Downward Nominal Wage Rigidity in the United States[*]

Yoon J. Jo[†]
Texas A&M University

February 22, 2020

Download the latest version here

Abstract

This paper documents cyclical properties of nominal wage change distributions across time and US states using nationally representative household surveys from 1979 to 2018. The novel finding is that the share of workers with no wage changes, which accounts for the large spike at zero in the nominal wage change distribution, is more countercyclical than the share of workers with wage cuts. This paper analyzes heterogeneous agent models with five alternative wage-setting schemes and concludes that the model with downward nominal wage rigidity is the most consistent with empirical findings regarding the shape and cyclicality of wage change distributions.

JEL classification: E24, E32, J30.

Keywords: Nominal wage rigidity, Countercyclicality, Employment

[*]I am highly indebted to Stephanie Schmitt-Grohé, Martìn Uribe, and David Weinstein for invaluable guidance, support, and encouragement. I am grateful to Gadi Barlevy, Robert Barsky, Jeff Campbell, Stefania D'Amico, Ross Doppelt, Andreas Drenik, Jason Faberman, Sebastian Heise, Mark A. Klee, Andreas Mueller, Gernot Müller, Robert Munk, Anton Nakov, Suanna Oh, Michael Woodford, Jing Zhang, and all participants in EF colloquium in Columbia University for comments. All errors are my own.

[†]Email:yoonjo@tamu.edu

1 Introduction

The sluggish adjustment of nominal variables matters for allocation of resources. Recent studies have theorized that downward nominal wage rigidity (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 downward. However, because inflation stayed low during the Great Recession, it is believed that DNWR also prevented real wages from falling, resulting in greater unemployment.

Not only DNWR, but also other theories of nominal wage rigidity have various consequences for employment along the business cycles. However, discussion of which theory of nominal wage rigidity is the most consistent with the cyclical movement of micro-wage data is still lacking. To shed light on this discussion, I examine the cyclical properties of the nominal wage change distribution in relation to employment and inflation and ask which type of nominal wage rigidity in the existing literature is able to match empirical regularities. I show that among heterogeneous-agent models with five alternative wage-setting schemes, the model with DNWR has the most consistent implications with the empirical patterns.

This paper uses two nationally representative household surveys in the US: the Current Population Survey (CPS, 1979 - 2018) and the Survey of Income and Program Participation (SIPP, 1984 - 2013). 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 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 the study of a long time series containing multiple recessions. On the other hand, the SIPP contains an employer ID for each job of each respondent, allowing a comparison of 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 in 2010 for the nation as a whole. Consistent with the findings of previous authors,[1] 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 only at the national level but also at the state level.

[1] Kahn (1997); Card and Hyslop (1996); Lebow, Sacks, and Anne (2003); Barattieri, Basu, and Gottschalk (2014); Daly and Hobijn (2014); Elsby, Shin, and Solon (2016); Fallick, Lettau, and Wascher (2016); Grigsby, Hurst, and Yildirmaz (2019), and so on.

While it is apparent that nominal wages are more often moving upward than downward, 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 nominal wage change distribution changes over business cycles, and whether these changes are related to employment and inflation.

My analysis focuses mainly 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 of workers with wage cuts and raises. The theory of nominal wage rigidity suggests that nominal wage rigidity would have little effect on employment during periods of high inflation, but could adversely affect employment during periods of low inflation. 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 finding is consistent with the prediction that in years when nominal wage rigidity is more restricted downward, 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.

Furthermore, I document a novel empirical finding, namely, that the share of workers with no wage changes has greater countercyclical fluctuations than does the share of workers with wage cuts. With DNWR, because the movement of wages is restricted downward, it is plausible that the share of workers with 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 comovement with employment while controlling for inflation. I find that a one percentage point decline in employment is associated with a 0.6 percentage point increase in the share of workers with no wage changes and a 0.3 percentage point increase in the share of workers with a wage cut. That is, as employment falls during recessions, the share of workers with no wage changes increases substantially more than does 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 US 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

Table 1: Empirical regularities on wage change distribution and model predictions

Empirical regularities	Model predictions					
		Symmetric rigidity			Asymmetric rigidity	
	Perfectly flexible	Calvo	LTC	Menu	DNWR Menu	DNWR Calvo
When employment decreases						
1. The spike at zero increases	No	No	No	Yes	Yes	Yes
2. The share of workers with wage cuts also increases	Yes	Yes	Yes	Yes	Yes	Yes
3. The increase in the spike at zero is larger than increase in the share of workers with wage cuts	No	No	No	No	Yes	Yes

workers with no wage changes compared to that of workers with wage cuts.

At first sight, this finding 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 that wages were "fairly flexible", as lower employment growth was associated with lower wage growth. However, also using the state-level data for the same 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.

My empirical analysis documents the cyclical properties of the nominal wage change distribution. The findings are established using both the CPS and the SIPP data and at both the national and state level.[2] In summary, my empirical analysis presents three stylized facts about inflation, employment, and the nominal wage change distributions, shown in the left part of Table 1. 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 which models of wage-setting schemes are able to match these stylized facts. I build heterogeneous agent models with 5 alternative wage-setting schemes widely discussed in the literature - perfectly flexible, Calvo, long-term contracts, menu cost, and DNWR. The models feature not only idiosyncratic uncertainty but also

[2] The main analysis includes both job stayers and job switchers, and while the patterns that suggest DNWR are starker for job stayers (who comprise a large majority of the sample), the patterns hold for job switchers 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. The right part of Table 1 summarizes predictions of each wage-setting scheme.

