firm, which produces consumption goods using the aggregate labor. The firm has a constant returns to scale production function in aggregate labor, which is,

$$Y_t = L_t$$

, where L_t represents the aggregate labor. The profit function of the firm is

$$\Pi_t = P_t Y_t - W_t L_t$$

, where P_t is the price of goods and W_t is the aggregate nominal wage in the economy. There is no product price rigidity, and the firm's profit will be redistributed to households. Firm's problem to maximize profits is equivalent to minimize the cost of labor. Hence, the firm chooses differentiated labor $l_t(i)$, indexed by $i \in [0,1]$, to minimize the total production cost

$$\min_{l_t(i)} \int W_t(i) l_t(i) di \quad \text{(s.t.)} \quad L_t = (\int_0^1 (q_t(i) l_t(i))^{\frac{\theta-1}{\theta}} di)$$

, given $W_t(i)$ is nominal wage for each individual i and $q_t(i)$ is idiosyncratic productivity for i. The problem of minimizing the cost of labor gives the labor demand function by the firm,

$$l_t^d(i) = q_t(i)^{\theta-1} (\frac{W_t(i)}{W_t})^{-\theta} L_t, \quad \theta > 1$$

, where θ governs the elasticity of substitution across differentiated labor. The quantity of labor demand increases in the level of productivity and decreases in the relative wage. The aggregate wage W_t is given by the Dixit-Stiglitz aggregate wage index,

$$W_t = \left[\int \left[\frac{W_t(i)}{q_t(i)} \right]^{1-\theta} di \right]^{\frac{1}{1-\theta}}.$$

7.2 Households

There is a continuum of household, indexed by $i \in [0,1]$ and each household chooses the consumption, saving, nominal wage, and labor supply to maximize life-time utility subject to intertemporal budget constraint, the labor demand function, and a wage setting constraint. Assume households have an additively separable preference between consumption and labor supply, similar to Erceg, Henderson, and Levin (2000).

Each household chooses the $\{C_t(i), B_{t+1}(i), W_t(i), l_t(i)\}$ to maximize

$$\max_{\{C_t(i), B_{t+1}(i), W_t(i), l_t(i)\}} \mathbb{E}_t \Sigma_{t=0}^{\infty} \beta^t \left[\frac{C_t(i)^{1-\gamma}}{1-\gamma} - \frac{1}{1+\psi} l_t(i)^{1+\psi} \right]$$

subject to

$$
\begin{aligned}
P_t C_t(i) + Q_{t+1} B_{t+1}(i) \leq & B_t(i) + W_t(i) l_t(i) + \Pi_t, \\
l_t^d(i) = & q_t(i)^{\theta-1} (\frac{W_t(i)}{W_t})^{-\theta} L_t, \\
& \text{Wage setting constraint}
\end{aligned}
$$

, given with $\{P_t, Q_{t+1}, \Pi_t, B_0(i), L_t\}$. P_t is the price level of consumption goods. Each household saves by $B_{t+1}(i)$ and Q_{t+1} represents the risk-free price of 1unit of good for the next period. γ is the relative risk aversion parameter and ψ is the inverse Frisch elasticity parameter. There are complete contingent asset markets so that idiosyncratic labor income is fully insured and the household consumes the exactly same amount. However, the amount of leisure is not insured so that the level of utility is lower for those who worked more.

The Lagrangian of the households problem is given by

$$
\begin{aligned}
\mathcal{L} = \mathbb{E}_t \Sigma_{t=0}^{\infty} \beta^t \Bigg\{ \frac{C_t(i)^{1-\gamma}}{1-\gamma} - \frac{\omega}{\psi+1} l_t(i)^{1+\psi} + \lambda_t(i)[B_t(i) + W_t(i) l_t(i) + \Pi_t - P_t C_t(i) - Q_{t+1} B_{t+1}(i)] \\
+ \mu_t(i)[q_t(i)^{\theta-1} (\frac{W_t(i)}{W_t})^{-\theta} L_t - l_t(i)] \\
+ \theta_t(i)[\text{Wage setting constraint}] \Bigg\}
\end{aligned} \tag{5}
$$

The first-order conditions with respect to $C_t(i)$ and B_{t+1}(i) are

$$C_t(i)^{-\gamma} = \lambda_t(i) P_t,$$

$$\lambda_t(i) Q_{t+1} = \beta \mathbb{E}_t \lambda_{t+1}(i)$$

, respectively. As consumption risks are fully insured by complete state contingent asset markets, we can rewrite the first order conditions as follows.

$$\lambda_t(i) = \lambda_t = \frac{C_t^{-\gamma}}{P_t}$$

$$Q_{t+1} = \beta \mathbb{E}_t \Bigg[\frac{P_t}{P_{t+1}} \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \Bigg]$$

7.3 Wage setting restrictions

As the household utility is additively separable, we can isolate the wage relevant part of the Lagrangian (5) and households choose the wage $W_t(i)$ and labor supply $l_t(i)$ to maximize

$$\max_{\{W_t(i),l_t(i)\}} \mathbb{E}_t \Sigma_{t=0}^{\infty} \beta^t \Big\{ \lambda_t(i) W_t(i) l_t(i) - \omega \frac{l_t(i)^{1+\psi}}{1+\psi} \Big\} \quad \text{(s.t.)} \quad \underbrace{l_t^d(i) = q_t(i)^{\theta-1} (\frac{W_t(i)}{W_t})^{-\theta} L_t}_{\text{Wage setting constraint}} \tag{6}$$

This paper introduces five different wage setting schemes.The first is that a perfectly flexible case in which there is no wage setting constraint.

Second, consider Calvo wage rigidity, assuming only a constant fraction of workers can optimize wages. This is the most commonly used wage setting mechanism for nominal rigidity. [23] Followed by Calvo (1983), wage setters cannot optimize their wages with the constant probability of μ^{Calvo}, regardless of the state of the economy. Calvo wage setting constraint can be rewritten as following,

$$W_t(i) = \begin{cases} W_{t-1}(i) & \text{, with the prob } \mu^{\text{Calvo}} \\ W_t^*(i) & \text{, with the prob } (1-\mu^{\text{Calvo}}) \end{cases}$$

, where $W_t^*(i)$ is the desired wage, nominal wage that maximizes the equation (6) in the absence of wage setting constraint in a period t.

Third, consider long-term contracts model. As workers are often in a long-term contract with the firm, the present discounted value of an expected nominal wages over the contract is important to determine employment rather than the remitted wages or observed wages in each point of time. This is often called by Barro's critique (Barro (1977)) or efficiency-wage theory. To address this concern by Barro (1977), Basu and House (2016) introduced long-term contracts in New Keyensian model in which firms pay the same nominal wages (remitted wages) over the contract. In this model, there are two notions of wages: allocative wages and remitted wages. Allocative wages determine the level of employment and remitted wages are the one that the firm actually remits to the workers. Firms calculate allocative wages under the perfectly flexible case and find the remitted wages of which present discounted value is the same as the present discounted value of allocative wages over the contract. Following by Basu and House (2016), the remitted wages for each i type of labor, $x_t(i)$ can be determined as follows.

$$\mathbb{E}_t[\Sigma_{j=0}^{\infty}[\beta(1-s)]^j \frac{\lambda_{t+j}}{\lambda_t} w_{t+j}(i)] = \mathbb{E}_t[\Sigma_{j=0}^{\infty}[\beta(1-s)]^j \frac{\lambda_{t+j}}{\lambda_t} x_t(i)]$$

$$x_t(i) = \frac{\mathbb{E}_t[\Sigma_{j=0}^{\infty}[\beta(1-s)]^j \frac{\lambda_{t+j}}{\lambda_t} w_{t+j}(i)]}{\mathbb{E}_t[\Sigma_{j=0}^{\infty}[\beta(1-s)]^j \frac{\lambda_{t+j}}{\lambda_t}]}$$

[23] Erceg, Henderson, and Levin (2000); Christiano, Eichenbaum, and Evans (2005); Smets and Wouters (2007), and so on

, where s is the probability of renewing the contract.

Fourth, consider the menu-costs model of wage rigidity, motivated by the empirical evidence that changes in nominal wage change distribution is state-dependent. In the context of wage setting model, we may imagine the cost involved in changes in wages. For example, whenever the wage setters want to change their wage, they have to pay an additional cost of bargaining to bring them to the bargaining table. Wage setters have to pay menu-costs to change their wage with the probability of μ^{Menu}. With the other probability of $1-\mu^{\text{Menu}}$, wage setters can freely change their wage. This is often called as the random menu-cost model in the price rigidity literature (Alvarez, Le Bihan, and Lippi (2014)) to explain small changes in prices. This can be summarized as follows.

$$W_t(i) = \begin{cases} \begin{cases} W_t^*(i) & \text{if } W_t^*(i) \neq W_{t-1}(i) \text{, pays cost } K \\ W_{t-1}(i) & \text{No cost} \end{cases} & \text{,with the prob of } \mu^{\text{Menu}} \\ W_t^*(i) & \text{,with the prob of (1-}\mu^{\text{Menu}}\text{)} \end{cases}$$

The fifth wage setting scheme is DNWR model. If the optimal wage in a period t, $W_t^*(i)$, maximizing the equation (6) in the absence of wage setting constraint in a period t, is higher than the previous wage, $W_{t-1}(i)$, then the current wage can be the optimal wage, $W_t(i) = W_t^*(i)$. There is no explicit restriction to raise the current nominal wage. However, if the optimal wage in a period t , $W_t^*(i)$, is lower than the previous wage, $W_{t-1}(i)$, then wage setter cannot lower wage with the probability of μ^{DNWR}. With the other probability of $(1-\mu^{\text{DNWR}})$, wage setters can lower wages optimally. This wage setting restriction can be summarized, as follows.

$$\begin{aligned} &\text{if } W_t^*(i) \geq W_{t-1}(i) \begin{cases} W_t(i) = W_t^*(i) \end{cases} \\ &\text{if } W_t^*(i) < W_{t-1}(i) \begin{cases} W_t(i) = W_{t-1}(i) & \text{,with the prob } \mu^{\text{DNWR}} \\ W_t(i) = W_t^*(i) & \text{,with the prob } (1-\mu^{\text{DNWR}}) \end{cases} \end{aligned}$$

Although there is no explicit restriction on raising nominal wages, there is an implicit restriction on raising nominal wages as the wage setters solve the intertemporal problem. When wage setters find the optimal to increase their wage, they do not increase as much as they want to maximize current utility because they understand that they cannot lower their wages with the probability of μ^{DNWR} in the future. This is pointed out by Elsby (2009) and Mineyama (2018).

7.4 Closing the market

Goods market clearing condition is

$$Y_t = C_t.$$

In the economy, nominal output equals to the total wage payment in the economy, which is the same as total money supply in the economy, as following.

$$P_tY_t = P_tC_t = W_tL_t = M_t$$

, where M_t is the aggregate money supply. Monetary authority uses nominal output growth rate targeting rule, given by

$$\ln(M_{t+1}) = \mu + \ln(M_t) + \eta_{t+1} \quad \eta_{t+1} \sim \mathbb{N}(0, \sigma_\eta^2) \tag{7}$$

, where μ is the average growth of nominal output. Idiosyncratic productivity shock follows AR(1) process as following:

$$\ln(q_{t+1}(i)) = \rho_q \ln(q_t(i)) + \epsilon_{t+1}(i), \quad \epsilon_{t+1}(i) \sim \mathbb{N}(0, \sigma_\epsilon^2).$$

7.5 Value function

We can write down households' wage setting problem in a recursive way. Note that the value function is a function of the relative wage rather than both individual wage and aggregate wage, which allows us to reduce one dimension of the problem, followed by Nakamura and Steinsson (2008).

Under the Calvo wage rigidity, wage setters can optimize their wage with probability $(1-\mu^{\text{Calvo}})$ regardless of the sign of wage change. To introduce randomness, one more state variable, x_t, a binary variable, is added. Once x_t equals 1 with the probability of $(1-\mu^{\text{Calvo}})$, wage setters can re-optimze their wage. The recursive problem under the Calvo rigidity can be written as follows:

$$\begin{aligned} V(q_t(i), L_t, \frac{W_{t-1}(i)}{W_t}, x_t) = \max_{W_t(i)} & \left[H(q_t(i), L_t, \frac{W_t(i)}{W_t}) + \beta\mathbb{E}(V(q_{t+1}(i), L_{t+1}, \frac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(x_t = 1) \\ + \max_{W_t(i)} & \left[H(q_t(i), L_t, \frac{W_{t-1}(i)}{W_t}) - C \times \mathbb{I}(W_t(i) \neq W_{t-1}(i)) + \beta\mathbb{E}(V(q_{t+1}(i), L_{t+1}, \frac{W_{t-1}(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(x_t = 0) \end{aligned}$$

, where $C > \infty$ and

$$H(q_t(i), L_t, \frac{w_t(i)}{W_t}) = q_t(i)^{\theta-1}(\frac{w_t(i)}{W_t})^{1-\theta} L_t^{(1-\gamma)} - \omega \frac{[q_t(i)^{\theta-1}(\frac{w_t(i)}{W_t})^{-\theta} L_t]^{1+\psi}}{1+\psi}$$

, which can be derived from substituting labor demand into the current objective function in the equation, (6). When x_t is one, wage setters adjust nominal wages freely, whereas wage setters have to pay infinite cost of wage adjustment when x_t equals to zero.