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 at zero since they predict that the size of the spike at zero would remain constant over the business cycle. In contrast, the state-dependent models - both menu cost and DNWR - can generate the countercyclical spike at zero. However, according to the symmetric 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. 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 those 5 wage-setting schemes to the empirical findings. Section 9 concludes.

2 Related literature

This paper is related to various branches of the empirical literature on nominal wage rigidity. Early studies use individual-level panel data for the period of high inflation, 1970-1993, and document a relationship between nominal wage change distribution and inflation rather than the former and employment. Kahn (1997) uses data from the Panel Study of Income Dynamics (PSID) from 1970 to 1988 to show that nominal wage change distributions are asymmetric with a spike at zero. However, this author does not find a statistically significant relationship between the spike at zero and employment. This is because in her sample period, the average annual inflation was very high at 6.1 percent. Card and Hyslop (1996) use both PSID and CPS data from 1979 to 1993, a period during which the average annual inflation rate was approximately 5.3 percent per year. They argue that inflation can grease the wheels of the labor market by showing that the spike at zero is significantly negatively correlated with inflation: fewer workers experience zero wage changes when inflation is high. Like Kahn (1997), these authors do not find a statistically significant relationship between the spike at zero and employment.

A recent paper by Daly and Hobijn (2014) discusses the period of low inflation, 1986 -

2014, when the average annual inflation was 2.7 percent. These researchers find that the spike at zero is countercyclical: the share of workers with no wage changes increases when employment declines. In contrast to Daly and Hobijn (2014), Elsby, Shin, and Solon (2016) argue that the spike at zero has been acyclical since 1998. They argue that this increase in the spike at zero is secular rather than cyclical as a consequence of a secular decline in inflation.

Contrary to Elsby, Shin, and Solon (2016), I find that the spike at zero is countercyclical using the CPS data with the longest time period, 1979-2018, 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 provides a better understanding of the cyclicality of nominal wage change distribution.

In the studies noted above, wage change is defined to equal zero only when a worker reports the exact same hourly wage rate in the interviews one year apart. However, reported wages suffer from measurement error, which can over- or understate the size of the spike at zero. Barattieri, Basu, and Gottschalk (2014) use the SIPP panel data for the period from 1996 to 2000 to estimate the constant frequency of no wage changes after correcting for measurement error. They argue that this correction leads to 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.

A recent paper by Grigsby, Hurst, and Yildirmaz (2019) use payroll data from ADP, free of measurement error. The authors find that the share of workers with wage cuts is 8.7 percent per year and that the share of workers with no wage change is 28.6 percent for 2008-2016. They report a smaller share of workers with wage cuts and a larger spike at zero than reported in the present paper, which implies that household survey data underestimate the extent of downward nominal wage rigidity. Rather than focusing on the Great Recession and afterward, this paper uses a longer sample period from 1979 to 2018, including multiple business cycles.

Furthermore, Fallick, Lettau, and Wascher (2016) use data from the Employment Cost Index for the period from 1982 to 2014. This BLS survey includes information on the annual costs for specific job descriptions. One advantage of employer-reported wage data is that they do not have measurement errors, but a disadvantage is that it does not allow controlling for individual fixed effects since the base unit of observation is a job. The authors 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. They argue that wages cannot be quite rigid since they find a positive and strong correlation between state-level changes in nominal wages and employment during the Great Recession. However, as described in detail in Section 6.2, I argue that their finding still can be consistent with the existence of DNWR as I find a negative association between the share of workers with zero wage changes and employment at the state level.

Kurmann and McEntarfer (2018) use employer-reported earnings data from Washington State from Longitudinal Employer-Household Dynamics, and they argue that the increased incidence of wage cuts during the downturn suggests that DNWR may not be a binding constraint. However, their findings are consistent with this paper, presenting larger increases in the spike at zero compared to increases in the share of workers with wage cuts during downturns. Jardim, Solon, and Vigdor (2019) use the same data set to argue that the nominal wage cuts are prevalent. They show the average share of wage cut is 24.8 percent for job stayers in Washington State from 2005 to 2015, while this paper finds that 32.7 percent of workers had wage cuts in that state for the same sample period. A detailed comparison of figures from the previous work and this paper is provided in Appendix A.

My paper is also related to the theoretical literature on nominal wage rigidity. Schmitt-Grohé and Uribe (2016) build a representative agent model with DNWR. In this model, nominal wages cannot decrease by more than a fixed fraction. This model predicts the spike at that fixed negative wage growth rate during the recession and no spike during the boom. Although only predicting the discrete effect of DNWR, this model 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. Daly and Hobijn (2014) and Mineyama (2018) build a heterogeneous agent model with either perfectly flexible wages or DNWR They find that the spike at zero increases for the model with DNWR. I show that a symmetric nominal wage rigidity model with menu cost can also generate a countercyclical spike at zero; therefore, it is essential to examine how the whole wage change distribution moves rather than the change in the spike at zero only.

My theoretical analysis contributes to this literature by building models with all of the following components: (1) heterogeneous agents; (2) both idiosyncratic uncertainty and aggregate uncertainty; and (3) 5 alternative wage-setting schemes - perfectly flexible, Calvo, long-term contracts, menu cost, and DNWR. I compare the predictions of these models not only for the cyclical movement of the spike at zero but also for the share of workers with wage cuts in order to provide a comprehensive understanding of nominal wage change distributions.

3 Data

This paper uses two nationally representative household panel data sets in the United States, the CPS and the SIPP, 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. The 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. Almost 60,000 households are interviewed monthly. The sample period starts in 1979 and ends in 2018. The SIPP is also a US household survey conducted by the US 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 aggregate data at the national level. The sample period is from 1984 to 2013.