For the menu-costs model, wage setters have to pay an additional fixed cost, K, to adjust their wage with the probability of μ^{Menu}, when x_t equals to zero. With the other probability of

$(1-\mu^{\text{Menu}})$, wage setters can adjust wages without any cost. The recursive problem with menu-costs can be written as follows:

$$V(q_t(i), L_t, \frac{W_{t-1}(i)}{W_t}, x_t) = \max_{W_t(i)} \left[H(q_t(i), L_t, \frac{W_t(i)}{W_t}) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \frac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(x_t = 1)$$
$$+ \max_{W_t(i)} \left[H(q_t(i), L_t, \frac{W_t(i)}{W_t}) - K\mathbb{I}(W_t(i) \neq W_{t-1}(i)) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \frac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(x_t = 0).$$

Under the DNWR, wage setter's problem is

$$V(q_t(i), L_t, \frac{W_{t-1}(i)}{W_t}, x_t) = \max_{W_t(i)} \left[H(q_t(i), L_t, \frac{W_t(i)}{W_t}) \mathbb{I}(\frac{W_t(i)}{W_t} \geq \frac{W_{t-1}(i)}{W_t}) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \frac{W_t(i)}{W_{t+1}}, x_{t+1})) \right]$$
$$+ \max_{W_t(i)} \left[H(q_t(i), L_t, \frac{W_t(i)}{W_t}) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \frac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(\frac{W_t(i)}{W_t} < \frac{W_{t-1}(i)}{W_t}) \mathbb{I}(x_t = 1)$$
$$+ \max_{W_t(i) = W_{t-1}(i)} \left[H(q_t(i), L_t, \frac{W_{t-1}(i)}{W_t}) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \frac{W_{t-1}(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(\frac{W_t(i)}{W_t} < \frac{W_{t-1}(i)}{W_t}) \mathbb{I}(x_t = 0).$$

If the current desired wage is higher than the previous wage, wage setters can raise nominal wage. However, if the current desired wage is lower than the previous wage, wage setters can adjust downwardly only when $x_t = 1$, with the probability of $(1-\mu^{\text{DNWR}})$.

8 Numerical Results

Since the model has both idiosyncratic shock and aggregate shock, I solve the model numerically. This sections starts to explain calibrated parameters and solution methods. In addition, this section shows the stationary nominal wage change distribution and cyclical property of nominal wage change distribution from five different wage setting schemes. This paper shows only DNWR model exhibits consistent implications with empirical distribution. Finally, this paper compares data moments to moments generated by model.

8.1 Calibration

Table 14 shows calibrated parameters. Parameters in the top panel show parameters related to preference. The relative risk aversion parameter, γ, is 1, which implies the intertemporal elasticity of substitution as 1. The discount rate β is 0.97, which implies a steady-state annual real interest rate is 3%. ψ = 0.5 is the inverse of Frisch elasticity, which is in a permissible range of macro literature shown in Chetty, Guren, Manoli, and Weber (2011). Different from earlier parameters, there is no consensus regarding the wage elasticity of labor demand, θ. θ varies from 1.67 to 21 from the previous theory literature.[24] This paper sets θ to be 3, which implies steady state markup

[24] Erceg et al. (2000) set θ at 4. Christiano et al. (2005) set θ at 21. Smets and Wouters (2007) set wage markup at 1.5, which implies θ being 3. Daly and Hobijn (2014) set θ at 2.5. The model from the Daly and Hobijn (2014) has homogeneous differentiated labor but households have different disutility from the labor supply. Fagan and Messina

1.5, followed by Smets and Wouters (2007). Recent paper by De Loecker and Eeckhout (2017) mention that the average markup in 1980 was 1.18 and started to rise and it becomes 1.67 in 2014.

The second panel of table 14 shows the parameters governing shock processes in the economy. Since the nominal output is total wage payment in the model, this paper uses total wage payment[25] to estimate the aggregate shock process, given by the equation (7). I estimated the constant growth rate (μ) and the standard deviation from the growth rate of the total wage payment. Parameters related to idiosyncratic productivity are from the Guvenen (2009). Guvenen (2009) decomposed individual labor earnings into nonstationary and stationary components using more than 20 years of individual labor earnings data from PSID. For the individual labor productivity shock in this paper, I use the stationary process of labor earnings from Guvenen (2009), allowing heterogeneity growth rate of income.[26]

The last panel of table 14 shows parameters governing the degree of wage rigidity. The probability that workers constrained not to adjust their wages downwardly, μ^{DNWR}, comes from the table 7, aggregate evidence using the CPS. Among households whose desired wage is lower than the previous wage, only 37% of them can lower current wages at the desired level. Other 67% of workers cannot lower wage if the desired wage is below the previous wage. Therefore, μ sets to be 0.67. Other than DNWR wage setting, $\mu^{\text{Calvo}}$from Calvo model,s from long-term contracts model, and μ^{Menu} and K from menu costs model, are set to have the same size of the spike at zero at the steady-state spike at zero under the DNWR.

Table 14: Calibrated Parameters

Parameters	Value	Description	Target/Source
γ	1	Relative Risk Aversion	
β	0.971	Discount rate	Annual interest rate, 3%
ψ	0.5	Inverse of Frisch elasticity	
θ	3	Elasticity of substitution	
μ	0.044	Mean level of aggregate shock	Total wage payment
σ_m	0.021	Standard deviation of aggregate shock	
ρ_q	0.821	Persistence of idiosyncratic shock	Guvenen (2009)
σ_q	0.17	Standard deviation of idiosyncratic shock	Guvenen (2009)
μ^{DNWR}	0.67	The probability of DNWR	The cyclicality of DNWR
μ^{Calvo}	0.22	The frequency of no wage change	Matching the spike at zero, implied by DNWR model
$\mu^{\text{Menu cost}}$	0.8	The probability of facing menu cost	
K	0.002	Menu cost	
s	0.23	The probability of continuing contract	

Time unit is a year.

(2009) used $\theta = \frac{11}{12}$. Mineyama (2018) used θ at 9, which makes the steady state wage mark up 12.5%

[25]The total wage payment is defined as the median weekly earning (Series ID: LEU0252881500) times the number of people at work (CPS series LNU02005053). Source: https://www.bls.gov/data

[26]Table 1 row(4) from Guvenen (2009). HIP (heterogeneity income process) after assuming $\sigma_\beta \neq 0$

8.2 Solution methods

This paper solves the recursive problem using the policy function iteration over the discretized state space. Wage setter's problem is infinite dimensional as they have to take into account the entire wage and productivity distribution. Followed by Krusell and Smith (1998), this paper assumes agents use only partial information, the first and second moments of the distribution, to predict the law of motion of the aggregate wage growth. I choose the simple parametric function for the aggregate wage growth rate, as follows.

$$W_{t+1} = H(W_t, M_{t+1})$$
$$\ln(\frac{W_{t+1}}{W_t}) = H(\ln(\frac{M_{t+1}}{W_t})) = \gamma_0 + \gamma_1 \ln\frac{M_{t+1}}{W_t} + \gamma_2(\ln\frac{M_{t+1}}{W_t})^2 \tag{8}$$

Parameters, γ_0, γ_1, and γ_2, are estimated by the OLS using the realized wage inflation and aggregate state variables. Iterate the algorithm until the predicted wage inflation gets close enough to the realized wage inflation. Krusell and Smith (1998) reported R^2 to check the accuracy of the predicted law of motion and Den Haan (2010) argue that the maximum forecast error should be reported. R^2 is higher than 0.98 [27] and the maximum forecast error is less than 0.1%. The detailed algorithm is followed by Heer and Maussner (2009), which is available in the appendix D.1.

8.3 Stationary wage change distribution

Figure 7 shows stationary nominal wage change distribution generated from 5 different wage setting schemes. The red bar represents the fraction of workers with exact zero wage change and the size of blue bar is 0.01. The top left panel shows stationary wage change distribution under the perfectly flexible case. Nominal wage change distribution is symmetric around the median and there is no spike at zero.

Calvo model generates the spike at zero but symmetric stationary wage change distribution. The second left panel of figure 7 shows stationary wage change distribution generated by Calvo model. We can observe the spike at zero, which is shown as the red bar. The frequency of wage adjustment from the Calvo model is the assumed to be constant over the business cycle, so does the frequency of no wage change. However, we cannot find the asymmetry of nominal wage distribution - lack of wage cuts compared to raises. Instead, the stationary distribution is symmetric around the median, excluding the spike at zero. We can imagine one variant of the Calvo model in which the frequency of wage adjustment is stochastic, responding to the business cycle. In this way, we may be able to generate the countercyclical spike at zero, but we cannot generate the asymmetric wage distribution.

Long-term contracts wage setting generates the spike at zero but symmetric stationary wage change distribution. The second right panel of figure7 shows the remitted wage change distribution

[27] $R^{2,\text{Flex}} = 0.99$, $R^{2,\text{Calvo}} = 0.98$, $R^{2,\text{Menu}} = 0.99$, and $R^{2,\text{DNWR}} = 0.98$.

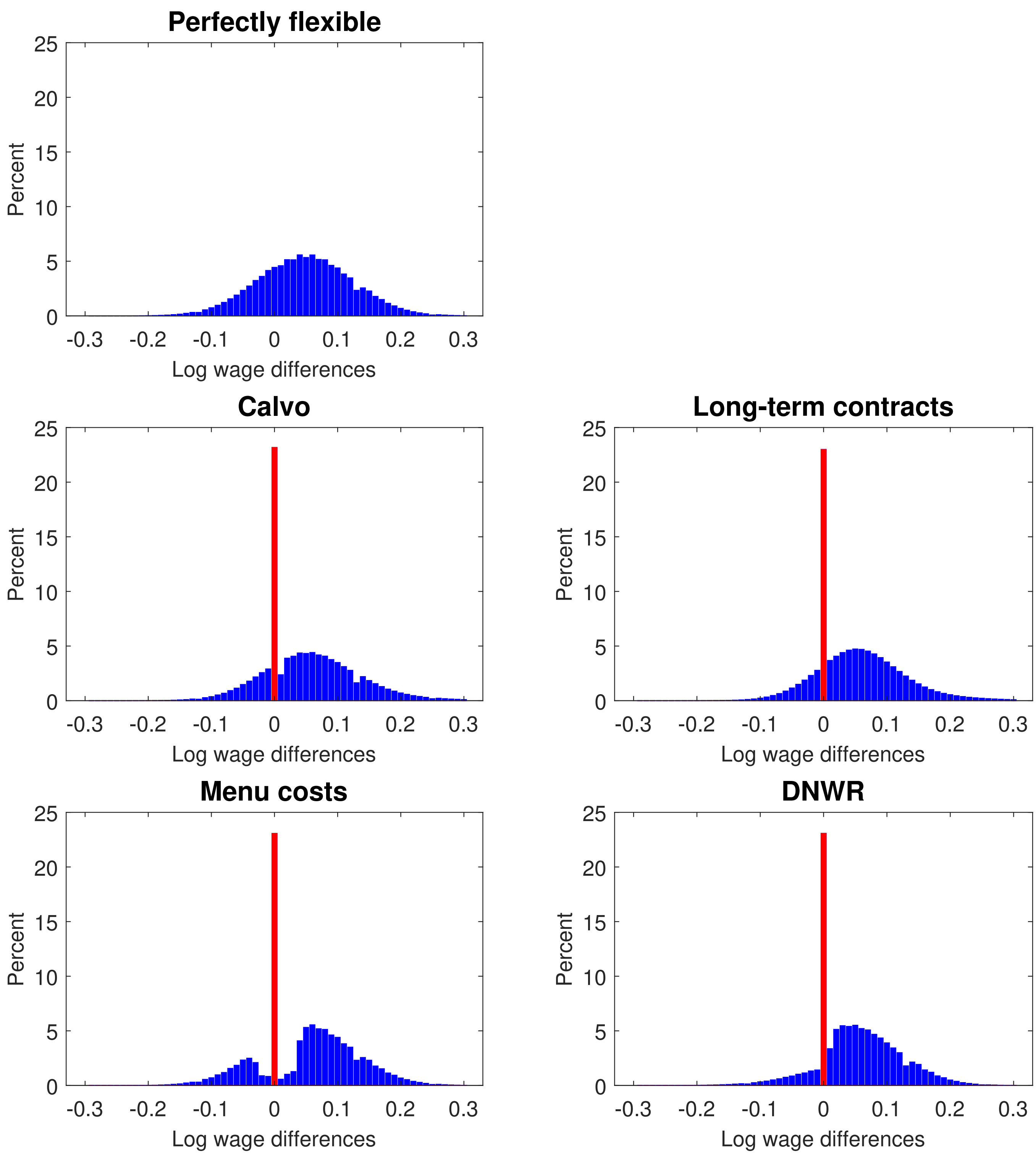


Figure 7: Staionary wage change distribution from 5 different wage setting schemes

Stationary distribution generated by 5 different wage setting schemes are drawn. The red bar represents the percentage of workers with no wage change and the size of the blue bin is 0.01. The top left panel is from a perfectly flexible case. The second row is from the Calvo model (left) and long-term contracts model (right). The bottom panel is from the menu-costs model (left) and DNWR (right).

from the long term contract under the perfect foresight. Allocated wages come from the perfectly flexible model, so its implications on employment should be the same as the perfectly flexible model. However, the nominal wage distribution has the spike at zero and is symmetric around the median, which is similar to the one from the Calvo model, which is again inconsistent with empirical findings.