The CPS has a special sampling design. Each household in the sample is 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 are interviewed 4 times again in the following 4 months. Due to special sampling design of the CPS, the monthly CPS can be exploited as panel data. However, CPS microdata do not provide unique individual identifiers within the households. Instead, IPUMS-CPS provides the unique individual identifiers to link individuals across monthly CPS. To take advantage of the longitudinal features of the CPS data, this paper uses the unique individual identifiers from IPUMS-CPS.

The main focus of this paper is hourly workers who directly report hourly pay rates both in the previous year and the current year.[3] For nonhourly workers, hourly wages can be obtained by dividing the usual weekly earnings by the usual hours worked per week. However, the imputed hourly rates 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 the division bias. To remove errors caused by imputing the hourly pay rates, the main results are shown only for hourly rated workers. In the US, approximately 58 percent of workers were hourly rated in 2014.[4]

Wages, the most important variable in this paper, are often imputed in the CPS for missing values. On average, 34 percent of the hourly wages of hourly rated workers have been

[3] 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 report that the easiest way to report their wage is hourly are considered hourly workers. While some workers report that 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 way other than hourly, they are asked again whether they are paid on hourly basis, and if so, their hourly pay rate.

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

imputed since 1996.[5] Hirsch and Schumacher (2004) show that including imputed wages in the analysis may cause bias due to imperfect matching of donors with nonrespondents. 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 combine the IPUMS-CPS data with the monthly CPS, merged with the Outgoing Rotation Group, and exclude imputed wages.

This paper focuses mainly on base wages for hourly workers, which excludes other types of benefits from total compensations, including paid leave, overtime payment, nonproduction bonuses, and so on. In December 2018, the BLS report on Employer Costs for Employee Compensation[6] stated that 1.8 percent of total compensation could be attributed to to nonproduction bonuses on average, while it was 1.4 percent of total compensation in December 2011. These findings suggest that nonproduction bonuses are small and not cyclical. Also, Grigsby, Hurst, and Yildirmaz (2019) use payroll data from ADP to summarize the decomposition of monetary compensations to workers. In particular, they show that median hourly workers earn 2.2 percent of annual gross earnings other than base wages and it is not cyclical. This finding suggests that base wages are the main source of earnings for hourly workers.

One disadvantage of the CPS is that it is difficult to define job stayers and job switchers. Although the CPS provides the variable to identify whether the respondent is employed by the same employer from the last month since 1994, this variable is missing in the MIS5 after the 8 months break between interviews. Thus, it is difficult to define job stayers in the CPS.[7] Therefore, this paper does not distinguish job stayers from job switchers for the empirical analysis using the CPS.

There are advantages of using the SIPP. First, the SIPP provides unique individual identifiers, allowing individuals to be matched across waves without an 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 unique and consistent job IDs across waves for each job that the respondent had, whereas the CPS does not provided job IDs. Since job IDs are allocated based on a respondent's employer information in the SIPP, I define job stayers as employer stayers.[8] Job switchers are those who reported to work for different employers

[5]Table C1 in Appendix shows the imputation ratio for usual weekly earnings and hourly wage.

[6]Source: https://www.bls.gov/news.release/archives/ecec_03192019.pdf

[7]For example, if the respondent has switched jobs during the 8-month break period, e.g., in calendar month 5, and stayed at the same job since then, he/she would respond as being employed by the same employer for MIS6-8. This respondent is likely to be identified as a job stayer from MIS4 to MIS8, although he/she is, in fact, a job switcher.

[8]After the major revision of the 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 for this problem using the method followed by Fujita and Moscarini (2017). For the panel data from 1990 - 1993, I used the revised job IDs.

in any given year, regardless of the jobless spell between employers. One disadvantage of SIPP data is that the time series data are discontinuous because of gaps between the panels.

This paper considers mainly hourly 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 in the CPS is 15,418 per year. The time series number of observations is available in Appendix B Table C2 The average number of observations in the SIPP is 13,937 per year. On average, 71 percent of them are job stayers. The time series number of observations is provided in Table D1, and the numbers of job stayers and job switchers are available in Table D2 in Appendix C.

4 Asymmetric nominal wage change distribution

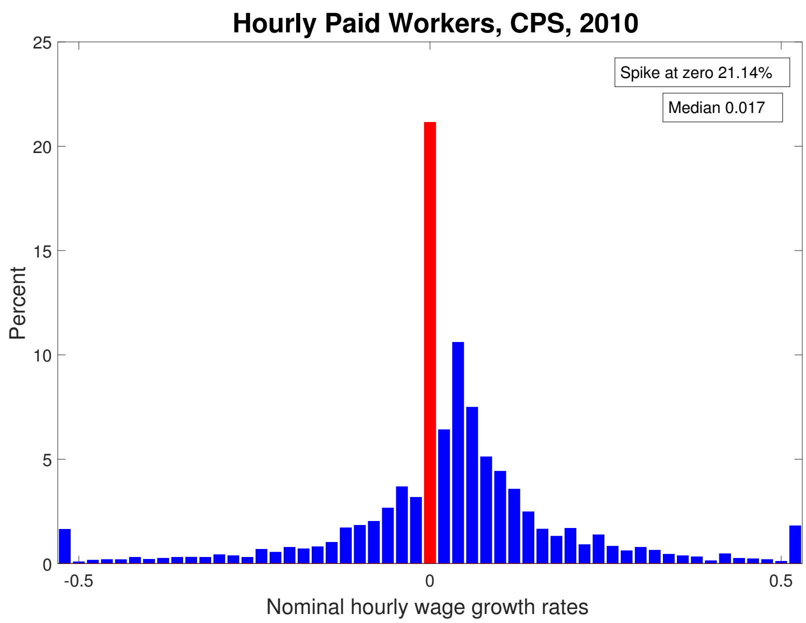

Figure 1: Year-over-year nominal hourly wage growth rates in 2010

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 size of the spike at zero in 2010 is 21 percent and the median nominal hourly wage growth rate in 2010 is 1.7 percent. 24.6 percent of hourly workers had wage cuts and 54.2 percent of workers had raises. The bin to the very right includes all the workers whose log nominal hourly wage differences are greater than 0.5, and the bin to the very left includes all the workers whose hourly wage growth rates are less than -0.5.

Figure 1 plots the distribution of individual's year-over-year changes in nominal hourly wages for the year 2009-2010. We can clearly observe that: 1) there is a large spike at zero, and 2) there are fewer wage cuts than raises. These characteristics appear common to all nominal wage change distributions for each year for the entire sample period, 1979 - 2018.[9]

[9]Figure C1 and C2 in Appendix B show similar distributions for each year from 1979 to 2018 using the CPS. Conducting the above analysis with the SIPP data from 1984 to 2013 also results in very similar findings. Figure

Table 2: Descriptive statistics by worker characteristic, CPS

	% of all workers	% of hourly workers	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$
Hourly Paid Workers	49.74		15.29	21.10	63.60
Exc.Minimum Wage Workers	45.17	90.89	15.15	20.62	64.22
Men	51.36	49.22	15.20	22.11	62.69
Women	48.64	50.78	15.38	20.08	64.54
$16 \leq$ Age <40	48.80	52.99	13.97	20.81	65.22
$40 \leq$ Age <64	47.61	43.05	16.01	21.65	62.34
Prime-Aged Men		46.27	16.30	21.69	62.01
Prime-Aged Women		49.91	16.54	20.80	62.66
High School Or Less	44.35	58.09	15.80	21.45	62.75
College Or More	55.65	41.91	14.52	20.65	64.83
White	85.74	85.02	15.41	20.56	64.03
Non-White	14.26	14.98	14.66	24.30	61.04

Data source: CPS and author's calculation. Sample Period: 1979-2018 (except 1995). This table shows the sample average of spike at zero and the share of workers with wage cuts and raises over time by worker characteristics.

Many researchers have interpreted the asymmetry and the spike of zero in the wage change distribution as suggestive of DNWR. Notably, focusing on the two bins immediately adjacent to the spike at zero, one observes a discontinuous drop in density approaching from the left compared to approaching from the right. Kahn (1997) interpreted the spike at zero as a "pile-up" of workers, who, without DNWR, would have had negative nominal wage changes. Similarly, Card and Hyslop (1996) stated that the spike at zero is mostly from "swept-up" workers, who would have been part of the bins to the left of zero if not for DNWR. Hence, the drop in density to the left of zero has also been interpreted as being consistent with the existence of DNWR.

Although it is clear that more workers experience raises than wage cuts, this fact itself can be due to positive inflation or technology growth. Thus, I exploit cyclical properties of nominal wage change distributions using three statistics from the distributions: the spike at zero (the share of workers with no wage changes), the share of workers with wage cuts, and raises. Table 2 reports the averages of these three statistics across the sample years, 1979 - 2018. On average, 15 percent of hourly workers had exact zero hourly wage changes, 21 percent of them had wage cuts, and 64 percent had raises. Excluding minimum wage workers[10] only has a marginal effect on these average estimates.

D1 in Appendix C shows nominal hourly wage change distributions for hourly workers for each year using the SIPP. All the distributions are asymmetric with a large spike at zero.

[10]Workers whose hourly wages are lower than the state's minimum wage in either the previous or current year are dropped. Data source: Vaghul and Zipperer (2016); https://www.dol.gov/whd/state/stateMinWageHis.htm.

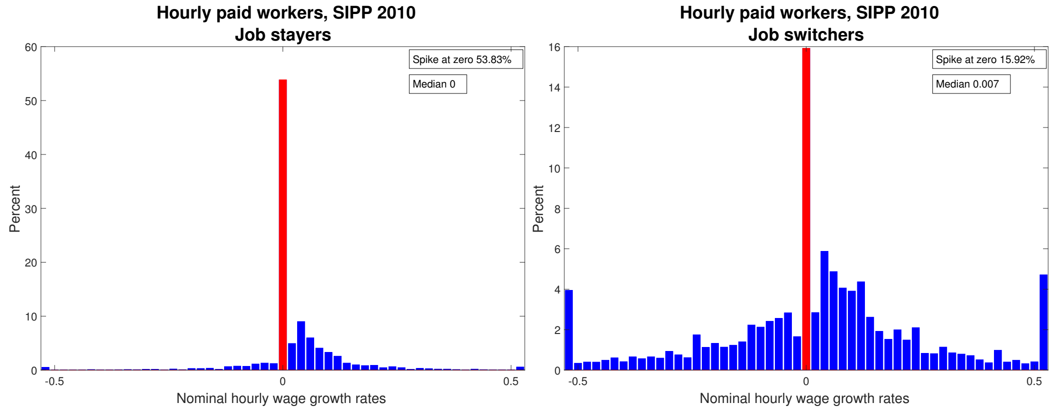

Figure 2: Nominal hourly wage distribution in 2010: job stayers vs. job switchers

Data source: SIPP and author's calculation. The figure shows nominal hourly wage change distribution for job stayers (left) and that for job switchers (right). 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. The width of blue bin is 0.02. The bin to the very right includes all the workers whose log nominal hourly wage differences are greater than 0.5, and the bin to the very left includes all the workers whose hourly wage growth rates are less than -0.5.