Menu-costs of wage adjustment generates the spike at zero, but there is no sudden drop in below zero from stationary wage change distribution compared to above zero. The stationary wage change distribution from the menu-costs model is shown at the bottom left panel of figure 7. As wage setters have to pay an additional fixed cost for any changes in wages, wage setters decide to change their wage only when the current wage is significantly different from the desired wage. Hence, the size of wage change is big and there are not many small wage changes compared to the Calvo model. Under the positive inflation, nominal wage change distribution has higher densities above zero than below zero. Therefore, more portion of the spike at zero comes from the right to the zero rather than the left to the zero of nominal wage distribution, which leads to the lack of raises compared to wage cuts. This is inconsistent with empirical nominal wage change distribution, shown in the section 4.

DNWR wage restriction generates a spike at zero and a sudden drop in below zero compared to above zero from stationary nominal wage change distribution. The bottom right panel of figure 7 displays nominal wage change distribution under the DNWR model. We can observe the spike at zero. Furthermore, nominal wage change distribution is asymmetric - fewer wage cuts compared to raises, and there is a sudden drop in the below zero compared to the above zero. Therefore, we can conclude that only DNWR model among 5 wage setting schemes generates the stationary distribution, consistent with empirical evidence.

8.4 The cyclicality of wage change distribution

This section runs the main regression (1) using simulated data from 5 different wage setting schemes to see which model has a consistent implication with the empirical finding: the spike at zero rises and the increase in the spike at zero is higher than the increase in the fraction of wage cuts when employment declines. Table 15 illustrates regression results from the data and models. The first panel of the table shows the aggregate cyclicality of nominal wage change distribution from data, which is shown at the last three columns of table 7 from the section 5.1.

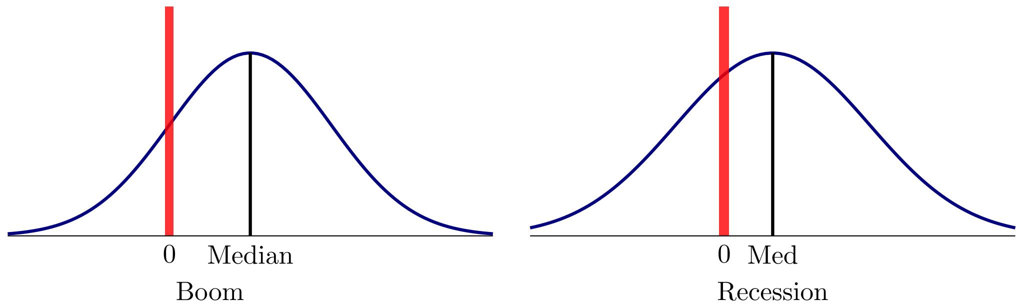
Nominal wage change distribution shifts left or right along the business cycle under a perfectly flexible wage model. The second panel of table 7 shows regression results using simulated data series under a perfectly flexible wage case. After controlling inflation, we can see that the increase in the fraction of workers with wage cuts is almost the same as the decrease in the fraction of workers with raises when employment declines without changing the spike at zero, which is inconsistent with the empirical finding.

The Calvo model presents the constant spike at zero along the business cycle. The third panel of table 7 shows regression results using simulated data under the Calvo model. The spike at zero

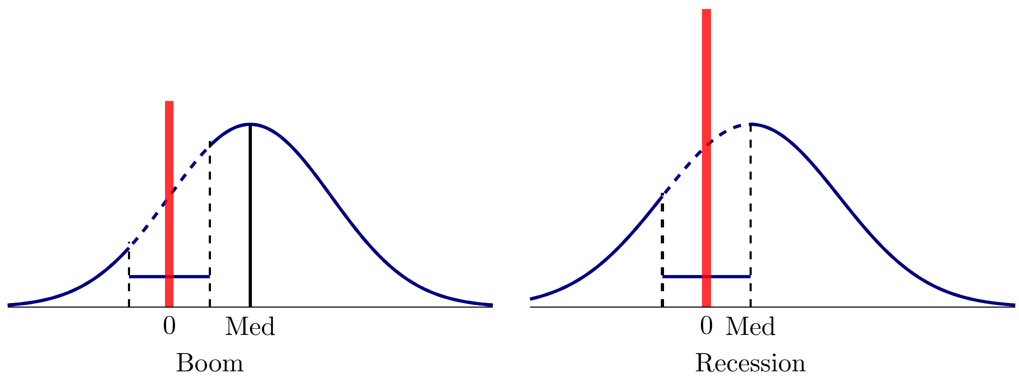
Table 15: The spike at zero, the fraction of wage cuts, and raises along the business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$
		Data	
Employment	-0.616	-0.305	0.921
Inflation	-1.181	-0.674	1.855
		Perfectly flexible	
Employment	-0.042	-0.414	0.456
Inflation	-0.042	-4.476	4.519
		Calvo	
Employment	0.089	-0.553	0.465
Inflation	-0.192	-3.919	4.111
		Long-term contracts	
Employment	0.005	-0.424	0.419
Inflation	-0.018	-4.207	4.225
		Menu costs	
Employment	-0.204	-0.305	0.509
Inflation	-1.613	-3.453	5.066
		DNWR	
Employment	-0.712	-0.329	1.041
Inflation	-3.699	-1.772	5.470

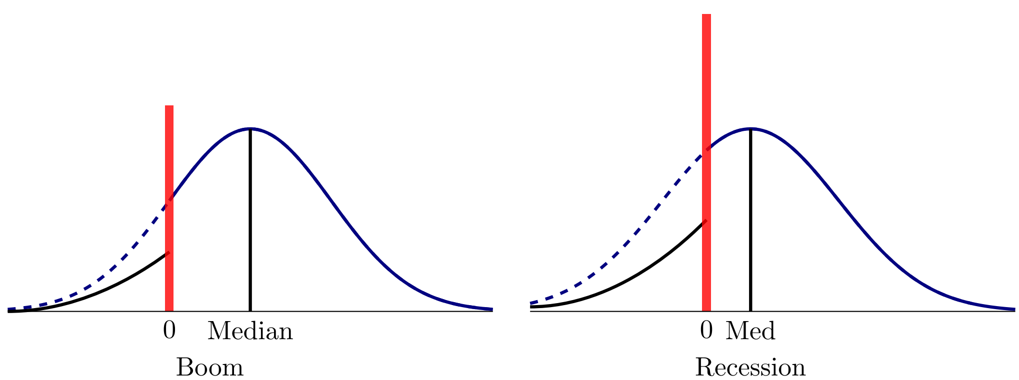
Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). Inflation rate is calculated from CPI-U. Regression results are shown using simulated data series under 5 different wage setting schemes.



Conceptual wage change distribution from Calvo model



Conceptual wage change distribution from menu costs model



Conceptual wage change distribution from DNWR model

Figure 8: Conceptual wage change distribution from different wage setting schemes

This figure shows conceptual wage change distribution under Calvo, menu costs, and DNWR wage setting restriction. Upon the business cycle, nominal wage change distribution in the absence of rigidity shifts right or left in a boom or a recession, respectively. Calvo rigidity implies the constant spike at zero along the business cycle. Menu costs model implies the countercyclical spike at zero, but more fraction of the spike at zero comes from workers otherwise would have positive wage growth. DNWR implies the countercyclical spike at zero and the increase in the spike at zero is higher than the increase in the fraction of workers with wage cuts when employment declines.

barely responds to employment because the Calvo wage adjustment assumes the spike at zero, the frequency of no wage change, does not respond to the business cycle. Thus, we can observe a small coefficient of the spike at zero on employment. The conceptual diagram of changes in wage distribution under the Calvo model is shown at the first panel of figure 8. Along the business cycle, nominal wage changes distribution shifts left or right. When employment declines, nominal wage change distribution shifts to the left and the fraction of workers with raises declines, leading to the increase in the fraction of workers with wage cuts to the same extent without any impacts on the spike at zero.

The long-term contracts model also shows the constant spike at zero along the business cycle similar to the Calvo model. The fourth panel of table 7 shows regression results using simulated data under the long-term contracts model. The decrease in the fraction of workers with raises leads to the increase in the fraction of workers with wage cuts by the same magnitude when employment declines.

The spike at zero implied by menu costs model responds to the employment, as the menu costs model is state- dependent. The fifth panel of table 7 shows regression results using simulated data under the menu costs model. The spike at zero rises when employment declines. Intuitively, nominal wage distribution in the absence of rigidity will shift to the left in the recession, shown at the second panel of figure 8. Then, there are more densities around the zero and this will increase the size of the spike at zero since fixed menu costs will be incurred to any changes in nominal wage with the probability of $(1-\mu^{\text{Menu}})$. However, menu costs model implies the higher responsiveness of workers with wage cuts than the spike at zero, which is inconsistent with empirical evidence.

DNWR model implies the spike at zero rises and the increase in the spike at zero is higher than the increase in the fraction of workers with wage cuts when employment declines, consistent with the empirical finding. The last panel of table 7 shows regression results using simulated data under the DNWR model. In the DNWR model, when there is a decrease in employment by 1 percentage point, there is a decrease in the fraction of workers with raises by 1 percentage point. Out of 1 percentage point, 0.7 percentage point of workers have no wage change, and the other 0.3 percentage point of workers have wage cuts, which is comparable to the first panel of table 7. In the recession, nominal wage change distribution in the absence of wage rigidity shifts to the left as shown in the third panel of figure 8. Under the DNWR wage setting constraint, 67% $(=\mu^{\text{DNWR}})$ of workers whose desired wage is lower than the previous wage experience no wage change, and the other 37% of worker cut their wages. In the recession, there are more workers whose desired wage is lower than the previous wage, and this leads to increase in the spike at zero, which is larger than the increase in the fraction of workers with wage cuts.

8.5 Data Moments

Table 16 shows empirical moments and moments from 5 different wage setting schemes. To compare moments across the model, wage rigidity parameters are calibrated to have the similar level of the spike at zero, the frequency of no wage change. Sluggish adjustment in nominal wages results in real effects of monetary policy on employment, which can be measured by the standard deviation of employment growth rates.

Table 16: Data and model generated moments

	Wage growth rates	Employment growth rates	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
			Data		
Mean	4.102	0.020	15.484	21.318	63.198
SD	1.539	0.792	3.059	2.436	4.686
Skewness	1.032	-1.492			
			Perfectly flexible		
Mean	4.374	0.000	1.822	27.013	71.165
SD	2.068	0.476	3.220	9.710	9.790
Skewness	0.094	-0.000	-	-	-
			Calvo		
Mean	4.378	0.000	23.171	17.626	59.203
SD	1.529	1.051	1.703	6.663	6.905
Skewness	0.006	0.032	-	-	-
			Long-term contracts		
Mean	4.363	0.001	22.994	15.944	61.062
SD	1.403	0.476	0.603	6.128	6.151
Skewness	0.051	-0.003	-	-	-
			Menu costs		
Mean	4.375	0.000	23.070	17.328	59.602
SD	2.068	0.505	3.605	7.343	10.583
Skewness	0.080	-0.006	-	-	-
			DNWR		
Mean	4.382	0.000	23.025	10.530	66.445
SD	1.645	0.812	6.820	3.219	9.901
Skewness	0.320	-0.061	-	-	-

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). Wage growth rate is average of the median hourly wage growth rate for hourly paid workers from 1979-2017. The model generated moments are calculated from the simulated data under 5 different wage setting schemes.

Let's compare moments generated by the Calvo model to long-term contracts model and menu costs model, shown at the third, fourth, and the fifth panel of table 16. The average spike at zero and the fraction of wage cuts and raises are comparable, and it is designed to be comparable by calibration. However, their implications on the standard deviation of employment growth rates are different.

The volatility of the employment from the Calvo model, the degree of monetary non-neutrality, is almost double of the long-term contracts or menu costs model. The standard deviation of employment growth rates from long-term contracts model is much smaller than the one from Calvo model because allocative wages from perfectly flexible model determine employment, not remitted wages.

Even if the fraction of wage adjustments from menu costs model is similar to the one from the Calvo model, the standard deviation of employment growth from menu costs model is smaller than the one from the Calvo model due to selection effects, noted by Caplin and Spulber (1987) and Golosov and Lucas (2007). For the menu costs model, only those workers whose current wages are far away from the desired wages would want to change their wages after paying an additional fixed cost incurred to change in wages. Workers willing to pay a fixed cost to change their wages, they would want to change their wages by a large amount, which leads to a smaller effect on employment from aggregate uncertainty.