Nominal hourly wage change distributions do not show significant heterogeneity by gender, age, race, and education. Table 2 reports descriptive statistics by those worker characteristics. As I focus only on hourly workers, there is some sample selection: female workers, young workers, and less educated workers are overrepresented. However, calculating the averages of the three statistics for different subsets of workers results in similar estimates. In contrast, nominal hourly wage change distributions exhibit heterogeneity by hourly wage level and industry. Detailed statistics are available in Table C3 and Table C4.

The SIPP data allow me to compare nominal wage change distributions between job stayers and job switchers. I find that the empirical patterns suggestive of DNWR - asymmetry and the spike at zero - are more pronounced for job stayers, but also hold for job switchers. Figure 2 displays nominal hourly wage change distributions in 2010 for job stayers (left) and job switchers (right). Both distributions display large spikes at zero, although the spike for job stayers is much larger than that for job switchers.[11]

Similarly, Table 3 shows that for job stayers, the average size of the spike from 1984 to 2013 is larger, whereas the average share of workers with wage cuts is smaller.[12] The median

[11]Table D6 in Appendix C shows the average of the spike at zero and the share of wage cuts and raises according to the reasons why hourly workers switched their employer in a given year. Contingent workers or temporarily employed workers, workers on layoff, and injured or ill workers show the high average spike at zero among job switchers.

[12]In fact, the spike at zero for job stayers is always higher than that for job switchers and the share of workers with wage cuts for job stayers is always lower than that for job switchers. Table D2 shows the time series spike at zero, the share of wage cuts and increases for both job stayers and job switchers.

Table 3: Descriptive statistics, SIPP

	% of all workers	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$
Hourly Paid workers		24.00	17.42	58.58
Exc.Minimum wage workers	89.25	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

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 for job stayers, job switchers, and both.

size of wage growth rates for job switchers is also much larger than that for job stayers.[13] These comparisons between job stayers and switchers appear overall consistent with the findings by Bils (1985), who argue that wages are more flexible for job switchers than for job stayers. However, my findings suggest that job switchers' wages may still be downwardly rigid, albeit to a lesser extent.

Because about 71 percent of hourly workers are job stayers in the SIPP and because nominal hourly wage change distributions for job switchers still exhibit asymmetry and the spike at zero - although to a lesser extent - the distributions using all hourly workers including both job stayers and job switchers, as shown in Figure D1, exhibit strong asymmetry and a large spike at zero.

5 The cyclicality of wage change distributions

This section contains the main empirical results of the paper, namely, that the spike at zero shows greater countercyclical fluctuations than does the share of workers with wage cuts. I focus on the three aggregate time series: the share of workers with zero wage changes (the spike at zero), the fraction of workers with wage cuts, and the fraction of workers with raises, constructed in Section 4 above.

Table C2 of Appendix B reports the spike at zero and the fraction of workers with wage cuts and raises along with the number of observations of individual hourly workers that went into constructing these summary statistics of the nominal wage change distributions for a given year from CPS for the period 1979 to 2018. Table D1 in Appendix reports the these statistics for all hourly workers for each year using the SIPP. From this aggregate time series, we can see a sudden increase in the level of the spike at zero in 2005 and , accordingly,

[13]Nominal hourly wage change distributions for job stayers and job switchers for the entire sample period are shown in Figure D2 and Figure D3. In addition, Table D4 shows that for both job stayers and job switchers, workers from a lower hourly wage quartile are more likely to have no wage changes or wage cuts than workers from a higher wage quartile.

Table 4: The spike at zero, the share of wage cuts, and raises along the business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero $\Delta W = 0$	(5) Share of cuts $\Delta W < 0$	(6) Share of raises $\Delta W > 0$
1-Epop ratio	0.437	0.201	-0.638	0.617***	0.303*	-0.919***
$(1 - e_t)$	(0.296)	(0.218)	(0.493)	(0.159)	(0.154)	(0.278)
Inflation rate				-1.181***	-0.673***	1.853***
(π_t)				(0.121)	(0.142)	(0.216)
Observations	38	38	38	38	38	38
Adjusted R^2	0.0442	-0.00342	0.0332	0.731	0.340	0.705

Data source: CPS and author's calculation. Sample Period: 1979-2018 (except 1995). Inflation rate is calculated from CPI-U. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

sudden decreases in the share of workers with wage cuts and raises. This pattern is due to the introduction of the new survey design to the 2004 panel and after – the dependent interviewing procedure. That is, if an hourly worker reports that s/he is paid the same wage as in the previous interview, the hourly pay rate from the current interview is automatically filled by the one from the previous interview.

To explore the cyclicality of the nominal wage change distributions, we can consider the following three regression equations:

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

where e_t denotes the employment to population ratio in year t. Adding the above three equations will give us $1 = \alpha_s + \alpha_n + \alpha_p + (\beta_s + \beta_n + \beta_p)(1 - e_t) + \epsilon_{st} + \epsilon_{nt} + \epsilon_{pt}$, as the sum of the three shares equals 1 by definition. Since the left-hand side of the previous equation is a constant, we know that $\beta_s + \beta_n + \beta_p = 0$.

Thus, β_p –, the change in the share of workers with raises associated with the change in $(1 - e_t)$, can be decomposed into two parts: either β_s – ,the change in the spike at zero –, or β_n –, the change in the share of workers with wage cuts. This framework allows us to study the changes in nominal wage change distributions more comprehensively, unlike most of the earlier studies that only focused on the cyclicality of the spike at zero.

Table 4 shows regression results based on the regression equation (1) without and with controlling for inflation. During periods of high inflation, nominal wage rigidity would have a limited impact on real wage rigidity and thus on employment. In contrast, during periods of low inflation, nominal wage rigidity could potentially have a substantial effect on employment. During my sample period, 1979 - 2018, inflation varied from negative rates (e.g., -0.4 percent in 2009) to high rates (e.g., 12.7 percent in 1980). Hence not controlling for inflation could understate the relationship between employment and nominal wage changes. Indeed, in the first three columns of Table 4 where I do not control for inflation, I do not find statistically significant relationships between the dependent variables and employment.

By contrast, when I control for inflation, I find statistically significant relationships between the dependent variables and employment. In particular, column (4) shows that the spike at zero increases when employment declines. This cyclical property of the spike at zero is consistent with the findings by Kahn (1997); Card and Hyslop (1996) and Daly and Hobijn (2014).

Furthermore, the spike at zero shows greater countercyclical fluctuations compared to the share of workers with wage cuts. I find that a 1 percentage point decline in employment is associated with 1) a 0.6 percentage point increase in the spike at zero: 2) a 0.3 percentage point increase in the share with wage cuts; and 3) a 0.9 percentage point decrease in the share with raises. In other words, when there is a 1 percentage point decrease in employment, the share of workers with raises declines by 0.9 percentage points, and mechanically, the share of workers with wage cuts or no wage changes would increase by 0.9 percentage points. In fact, 67 percent (= 0.6/0.9) of this increase is attributable to the share of workers with no wage changes. That is, the increase in the spike at zero is much greater than the increase in the share that have wage cuts. Table 5 additionally shows the spike at zero responds to employment greater than the share of wage cuts in a statistically significant way, controlling for both inflation and TFP. This result is also robust after controlling for changes in total factor productivity, shown in Table4 in Appendix B.2.[14]

The spike at zero shows greater responsiveness than the share of workers with wage cuts. Table 5 shows the excess responsiveness of the spike at zero than the share of workers with wage cuts simply by regressing the difference between the spike at zero and the share of workers with wage cuts on non-employment. Controlling for inflation and changes in the total factor productivity, we can observe that the spike at zero more reacts to employment to population ratio than the share of workers with wage cuts. These results are robust to both prime-age (ages between 25-54) men and women, after partially controlling for composition effects.

This pattern seems plausible given DNWR. During recessions with low inflation, the workers who may have experienced wage cuts if not for DNWR instead would experience zero wage changes, since nominal (and real) wages are restricted from adjusting downward. This could lead to a larger change in the share of workers with no wage changes associated with a decline in employment. When employment increases and more workers experience

[14]Section B.2 in Appendix shows that there are no asymmetric responses of nominal hourly wage change distributions to increases in employment to decreases.

Table 5: Greater fluctuations of the spike at zero

	All			Prim-Age Men		Prime-Age Women	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Spike at zero minus share of wage cuts						
1-Epop ratio	0.237	0.314**	0.424**	0.472***	0.497***	0.617***	0.662***
$(1 - e_t)$	(0.166)	(0.143)	(0.188)	(0.0776)	(0.0725)	(0.147)	(0.137)
Inflation rate		-0.508***	-0.471***	0.213	0.321***	-0.476***	-0.424***
(π_t)		(0.152)	(0.142)	(0.138)	(0.117)	(0.0845)	(0.105)
ΔTFP			0.551		0.729**		0.679**
			(0.455)		(0.287)		(0.261)
Observations	38	38	38	38	38	38	38
Adjusted R^2	0.000989	0.153	0.190	0.590	0.658	0.428	0.517

Data: CPS and author's calculation. Inflation rate is calculated from CPI-U. Sample Period: 1979-2018 (except 1995). This table shows the results of the regression of the difference between the spike at zero and the share of workers with wage cuts on 1-Epop ratio, controlling for inflation and changes in total factor productivity. The first three columns show the results for all hourly-paid workers, columns 4 and 5 are for prime-age men, and columns 6 and 7 are for prim-age women. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

wage increases, because a large number of workers are "piled up" at zero, the decrease in the spike at zero could be larger than the decrease in the share of workers with wage cuts. In conclusion, I find that the spike at zero exhibits greater countercyclicality compared to the share of workers with wage cuts, and interpret this to be possibly consistent with the implication of DNWR.

Regarding the regressions above, one may be concerned about error in self-reported hourly wages (Bound and Krueger (1991)); however, measurement error on the dependent variables, orthogonal to independent 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 wages, they may report their true wages with some error. This type of measurement error would understate the wage rigidity, the spike at zero. Second, workers may report rounded hourly wages, and this would overstate the spike at zero. However, these measurement errors do not vary with employment. In addition, the fraction of imputed wages in the CPS, which is available from the last column of Table C1 , can be a proxy for the degree of measurement error, and it does not exhibit cyclicality. As measurement errors do not have a cyclical component, we can argue that measurement errors on hourly wages do not add bias on the cyclicality of the spike at zero, the share of workers with raises, and cuts.