The spike at zero from the DNWR model is similar to the other rigidity model. However, the fraction of wage cut is smaller and the fraction of raises is higher than other rigidity model as a result of the DNWR restriction. The standard deviation from the DNWR model is in between that the once from the Calvo and menu costs model. Compared to the Calvo model, the standard deviation of the DNWR model is lower because DNWR has restrictions only to lower wages but not to raise. However, DNWR model shows many small wage changes below zero, which makes the standard deviation higher than the menu cost model. As wage adjustment is asymmetric in DNWR model, it has an asymmetric implication on employment. Although DNWR model does not explain the entire left skewness of employment growth rate, only DNWR model can explain left skewness of employment growth, consistent with Dupraz et al. (2017).

9 Conclusion

This paper uses two nationally representative US household surveys, the CPS and the SIPP to establish stylized facts regarding the cyclical variation of nominal wage change distribution: 1) nominal wage change distribution is asymmetric with the spike at zero, 2) the spike at zero increases when employment declines, controlling for inflation, and 3) the increase in the spike at zero is higher than the increase in the share of wage cuts, controlling for inflation. This paper shows among 5 widely used wage setting schemes - perfectly flexible wage, the Calvo, long-term contracts, menu costs model, and DNWR, only DNWR has consistent empirical implications with empirical findings. For this reason, I argue that there exists downward nominal wage rigidity in the United States.

The model with DNWR predicts the asymmetric response of employment – left skewness of employment growth - different from canonical symmetric wage rigidity model implying symmetric response of employment. This has important implications on monetary policy since there is a potential welfare gain in pursuing high inflation target from relaxing DNWR constraint. Thus, I aim to analyze optimal monetary policy under DNWR.

Appendix

A Appendix: CPS

Table A1 shows the unweighted number of population for age greater than 16 and the unweighted number of employed workers among the population greater than age 16. Table A1 also shows the imputation ratio for usual weekly earning and the hourly wage. Since the major revision in the CPS in 1994, about 34% of hourly wages are imputed by the CPS. The CPS imputes unreported data items to fill in based on the demographic characteristics and residential address.[28] Including imputed wages may amplify measurement error, so this paper drops imputed wages. Although IPUMS-CPS provides with the individual identifiers, they do not offer imputation flags for wage variables. Thus, this paper merges IPUMS - CPS data into CPS data to exclude imputed wages.

Table A2 shows the number of observations for hourly workers whose hourly wage growth rate is available. The spike at zero and the fraction of hourly workers with wage cuts and raises are also shown in the table A2.

Figure A1 and A2 show the nominal year-to-year hourly wage change distribution for each year from 1980-2017. Nominal hourly wage change distribution is highly asymmetric: there is an apparent spike at zero and fewer wage cuts compared to raises.

A.1 Time series spike at zero, fraction of wage cuts and raises

[28]https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/imputation-of-unreported-data-items.html

Table A1: The unweighted number of observation in the CPS and the imputation ratio

Year	Age $\geq$ 16	Employed	Usual weekly earning			Hourly wage		
			Including Imputation	Excluding Imputation	Imputation ratio	Including Imputation	Excluding Imputation	Imputation ratio
1979	1,314,693	787,170	171,595	142,839	16.8	101,392	86,323	14.9
1980	1,546,827	918,046	199,290	167,183	16.1	116,941	100,699	13.9
1981	1,456,261	861,395	186,766	157,760	15.5	109,545	95,055	13.2
1982	1,404,030	813,120	175,643	151,075	14.0	102,475	90,129	12.0
1983	1,394,390	808,514	173,763	149,358	14.0	102,126	89,857	12.0
1984	1,374,456	819,764	176,724	150,317	14.9	104,287	90,780	13.0
1985	1,375,158	828,675	179,671	153,633	14.5	106,174	92,556	12.8
1986	1,353,321	821,067	178,586	159,172	10.9	105,861	96,029	9.3
1987	1,348,579	828,009	180,272	155,604	13.7	108,033	95,385	11.7
1988	1,286,466	797,107	172,931	147,658	14.6	104,079	90,836	12.7
1989	1,301,108	814,698	176,411	169,438	4.0	106,594	104,732	1.7
1990	1,355,294	846,099	185,022	176,278	4.7	110,916	110,425	0.4
1991	1,341,040	822,621	179,555	170,083	5.3	108,088	107,590	0.5
1992	1,320,939	808,261	176,833	167,846	5.1	106,996	106,608	0.4
1993	1,302,955	798,202	174,587	164,720	5.7	105,595	105,188	0.4
1994	1,271,347	790,130	160,223	-	-	104,915	82,776	21.1
1995	1,251,928	784,129	159,344	39,798	75.0	104,976	25,991	75.2
1996	1,108,899	699,605	141,204	109,604	22.4	93,986	71,087	24.4
1997	1,114,451	708,705	143,999	111,214	22.8	95,571	72,226	24.4
1998	1,116,813	717,245	145,863	111,979	23.2	96,018	71,190	25.9
1999	1,123,666	723,156	147,726	107,929	26.9	96,545	67,801	29.8
2000	1,120,585	723,930	150,128	105,889	29.5	97,335	65,899	32.3
2001	1,236,870	793,912	157,460	110,480	29.8	102,410	68,712	32.9
2002	1,312,304	832,519	171,218	119,592	30.2	110,766	74,092	33.1
2003	1,302,483	818,795	167,393	114,282	31.7	108,915	70,976	34.8
2004	1,283,683	809,185	164,286	112,821	31.3	107,440	70,276	34.6
2005	1,279,052	810,893	165,522	114,632	30.7	108,662	71,531	34.2
2006	1,271,693	810,582	165,913	114,399	31.0	107,615	70,545	34.4
2007	1,260,380	801,226	165,246	115,224	30.3	104,945	70,299	33.0
2008	1,257,619	790,341	163,481	113,608	30.5	103,028	68,438	33.6
2009	1,273,634	766,660	158,331	110,588	30.2	100,010	66,815	33.2
2010	1,277,199	759,458	156,774	104,822	33.1	99,623	63,812	35.9
2011	1,265,607	749,778	155,636	102,360	34.2	98,885	62,345	37.0
2012	1,258,730	749,477	155,224	103,294	33.5	98,333	62,489	36.5
2013	1,253,663	745,840	155,474	99,965	35.7	97,570	60,185	38.3
2014	1,261,811	751,675	156,940	98,865	37.0	98,310	59,167	39.8
2015	1,245,862	739,222	155,734	94,674	39.2	97,108	56,410	41.9
2016	1,244,166	740,071	156,416	95,959	38.7	97,585	57,406	41.2
2017	1,227,127	731,896	154,809	94,638	38.9	95,955	56,385	41.2

Source: CPS and author's calculation. Sample period: 1979 - 2017
This table shows the unweighted number of observation. The second column shows the unweighted number of individuals greater or equal to 16 for each year in the CPS. The third column shows the unweighted number of employed workers, greater or equal to age 16. Column 4-5 show the unweighted number of workers whose usual weekly earning is available including imputation (column 4), excluding imputation (column 5). Column 6 shows the imputation ratio for usual weekly earning. Column 7-8 show the unweighted number of workers whose hourly wages are available, including imputation (column 7), excluding imputation (column 8). Column 9 shows the imputation ratio for the hourly wage.

Table A2: Nominal hourly wage change distribution in the CPS

	Unweighted count of		Spike at zero (%)		Fraction of	Fraction of
year	Δw	$\Delta w = 0$	Unweighted	Weighted	$\Delta W < 0$	$\Delta W > 0$
1980	21,029	1,403	6.67	6.66	14.24	79.11
1981	23,641	1,605	6.79	6.70	14.32	78.98
1982	23,211	2,839	12.23	12.08	18.90	69.01
1983	22,869	3,397	14.85	14.65	20.64	64.71
1984	22,840	3,398	14.88	14.68	20.21	65.11
1985	11,115	1,608	14.47	14.25	20.65	65.10
1986	6,202	956	15.41	15.52	21.48	63.00
1987	24,569	3,807	15.50	15.36	21.41	63.23
1988	23,302	3,414	14.65	14.62	20.38	65.01
1989	24,648	3,293	13.36	13.16	21.26	65.58
1990	29,434	3,327	11.30	11.24	23.58	65.17
1991	30,034	3,549	11.82	11.64	24.91	63.44
1992	29,816	4,057	13.61	13.52	25.52	60.96
1993	29,751	3,989	13.41	13.45	26.42	60.13
1994	22,974	3,255	14.17	14.12	23.89	62.00
1995						
1996	6,085	887	14.58	14.50	19.89	65.62
1997	18,058	2,533	14.03	13.66	19.56	66.78
1998	17,866	2,458	13.76	13.50	18.30	68.20
1999	16,880	2,348	13.91	13.47	18.95	67.58
2000	15,796	2,251	14.25	14.18	18.24	67.58
2001	14,721	2,062	14.01	13.98	18.65	67.38
2002	15,789	2,558	16.20	16.12	20.12	63.76
2003	17,336	2,932	16.91	17.46	21.09	61.45
2004	16,243	2,791	17.18	17.55	21.36	61.09
2005	14,991	2,466	16.45	16.91	20.63	62.46
2006	16,374	2,513	15.35	15.80	20.87	63.33
2007	16,249	2,310	14.22	14.25	20.43	65.32
2008	16,437	2,492	15.16	15.49	20.55	63.96
2009	16,077	2,906	18.08	18.30	23.59	58.11
2010	15,620	3,272	20.95	21.14	24.61	54.25
2011	14,776	3,030	20.51	20.88	24.30	54.82
2012	14,463	2,947	20.38	20.45	24.73	54.82
2013	14,467	2,897	20.02	20.46	23.07	56.47
2014	13,342	2,538	19.02	19.50	22.15	58.35
2015	10,758	1,975	18.36	18.86	21.58	59.56
2016	12,125	2,155	17.77	17.55	20.95	61.50
2017	12,676	2,322	18.32	18.41	20.26	61.33

Source : CPS and author's calculation. Sample period : 1979 - 2017
This table shows the number of observation and the spike at zero, the fraction of workers with wage cuts and raises for all hourly paid workers. Household identifiers were scrambles in 1995 so there were no observations available in 1995 and it leads to small observations in 1996.

Table A3: Descriptive statistics by industry, CPS

	% hourly workers	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
Agriculture, Forestry, Fishing and Hunting	1.04	23.74	21.00	55.25
Other Services (except Public Administration)	3.69	22.07	22.04	55.90
Administrative, Support, Waste Management, and Remediation Services	1.59	20.65	23.33	56.03
Real Estate and Rental and Leasing	0.95	18.29	20.33	61.38
Arts, Entertainment, and Recreation	1.86	18.21	22.87	58.92
Accommodation and Food Services	7.65	18.15	26.32	55.54
Professional, Scientific, and Technical Services	3.25	17.67	17.63	64.70
Construction	6.43	17.66	21.11	61.23
Wholesale Trade	3.09	16.31	19.68	64.02
Retail Trade	14.51	15.82	20.53	63.65
Educational Services	5.18	14.68	21.73	63.60
Mining, Quarrying, and Oil and Gas Extraction	0.71	14.45	24.05	61.50
Manufacturing	20.91	13.65	20.83	65.52
Transportation and Warehousing	4.53	13.61	22.83	63.57
Health Care and Social Assistance	15.03	13.24	19.57	67.19
Finance and Insurance	2.66	12.72	18.74	68.55
Information	1.43	11.97	20.55	67.48
Utilities	1.69	11.54	20.07	68.39
Public Administration	3.81	11.15	19.93	68.92

Data source: CPS and author's calculation. Sample Period : 1979-2017 (except 1995). This table shows the sample average of the spike at zero and the fraction of workers with wage cuts and raises over time by 2017 2 digit NAICS industry classification.