The primary results are also robust to salaried workers and subgroups of workers by worker characteristics such as gender, age, race, and education. The excess sensitivity of the spike at zero than the share of wage cuts are apparent for those workers with college or more education, your workers, female, non-white, or hourly workers with low income quartiles. These robustness checks are available in Appendix B.2. In addition, low-paid young workers, who are less likely to be in a long-term contract, also show the main empirical findings on the cyclicality of nominal wage change distribution.[15] They exhibit a sizable, and in fact, a greater spike at zero than the overall sample and also show a higher share of workers with wage cuts.[16] Low-paid young workers still show a similar cyclical pattern of nominal wage change distribution to that of overall sample: greater, but not statistically different, fluctuations of spike at zero than the share of workers with wage cuts, controlling for inflation, shown in Table C14. This finding suggests that nominal wages are also rigid for those workers without a long-term contract.

To analyze the cyclicality of nominal wage change distributions for job stayers and job switchers separately, I construct the same three aggregate time series using three different samples using the SIPP data: all workers, only job stayers and only job switchers.[17] The spike at zero of job stayers appears to respond to employment more than does the spike at zero of job switchers. However, I still find that the spike at zero of job switchers exhibits countercyclical fluctuations. This finding implies that the cyclical property of nominal wage change distributions for all hourly workers is not solely driven by job stayers. This analysis with the SIPP data suggests that nominal wages are still rigid for job switchers, and more rigid for job stayers. Details are available from D5 in Appendix C.

6 The cyclicality of state-level wage change distributions

In this section, I validate the above results using the annual state-level panel data. This allows me to use more observations to examine the relationship between employment, inflation and nominal wage change distribution while controlling for state and year fixed effects. To explore the cyclicality of state-level nominal wage change distributions, I now construct the following statistics for each state: the share of workers with zero year-over-year changes in hourly wages (the spike at zero), the share of workers with wage cuts and with raises. The state-level data analysis leads to similar findings as the aggregate data analysis. I interpret these results to be consistent with DNWR and contrast them with the arguments from a recent study by Beraja, Hurst, and Ospina (2016).

Table 6: The spike at zero, the fraction of wage cuts and raises across states

	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts
1-Epop ratio	0.396***	0.287***	-0.683***	0.110
$(1 - e_{it})$	(0.0798)	(0.0628)	(0.0860)	(0.115)
State Fixed Effect, α_i	Yes	Yes	Yes	Yes
Time Fixed Effect, γ_t	Yes	Yes	Yes	Yes
Observations	1750	1750	1750	1750
Adjusted R^2	0.598	0.530	0.707	0.300

Data source: CPS and author's calculation. Sample Period: 1980-2018 (except 1985, 1986, 1995, and 1996 due to small sample sizes). The sample consists of 50 states over 35 years. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table 7: The spike at zero, the fraction of wage cuts and raises - job-stayers vs. job-switchers across states, SIPP

	All hourly paid workers			Job stayers			Job switchers		
	(1) Spike at zero	(2) Share of cuts	(3) Share of raises	(4) Spike at zero	(5) Share of cuts	(6) Share of raises	(7) Spike at zero	(8) Share of cuts	(9) Share of raises
1-Epop ratio	0.407***	0.0989	-0.506***	0.489***	0.121	-0.610***	0.348***	0.124	-0.471**
$(1 - e_{it})$	(0.101)	(0.0767)	(0.111)	(0.123)	(0.0789)	(0.121)	(0.101)	(0.176)	(0.182)
State Fixed Effect, α_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect, γ_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

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. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses. Standard errors in parentheses.

6.1 State-level analysis from 1979 to 2018

Similar to the regression equations (1) in the aggregate analysis, we can consider the following state-level regression equations:

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

where e_{it} is the employment to population ratio for each state i ($i = 1, \cdots, 50$) and time t. α_i ($\alpha_{i,s}$, $\alpha_{i,n}$, and $\alpha_{i,p}$) capture state fixed effects, γ_t ($\gamma_{t,s}$, $\gamma_{t,n}$, and $\gamma_{t,p}$) absorb time fixed effects. State fixed effects control for state-specific differential time trends. Time fixed effects control for the factors that are common across states for each year such as monetary policy or aggregate inflation. As shown in Section 5, controlling for inflation is important for obtaining a statistically significant relationship between employment and the three statistics summarizing nominal wage change distributions. I estimate these equations using data from 50 states for the years 1979-2018 (except 1985, 1986, 1995, and 1996).[18]

Table 6 shows the regression results using the regression specification (1), exploiting state-level variations. The table shows that a 1 percentage point decrease in employment is associated with 1) an increase in the spike at zero by 0.38 percentage points: 2) an increase in the share of workers with a wage cut by 0.29 percentage points; and mechanically, 3) a decrease in the share of workers with raises by 0.67 percentage points. In other words, when employment declines by 1 percentage point, the share of workers with raises also declines, and 57 percent (=0.38/0.67) of this change is attributed to the change in the share of workers with zero wage changes. The higher responsiveness of the spike at zero compared to the fraction of workers with wage cuts in the cross-section of US states implies that state-level cyclical variations in nominal wage change distributions are still consistent with the results obtained in Section 5 for time variations in data for the US as a whole.

The point estimate of the excess responsiveness of the spike at zero compared to that of the share of workers with wage cuts is slightly smaller in the state-level analysis than in the aggregate analysis and it is not statistically significant, as shown at the forth column of Table 6. This difference is likely because time fixed effects absorb all aggregate variations and the state-level analysis only exploits the deviations from state-specific averages and time-specific aggregate averages.

[15] I define low-paid young workers as hourly workers whose ages are less than 30 and hourly pay rates are less than the 25th percentile of hourly wages for each year and greater than the minimum wage. These workers constitute about 6 percent of the overall sample.

[16] The average spike at zero for low-paid young workers is 18.7 percent, and the average share of workers with wage cuts is 32.3 percent over the period from 1979 to 2018. Both of these values are greater than the overall sample averages, 15.2 percent, and 21.1 percent, respectively.