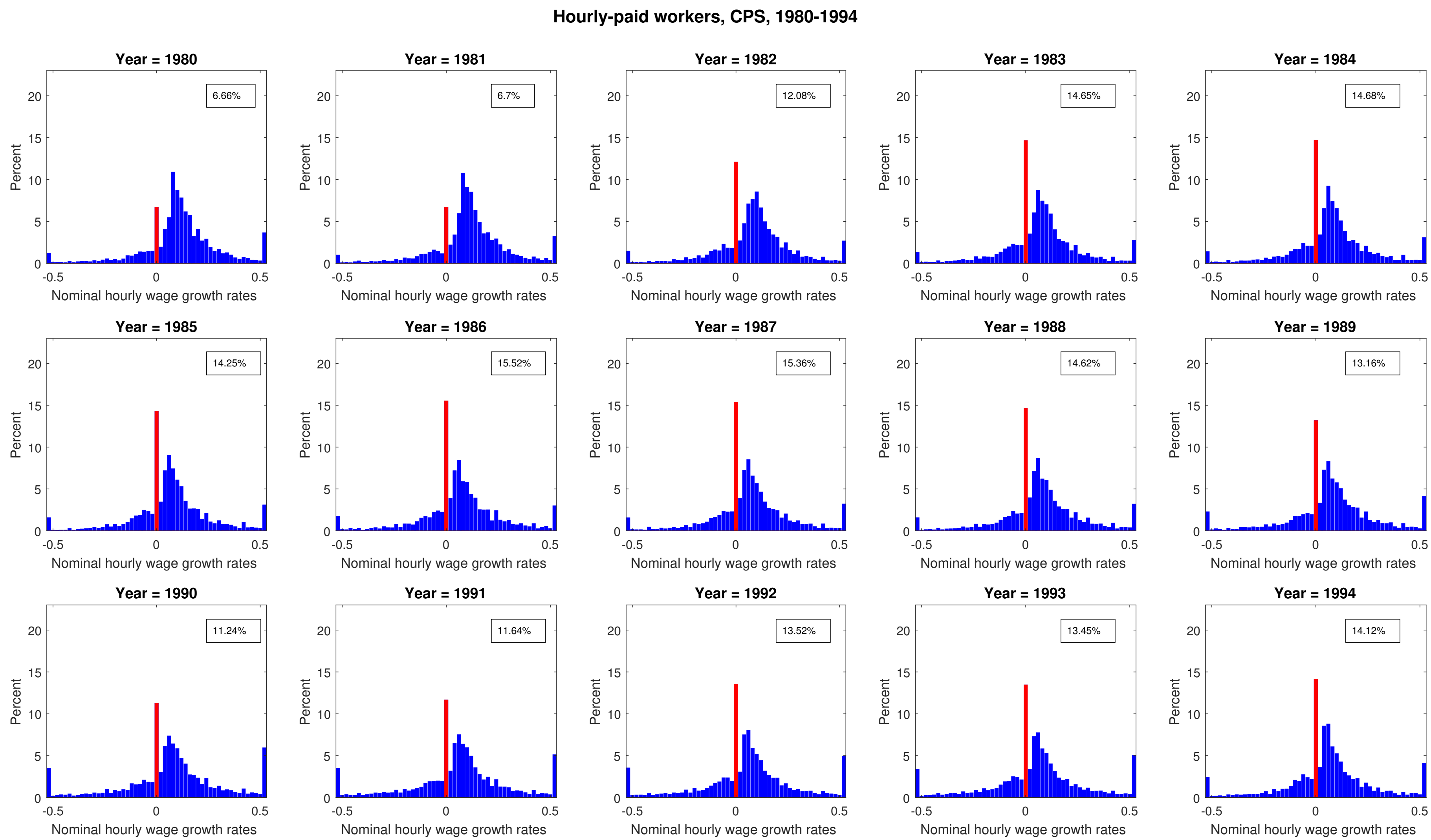


Figure A1: Nominal hourly wage growth rates from 1980 to 1994

Data source: CPS. Bin size is 0.02. The red bin shows the spike at zero, the percentage of workers whose hourly wage growth rate is exactly zero.

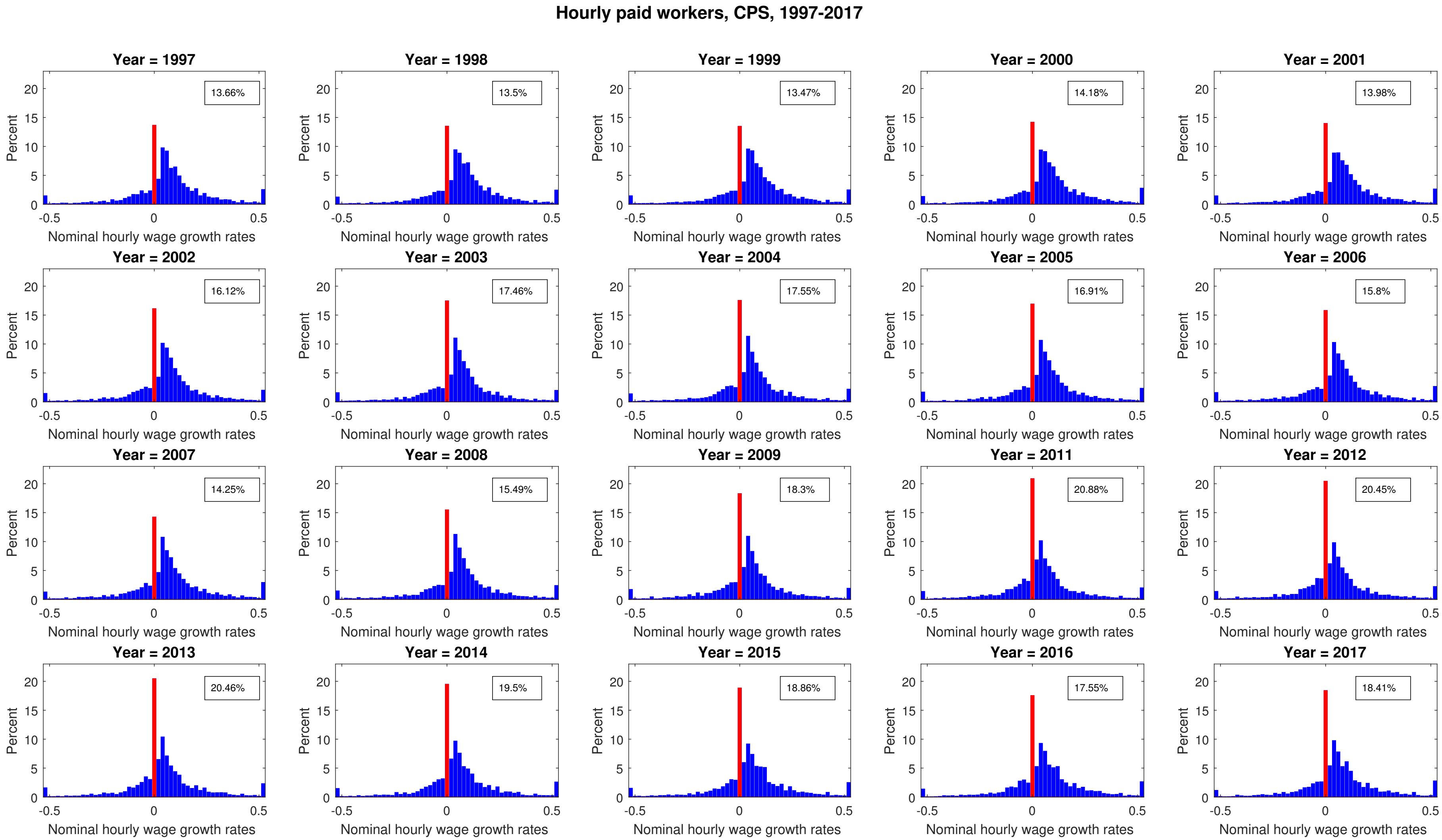


Figure A2: Nominal hourly wage growth rates from 1997 to 2017

Data source: CPS. Bin size is 0.02. The red bin shows the spike at zero, the percentage of workers whose hourly wage growth rate is exactly zero.

A.2 Robustness checks for aggregate time series evidence

Table A4 shows regression results based on (1), excluding minimum wage workers. Table A5 shows regression results based on (1) using only working age population from 16 to 64. Main results are robust even if we exclude minimum wage workers and we use only working age population.

Table A4: Exluding minimum wage workers, the spike at zero, the fraction of wage cuts, and raises

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Size of peak $\Delta W = 0$	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$
1-Epop	0.363	0.197	-0.559	0.555***	0.302*	-0.857**
	(0.336)	(0.222)	(0.532)	(0.201)	(0.156)	(0.316)
Inflation rate				-1.237***	-0.678***	1.915***
				(0.133)	(0.141)	(0.195)
				0.555/0.857 = 0.648		
Observations	37	37	37	37	37	37
Adjusted R^2	0.0150	-0.00620	0.0152	0.675	0.325	0.683

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source : CPS and author's calculation. Sample Period : 1980-2017 (except 1995). Inflation rate is calculated from CPI-U.

Table A5: The spike at zero, the fraction of wage cuts, and raises along the business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero $\Delta W = 0$	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$
1-Epop ratio	0.283	0.105	-0.388	0.507***	0.237*	-0.743***
	(0.270)	(0.210)	(0.463)	(0.145)	(0.140)	(0.253)
Inflation rate				-1.168***	-0.688***	1.856***
				(0.124)	(0.145)	(0.214)
				0.507/0.743 = 0.68		
Observations	37	37	37	37	37	37
Adjusted R^2	0.0184	-0.0192	0.00542	0.717	0.318	0.684

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: CPS and author's calculation. Sample Period : 1979-2017 (except 1995). Inflation rate is calculated from CPI-U.

Table A6 shows regression results based on (1) by varying the level of education. Table A7, A8, A9, A10 show regression results based on the level of age, gender, race, and income quartiles. Main results: the spike at zero increases when employment declines, controlling for inflation and the increase in the spike at zero is higher than the increase in the share of wage cuts when employment declines hold for different worker characteristics.

Table A6: The spike at zero, the fraction of wage cuts and raises by education

	All hourly paid workers			High School or less			College or more		
	(1) Spike at zero	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$	(7) Spike at zero	(8) Fraction of $\Delta W < 0$	(9) Fraction of $\Delta W > 0$
1 - Epop	0.616***	0.305	-0.921***	0.551***	0.300	-0.851***	0.663***	0.323*	-0.986***
	(0.145)	(0.181)	(0.240)	(0.156)	(0.187)	(0.254)	(0.159)	(0.180)	(0.249)
Inflation	-1.181***	-0.674***	1.855***	-1.189***	-0.721***	1.910***	-1.232***	-0.628***	1.860***
	(0.125)	(0.156)	(0.207)	(0.134)	(0.161)	(0.219)	(0.137)	(0.156)	(0.215)
	0.616/0.921=0.67			0.551/0.851=0.65			0.663/0.986 =0.67		
Observations	37	37	37	37	37	37	37	37	37
Adjusted R^2	0.727	0.331	0.702	0.695	0.346	0.687	0.709	0.305	0.691

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: CPS and author's calculation. Sample period: 1979-2017 (except 1995).

Table A7: The spike at zero, the fraction of wage cuts and raises by age

	All hourly paid workers			$16 \leq$ age < 40			$40 \leq$ age < 64		
	(1) Spike at zero	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$	(7) Spike at zero	(8) Fraction of $\Delta W < 0$	(9) Fraction of $\Delta W > 0$
1-Epop	0.616***	0.305	-0.921***	0.581***	0.247	-0.828***	0.614***	0.359	-0.973***
	(0.145)	(0.181)	(0.240)	(0.131)	(0.167)	(0.245)	(0.150)	(0.223)	(0.249)
Inflation	-1.181***	-0.674***	1.855***	-1.093***	-0.699***	1.792***	-1.178***	-0.613***	1.791***
	(0.125)	(0.156)	(0.207)	(0.113)	(0.144)	(0.212)	(0.129)	(0.192)	(0.215)
	0.617/0.920=0.67			0.552/0.851=0.65			0.664/0.986 =0.67		
Observations	37	37	37	37	37	37	37	37	37
Adjusted R^2	0.727	0.331	0.702	0.737	0.383	0.675	0.713	0.209	0.676

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: CPS and author's calculation. Sample period: 1979-2017 (except 1995).

Table A8: The spike at zero, the fraction of wage cuts and raises by gender

	All hourly paid workers			Male			Female		
	(1) Spike at zero	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$	(7) Spike at zero	(8) Fraction of $\Delta W < 0$	(9) Fraction of $\Delta W > 0$
1-Epop	0.616***	0.305	-0.921***	0.516***	0.345*	-0.861***	0.714***	0.251	-0.964***
	(0.145)	(0.181)	(0.240)	(0.153)	(0.202)	(0.251)	(0.147)	(0.182)	(0.256)
Inflation	-1.181***	-0.674***	1.855***	-1.104***	-0.510***	1.614***	-1.262***	-0.876***	2.139***
	(0.125)	(0.156)	(0.207)	(0.132)	(0.174)	(0.217)	(0.126)	(0.157)	(0.221)
	0.616/0.921=0.67			0.515/0.861=0.60			0.714/0.964=0.74		
Observations	37	37	37	37	37	37	37	37	37
Adjusted R^2	0.727	0.331	0.702	0.671	0.188	0.622	0.754	0.451	0.731

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: CPS and author's calculation. Sample period: 1979-2017 (except 1995).

Table A9: The spike at zero, the fraction of wage cuts and raises by race

	All hourly paid workers			White			Non-white		
	(1) Size of peak	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Size of peak	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$	(7) Size of peak	(8) Fraction of $\Delta W < 0$	(9) Fraction of $\Delta W > 0$
1-Epop	0.616***	0.305	-0.921***	0.630***	0.333*	-0.964***	0.554***	0.0862	-0.641**
	(0.145)	(0.181)	(0.240)	(0.144)	(0.174)	(0.242)	(0.171)	(0.239)	(0.250)
Inflation	-1.181***	-0.674***	1.855***	-1.199***	-0.678***	1.877***	-1.079***	-0.598***	1.677***
	(0.125)	(0.156)	(0.207)	(0.124)	(0.150)	(0.208)	(0.148)	(0.206)	(0.215)
	0.616/0.921=0.67			0.630/0.964=0.66			0.556/0.641 =0.87		
Observations	37	37	37	37	37	37	37	37	37
Adjusted R^2	0.727	0.331	0.703	0.736	0.359	0.707	0.611	0.152	0.629

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: CPS and author's calculation. Sample period: 1979-2017.

Table A10: Regression results by income quantiles

	25th below			from 25th to Median		
	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
1-Epop	0.972***	0.220	-1.192**	0.624***	0.131	-0.756**
	(0.272)	(0.271)	(0.448)	(0.204)	(0.247)	(0.339)
Inflation	-1.250***	-0.938***	2.188***	-1.218***	-0.689***	1.907***
	(0.235)	(0.234)	(0.387)	(0.176)	(0.213)	(0.292)
Observations	37	37	37	37	37	37
Adjusted R^2	0.491	0.282	0.483	0.584	0.191	0.541
	Median to 75th			Above 75th		
	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
1-Epop	0.429**	0.386**	-0.814***	0.547***	0.439**	-0.986***
	(0.200)	(0.177)	(0.283)	(0.163)	(0.164)	(0.234)
Inflation	-1.115***	-0.405**	1.521***	-1.144***	-0.703***	1.847***
	(0.173)	(0.152)	(0.244)	(0.141)	(0.141)	(0.202)
Observations	37	37	37	37	37	37
Adjusted R^2	0.535	0.191	0.532	0.659	0.427	0.716

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source : CPS and author's calculation. Sample Period : 1979-2017 (except 1995). This table shows the average of size of peak and the fraction of workers with wage cut and raises over time by demographic group.

B Appendix: SIPP

Table A11 shows the unweighted count of observations of hourly workers whose hourly wage growth rate is available for each year and the time series of the spike at zero, the share of wage cuts and raises. Table A12 divides hourly workers into two: job stayer and jobs switchers and shows the unweighted count of observations, the spike at zero, the share of wage cuts and raises, respectively.

Figure A3 shows year-over-year hourly wage change distribution for hourly workers including both job stayers and job switchers for each year from 1985-2013 with some gaps. The red bar presents the spike at zero, the share of workers with no wage change and the size of blue bin is 0.02. Figure A4 shows year-over-year hourly wage change distribution for hourly job stayers and figure A5 shows one for job switchers.

B.1 Time series spike at zero, fraction of wage cuts and raises

Table A11: Nominal hourly wage change distribution in the SIPP

Year	Obs Δw	Spike at zero $\Delta w = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
1985	9,827	16.75	18.76	64.50
1986	13,490	17.26	19.36	63.38
1987	11,171	17.92	20.11	61.97
1988	10,508	14.95	18.12	66.93
1989	10,930	14.63	17.92	67.44
1990				
1991	11,820	14.30	18.74	66.96
1992	17,241	17.31	19.32	63.37
1993	16,318	18.58	20.29	61.14
1994	19,430	18.28	20.66	61.07
1995	9,347	18.31	18.58	63.12
1996				
1997	16,951	14.02	18.68	67.30
1998	15,877	14.31	16.33	69.37
1999	14,939	16.98	16.91	66.11
2000	5,408	17.52	15.29	67.20
2001				
2002	13,727	16.12	21.85	62.04
2003	12,287	19.27	19.51	61.21
2004				
2005	20,055	30.13	17.31	52.57
2006	17,621	30.05	14.19	55.76
2007	7,922	31.48	13.64	54.88
2008				
2009	13,909	39.85	16.85	43.29
2010	16,080	42.22	16.00	41.77
2011	14,228	45.59	13.24	41.17
2012	13,242	43.84	13.72	42.44
2013	11,943	46.46	12.61	40.93

Source: SIPP and author's calculation. Sample period: 1984 - 2013 except 1990, 1996, 2001, and 2008
This table shows the unweighted number of observation and the size of peak, the fraction of workers with wage cuts and raises for hourly paid workers.

Table A12: Nominal hourly wage change distribution in the SIPP by job stayers and job switchers

	Job stayers				Job switchers			
Year	Obs Δw	Spike at zero $\Delta w = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$	Obs Δw	Spike at zero $\Delta w = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
1985	7,724	16.95	16.08	66.97	2,103	15.99	28.52	55.49
1986	9,735	18.58	16.14	65.28	3,755	13.50	28.50	58.00
1987	8,489	19.46	16.80	63.74	2,682	12.88	30.96	56.16
1988	7,593	16.70	14.00	69.30	2,915	10.35	28.92	60.73
1989	7,949	16.45	14.09	69.46	2,981	9.66	28.44	61.90
1990								
1991	8,699	16.41	13.70	69.89	3,121	8.43	32.78	58.79
1992	13,226	19.30	15.02	65.67	4,015	10.70	33.52	55.77
1993	12,514	20.97	16.34	62.69	3,804	10.66	33.36	55.98
1994	14,422	20.64	16.54	62.82	5,008	11.54	32.39	56.07
1995	6,935	20.56	14.92	64.52	2,412	11.86	29.03	59.11
1996								
1997	11,184	16.20	14.84	68.96	5,767	9.86	26.04	64.11
1998	10,290	17.05	12.05	70.91	5,587	9.30	24.16	66.55
1999	9,851	19.71	12.38	67.91	5,088	11.73	25.61	62.66
2000	3,938	20.00	11.54	68.45	1,470	10.93	25.20	63.87
2001								
2002	8,926	18.92	16.34	64.74	4,801	10.91	32.06	57.03
2003	8,491	22.17	14.25	63.57	3,796	12.81	31.25	55.94
2004								
2005	13,282	38.87	10.14	50.99	6,773	13.29	31.10	55.61
2006	11,937	38.60	7.42	53.98	5,684	12.75	27.90	59.35
2007	5,339	40.88	6.81	52.31	2,583	12.04	27.78	60.18
2008								
2009	10,194	49.10	10.21	40.69	3,715	15.44	34.41	50.16
2010	11,292	53.83	8.44	37.73	4,788	15.92	33.15	50.93
2011	10,076	57.39	6.46	36.15	4,152	18.01	29.08	52.92
2012	9,333	56.21	6.21	37.58	3,909	15.84	30.73	53.43
2013	8,695	58.39	5.07	36.54	3,248	16.18	31.75	52.08

Source: SIPP and author's calculation. Sample period: 1984 - 2013 except 1990, 1996, 2001, and 2008
This table shows the number of observation and the spike at zero, the fraction of workers with wage cuts and raises for hourly paid job stayers and job switchers.

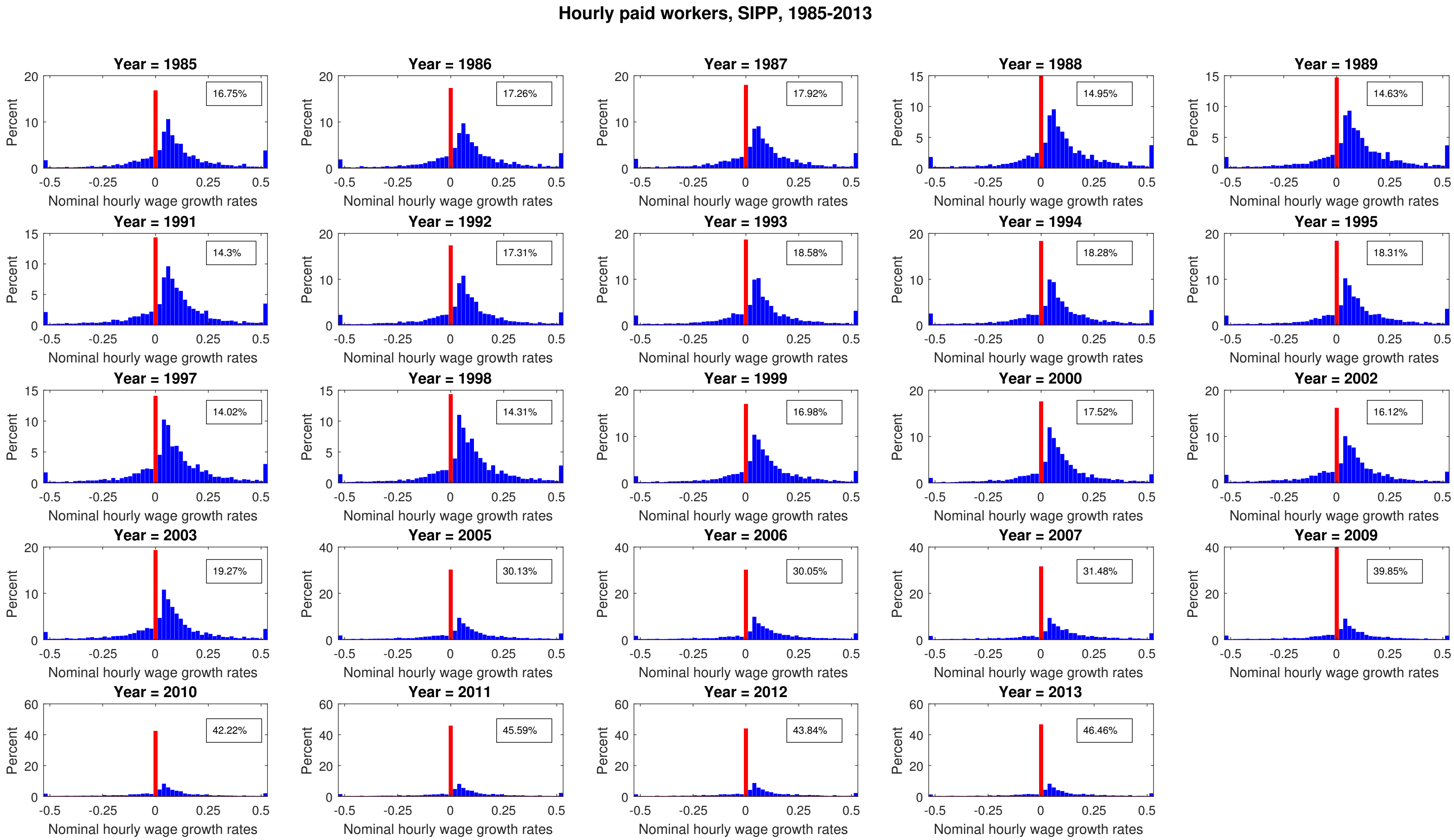


Figure A3: Nominal hourly wage growth rates 1985-2013

Data source: SIPP and author's calculation. The red bin shows the spike at zero, the percentage of workers whose hourly wage growth rate is exactly zero. Other than red bin, bin size is 0.02.

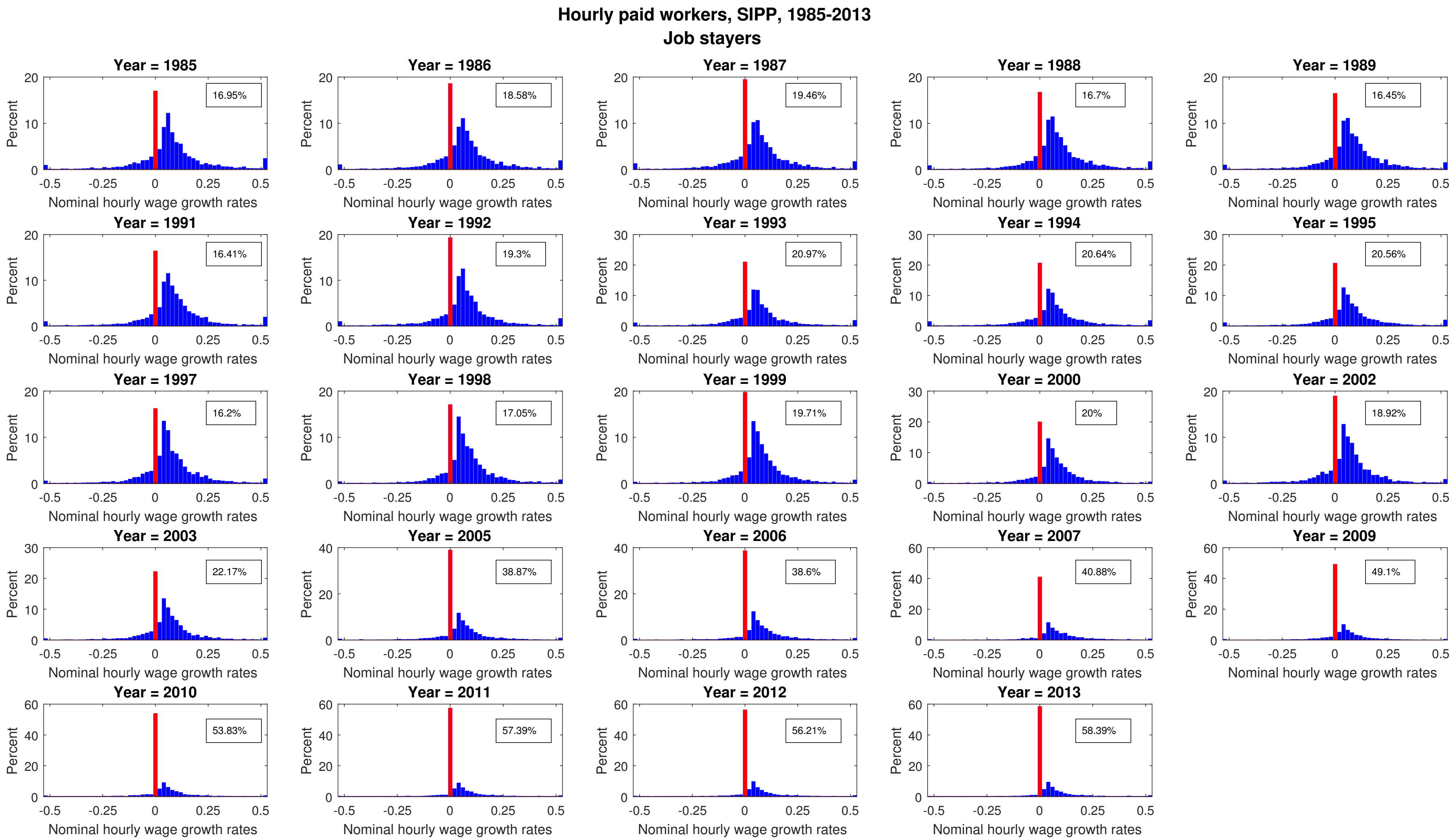


Figure A4: Nominal hourly wage growth rates 1985-2013 for job stayers

Data source: SIPP and author's calculation. For hourly paid job stayers. The red bin shows the spike at zero, the percentage of workers whose hourly wage growth rate is exactly zero. Other than red bin, bin size is 0.02.

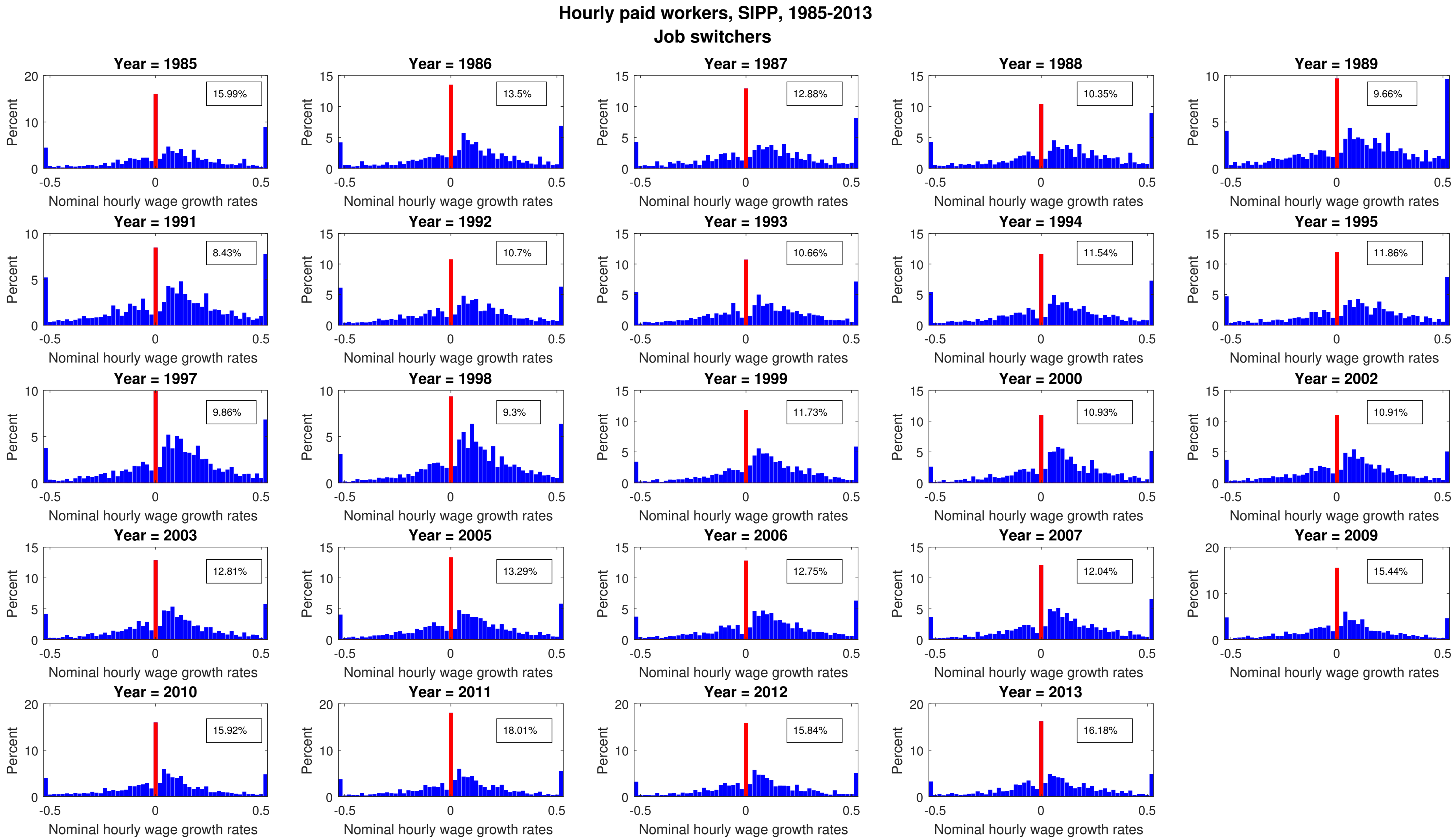


Figure A5: Nominal hourly wage growth rates 1985-2013 for job switchers

Data source: SIPP and author's calculation. For hourly paid job switchers. The red bin shows the spike at zero, the percentage of workers whose hourly wage growth rate is exactly zero. Other than red bin, bin size is 0.02.

B.2 The nominal wage change distribution for job switchers by reasons of job switching

This section reports the average spike at zero, the share of wage cuts and increases for job switchers by reasons of job switching. SIPP asks the reasons why respondents have stopped working for the previous employer. About 50% of job switchers do not respond to this question. Among the other 50%, workers on layoff, or injured, or temporary workers record the higher spike at zero.

Fired/Discharged workers presents the similar level of the spike at zero compared to workers who quit the job to take another jobs. However, workers who quit the job to take the another job tend to have higher fraction of raises and the less share of cuts. Fired or discharged workers tend to show the higher share of wage cuts. A13

Table A13: The spike at zero, the fraction of wage cuts, and raises(%) for job-switchers by reasons of switching, SIPP

	% of job switchers	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
On layoff	11.53	14.06	37.05	48.89
Fired/Discharged	2.35	9.96	43.98	46.07
Quit to take another job	8.27	9.33	22.89	67.78
Contingent worker/temporary employed	4.22	14.38	29.97	55.65
Illness/Injury	1.26	14.26	38.69	47.05
Others	19.54	12.17	32.79	55.04
Missing	52.82	12.23	27.79	59.98

Data source: SIPP and author's calculation. Sample Period: 1984-2013 (except 1990, 1996, 2001, 2004, 2008). This table shows the sample average of the spike at zero and the fraction of workers with wage cuts and raises over time by reasons of job switching. The category others include attending schools, childcare problems, family/personal obligations, unsatisfactory work arrangements, retirement and so on.

C Counterfactual analysis: Missing mass

Lack of nominal wage cuts compared to nominal wage increases is often suggested as the existence of DNWR. To measure how absent of nominal wage cuts in the nominal wage growth distribution, this paper introduces the concept of missing mass. This concept is often used to show the asymmetry of wage change distribution in the previous literature, Card and Hyslop (1997), Lebow et al. (2003), and Kurmann and McEntarfer (2017).

To define missing mass, let us assume that nominal wage growth rate distribution is symmetric around the median without any types of wage rigidity, which is shown as the left panel of figure A6. However, instead of symmetric distribution around the median, what we can observe in the data is that an apparent peak at zero wage change and shortages of wage growth rates around the zero compared to nominal wage change distribution above median, displayed at the right panel of figure. 2

An apparent peak at zero, referred as the spike at zero in this paper, can be decomposed into

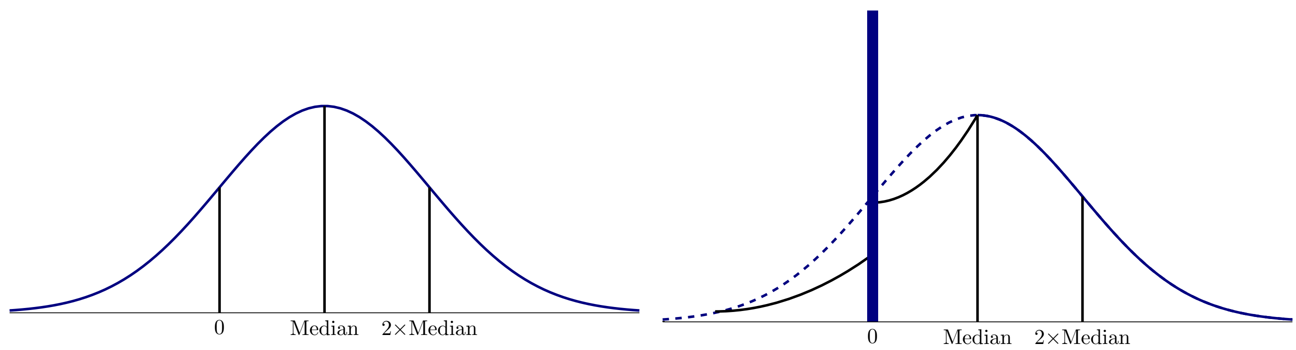


Figure A6: Conceptual diagram of nominal wage distribution

Left panel shows the nominal wage change distribution under the assumption in the absence of wage rigidity and the right panel shows how nominal wage change distribution looks like

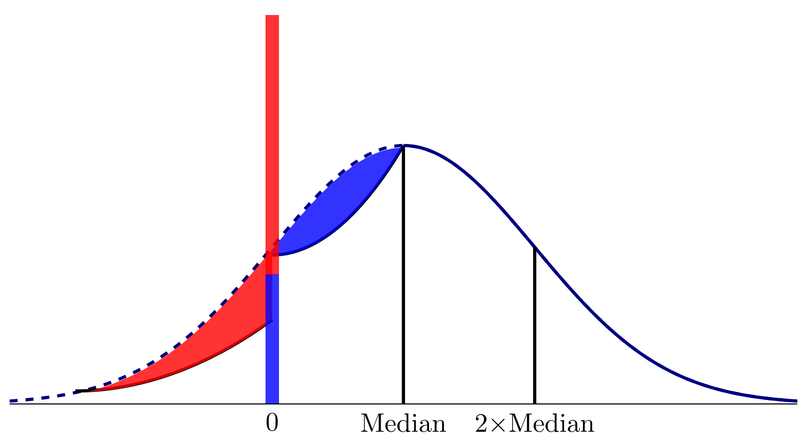


Figure A7: Missing mass left to the zero vs. missing mass right to the zero

two: one is the share of workers with no wage change who would have otherwise wage cut without wage rigidity and the other is the share of workers with zero wage change who would have positive wage growth rate in the absence of wage rigidity. The red colored area left to the zero in figure A7 shows the missing share of wage cuts due to wage rigidity, which becomes the part of the spike at zero. The blue colored area right to the zero in the figure A7 represents the lack of share of raises due to wage rigidity, which becomes part of the spike at zero. From now on, this paper refers the red shaded area as the missing mass left to the zero and the blue shaded area as the missing mass right to the zero.

Formally, we can write the missing mass left to the zero as

$$\frac{\Sigma_i 1(\Delta w > 2 \times \text{Med}) - \Sigma_i 1(\Delta w < 0)}{N} \tag{9}$$

and the missing mass right to the zero can be written as

$$\frac{\Sigma_i 1(\text{Med} < \Delta w \leq 2 \times \text{Med}) - \Sigma_i 1(0 < \Delta w \leq \text{Med})}{N}. \tag{10}$$

Table A14 shows missing masses calculated using the equation 9 and 10. We can clearly see the most of missing mass comes from the left using the CPS and the SIPP. In the CPS, 85% of the spike at zero comes from the left to the zero. In the SIPP, 90% of the spike at zero for job stayers comes from the left to the zero and 87% of the spike at zero comes from the left to the zero for job switchers.

Table A14: Missing mass from left to the zero vs. right to the zero

	CPS		
	Spike at zero	Missing mass from left to zero	Missing mass from right to zero
Hourly workers	15.25	12.97	2.15
	SIPP		
	Spike at zero	Missing mass from left to zero	Missing mass from right to zero
Job-stayer	23.74	21.25	2.49
Job-switcher	12.19	10.58	1.61

Data source: CPS, SIPP, ans author's calculation. Sample period for CPS: 1979 - 2017. Sample period for SIPP: 1984-2013 (except 1990, 1996, 2001, 2004, and 2008)

D Appendix: Model

D.1 Solution Algorithm

- Step 1: Guess a parameterized functional form of H and choose the initial parameter, γ_0, γ_1, and γ_2

$$W_{t+1} = H(W_t, M_{t+1})$$
$$\ln(\frac{W_{t+1}}{W_t}) = H(\ln(\frac{M_{t+1}}{W_t})) = \gamma_0 + \gamma_1 \ln\frac{M_{t+1}}{W_t} + \gamma_2(\ln\frac{M_{t+1}}{W_t})^2$$

- Step 2 : Solve the wage setter's optimization problem $V_t(q_t(i), L_t, \frac{w_{t-1}(i)}{W_t}, x_t)$, given the law of motion H.

- Step 3 : Simulate the dynamics of the distribution for NH households for T periods using the policy function obtained by step 2.

- Step 4 : Burn first initial Tburn periods. And estimate the parameters γ_0, γ_1, and γ_2.

– Calculate the simulated wage inflation

$$\frac{W_{t+1}}{W_t}^S = \frac{\left\{ \int \left[\frac{w_{t+1}(i)}{q_{t+1}(i)}\right]^{1-\theta} dj \right\}^{\frac{1}{1-\theta}}}{\left\{ \int \left[\frac{w_t(i)}{q_t(i)}\right]^{1-\theta} dj \right\}^{\frac{1}{1-\theta}}}$$

$$\approx \left[\frac{\Sigma_j \left[\frac{w_{t+1}(i)/W_{t+1}}{q_{t+1}(i)}\right]^{1-\theta}}{\Sigma_j \left[\frac{w_t(i)/W_{t+1}}{q_t(i)}\right]^{1-\theta}} \right]^{\frac{1}{1-\theta}}$$

– Estimate parameters using the OLS

$$\ln(\frac{W_{t+1}}{W_t}^S) = H(\ln(\frac{M_{t+1}}{W_t})) = \gamma_0 + \gamma_1 \ln \frac{M_{t+1}}{W_t} + \gamma_2 (\ln \frac{M_{t+1}}{W_t})^2$$

– Update γ_0, γ_1, and γ_2 using the OLS until the parameters converge

– Test the goodness of fit for H using R^2. If the fit is satisfactory, stop.

D.2 Sensitiveness

As the parameter governing the degree of DNWR(μ^{DNWR}) increases, model predicts the higher degree of DNWR. When employment declines, the desired nominal wage change distribution shifts to the left. For those workers whose desired wage is lower than the previous wage, μ^{DNWR} fraction of workers cannot change their wage and the other $(1-\mu^{\text{DNWR}})$ fraction of workers would experience wage cuts. Thus, we can expect that as μ^{DNWR} increases, the average spike at zero increases and the average share of wage cuts decreases, which is shown at table A16 and figure A8. Similarly, the degree countercylicality of the spike at zero increases as μ^{DNWR} increases, which is shown at table A15.

Lowering the persistence of idiosyncratic shock to $\rho_q = 0.3$ does not make changes in the average wage change distribution. The second panel of table A17 shows the similar level of the average spike at zero and the share of workers with wage cuts and raises. On the contrary, increasing σ_q raises the level of spike at zero and the share of wage cuts, shown at the table A17. Table A18 shows that as long as μ^{DNWR} is the same, the degree of higher responsiveness of the spike at zero compared to the share of wage cut is the same, the ratio of two coefficients from the regression of the spike at zero on employment to the that of the share of wage cuts on employment.

D.2.1 By varying μ

D.2.2 By varying idiosyncratic shock

Table A15: The spike at zero, the fraction of wage cuts, and raises along the business cycle by varying μ^{DNWR}

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$
	Data		
Employment	-0.616	-0.305	0.921
Inflation	-1.181	-0.674	1.855
	DNWR ($\mu = 0.3$) model		
Employment	-0.194	-0.429	0.623
Inflation	-1.467	-3.365	4.832
	DNWR ($\mu = 0.5$) model		
Employment	-0.440	-0.373	0.813
Inflation	-2.658	-2.517	5.176
	DNWR ($\mu = 0.67$) model		
Employment	-0.712	-0.329	1.041
Inflation	-3.699	-1.772	5.470
	DNWR($\mu = 0.9$) model		
Employment	-1.456	-0.144	1.600
Inflation	-5.124	-0.574	5.698

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). Inflation rate is calculated from CPI-U.

Table A16: Data and model generated moments, varying μ^{DNWR}

	Wage growth rates	Employment growth rates	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
		DNWR ($\mu = 0.3$) model			
Mean	4.373	0.000	10.092	20.290	69.618
SD	1.931	0.677	3.350	6.789	9.729
Skewness	0.204	0.021	-	-	-
		DNWR ($\mu = 0.5$) model			
Mean	4.401	0.000	16.681	15.120	68.199
SD	1.769	0.766	5.204	4.757	9.749
Skewness	0.203	-0.017	-	-	-
		DNWR ($\mu = 0.67$) model			
Mean	4.381	0.000	23.026	10.531	66.443
SD	1.645	0.812	6.820	3.219	9.902
Skewness	0.320	-0.061	-	-	-
		DNWR ($\mu = 0.9$) model			
Mean	4.345	0.000	32.994	3.495	63.510
SD	1.510	1.045	9.303	1.052	10.310
Skewness	0.448	-0.077	-	-	-

Data source: CPS and author's calculation. Sample Period: 1980-2017 (except 1995). Wage growth rate is average of the median hourly wage growth rate for hourly paid workers from 1980 - 2017. model generated moments are from stat.m

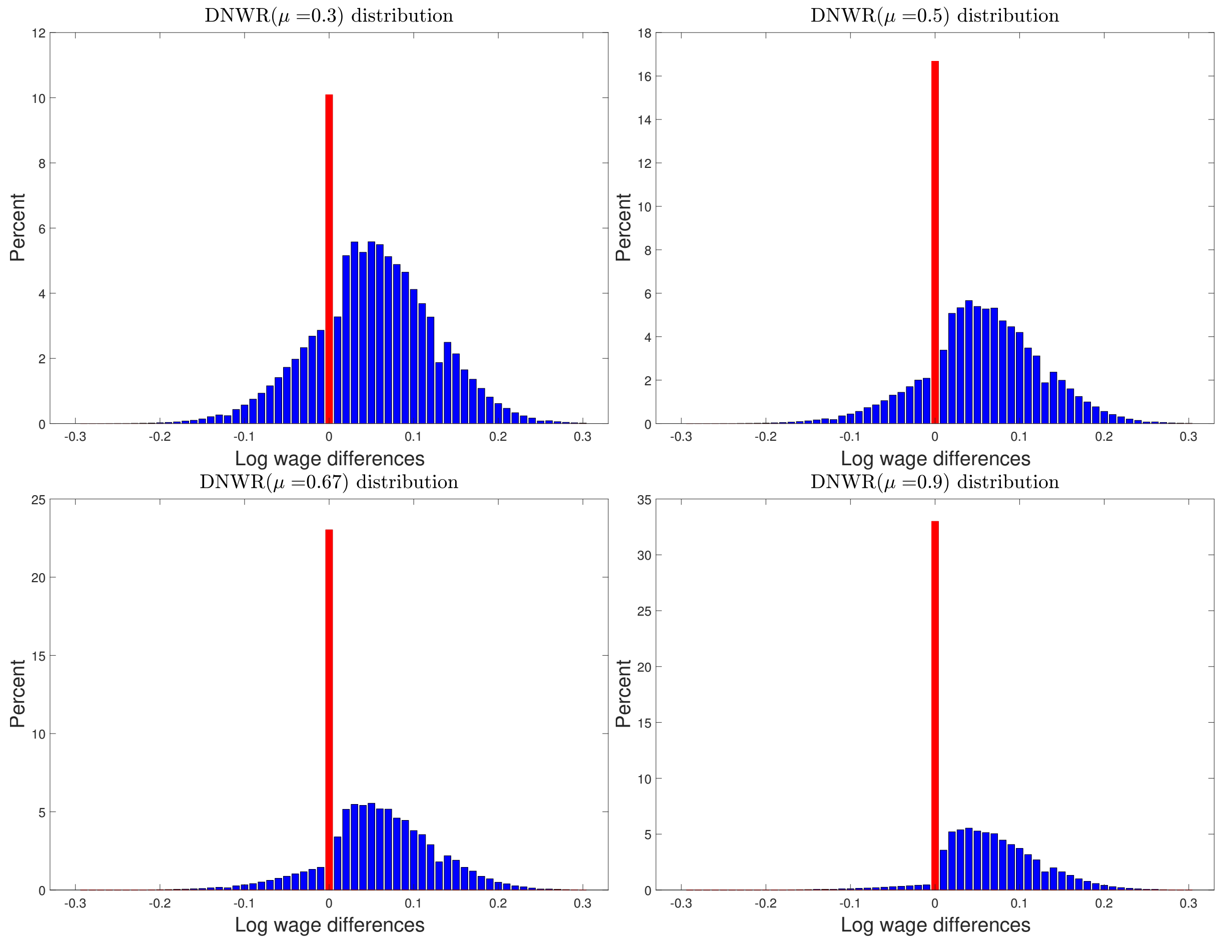


Figure A8: Staionary wage change distribution by varying μ^{DNWR}

Table A17: Data and model generated moments by varying idiosyncratic shock

	Wage growth rates	Employment growth rates	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
DNWR ($\mu = 0.67, \rho_q = 0.821, \sigma_q = 0.17$) model					
Mean	4.381	0.000	23.026	10.531	66.443
SD	1.645	0.812	6.820	3.219	9.902
Skewness	0.320	-0.061	-	-	-
DNWR ($\mu = 0.67, \rho_q = 0.3, \sigma_q = 0.17$) model					
Mean	4.380	0.000	23.762	11.166	65.073
SD	1.633	0.920	6.331	3.079	9.364
Skewness	0.288	0.023	-	-	-
DNWR ($\mu = 0.67, \rho_q = 0.821, \sigma_q = 0.254$) model					
Mean	4.382	0.000	29.305	13.693	57.002
SD	1.576	1.119	4.934	2.370	7.153
Skewness	0.230	-0.038	-	-	-

Data source: CPS and author's calculation. Sample Period: 1980-2017 (except 1995). Wage growth rate is average of the median hourly wage growth rate for hourly paid workers from 1980 - 2017. model generated moments are from stat.m

Table A18: The spike at zero, the fraction of wage cuts, and raises along the business cycle by varying idiosyncratic shock

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$
DNWR ($\mu = 0.67, \rho_q = 0.821, \sigma_q = 0.17$) model			
Employment	-0.712	-0.329	1.041
Inflation	-3.699	-1.772	5.470
DNWR ($\mu = 0.67, \rho_q = 0.3, \sigma_q = 0.17$) model			
Employment	-1.605	-0.680	2.285
Inflation	-3.319	-1.637	4.956
DNWR ($\mu = 0.67, \rho_q = 0.821, \sigma_q = 0.254$) model			
Employment	-0.447	-0.200	0.647
Inflation	-2.740	-1.339	4.079

Data source: CPS and author's calculation. Sample Period: 1980-2017 (except 1995). Inflation rate is calculated from CPI-U.

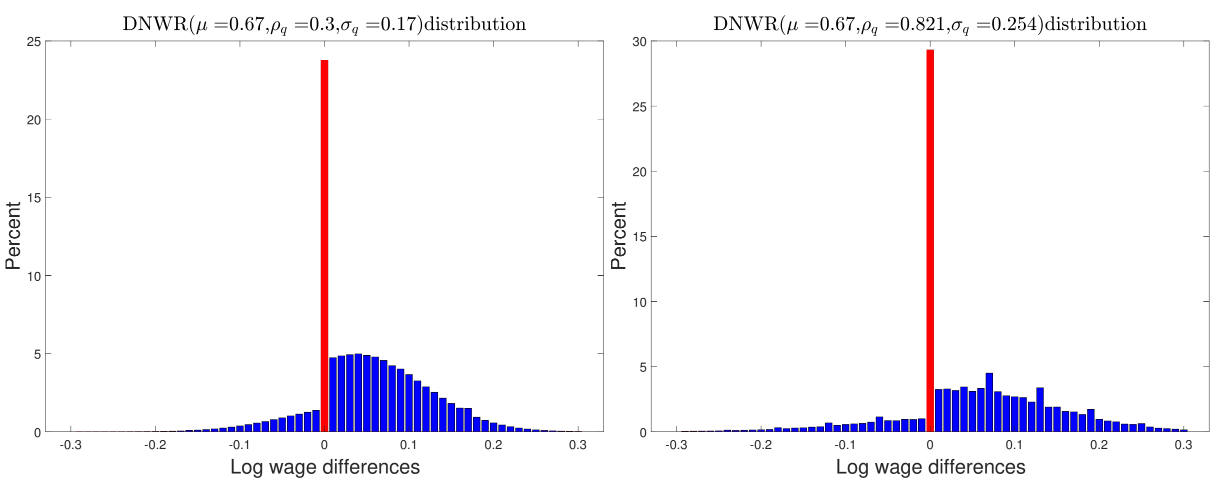


Figure A9: Staionary wage change distribution by varying idiosyncratic productivity shock

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