[17] Table **??** reports the time series of the three statistics for job stayers and job switchers.

[18] These 4 years are dropped due to small sample size.

The pattern - greater countercyclicality of the spike at zero than the share of workers with wage cuts - holds for both job stayers and job switchers. Table 7 shows regression results based on the equation (2) using the SIPP, controlling for both time and state fixed effects. Job stayers show higher responsiveness of the spike at zero than job switchers, but the pattern still holds for job switchers as well. This again shows that job stayers are not the sole ones driving the results for all hourly workers, but the wages of job switchers also exhibit patterns consistent with DNWR.

6.2 The Great Recession of 2007 - 2010

In a recent study, Beraja, Hurst, and Ospina (2016) (BHO, hereafter) argue that wages were "fairly flexible" during the Great Recession. These authors show that nominal wage growth rates were strongly and positively correlated with employment growth rates across states during the Great Recession. This finding is represented in the left panel of Figure 3, which plots the percentage change in the median nominal wage growth rate against the percentage change in employment from 2007 to 2010 for each state. This figure uses CPS data to replicate Figure 4 of BHO.[19] Given the strong positive correlation of nominal wage growth and employment across states shown in the figure, the authors estimate the wage stickiness parameter using a wage setting model and argue that wages were fairly flexible during the Great Recession.[20]

In the right panel of Figure 3, I present a similar plot, but use the spike at zero on the y-axis instead. That is, I plot the percentage changes in the spike at zero against the percentage changes in employment from 2007 to 2010 for each state. This plot shows that the changes in the spike at zero are negatively correlated with changes in employment for the same time period. In other words, a state with a higher fall in employment had a higher increase in the spike at zero; more workers experienced downwardly rigid wages in the states that had greater declines in employment.

I corroborate this finding by estimating the following regression equations for 2007-2010:

$$\begin{array}{rcl} \Delta[\text{Spike at zero}]_i & = & \alpha_s + \beta_s \Delta e_i + \epsilon_{i,s} \\ \Delta[\text{Fraction of wage cuts}]_i & = & \alpha_n + \beta_n \Delta e_i + \epsilon_{i,n} \\ \Delta[\text{Fraction of raises}]_i & = & \alpha_p + \beta_p \Delta e_i + \epsilon_{i,p} \\ \ln W_{i2010} - \ln W_{i2007} & = & \alpha + \beta \Delta e_i + \epsilon_i \end{array}, \tag{3}$$

[19] The difference between the wage data used in the study of BHO and my study is that these authors compute the composition adjusted average nominal wage for each state every year using the ACS, 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.

[20] To estimate the wage rigidity parameter, they use the partial wage adjustment equation, proposing that the current wage is determined by the weighted average of the optimal wage and the previous wage. Based on their estimation, they find that the weight on the previous wage is 0.31 to determine the current wage. Therefore, they conclude that there was only a modest amount of wage stickiness or a fair degree of wage flexibility.

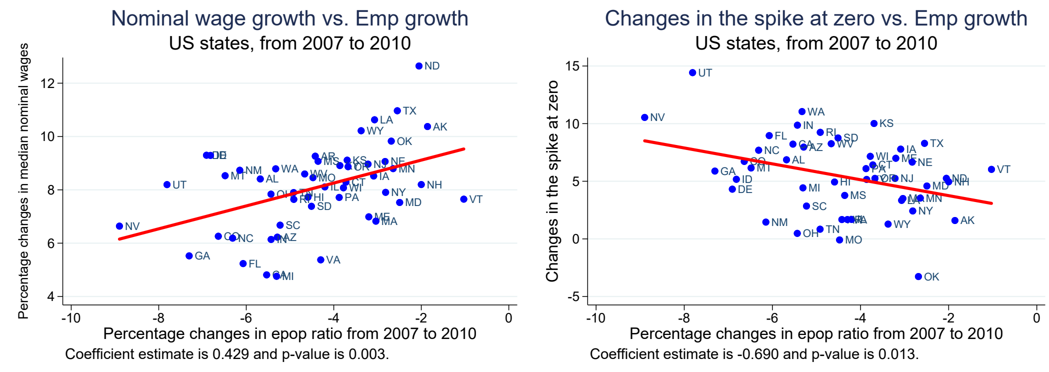

Figure 3: Nominal wage growth rates and changes in the spike at zero vs. employment growth across states from 2007 to 2010

Data source: CPS and author's calculation. The left panel shows the median nominal wage growth versus employment growth rates from 2007 to 2010 across states. The right panel shows the changes in the spike at zero versus employment growth from 2007 to 2010 across states. From 2007 to 2010, the annualized inflation rate was 1.7 percent, and the cumulative inflation was 5 percent.

Table 8: Changes in nominal wage distribution from 2007 to 2010 across states

	(1) Changes in Spike at zero $\Delta W = 0$	(2) Changes in Share of cuts $\Delta W < 0$	(3) Changes in Share of raises $\Delta W > 0$	(4) Changes in Spike at zero minus Share of cuts	(5) $\ln \frac{W_{s2010}}{W_{s2008}}$
Percent change in employment rate	-0.694**	-0.213	0.907**	-0.480	0.428***
	(0.267)	(0.320)	(0.397)	(0.436)	(0.136)
Observations	50	50	50	50	50
Adjusted R^2	0.104	-0.0104	0.0699	0.0103	0.183

Data source: CPS and author's calculation. Sample Period: 2007 - 2010. This table shows changes in nominal wage change distributions along with employment for each state from 2007 - 2010. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

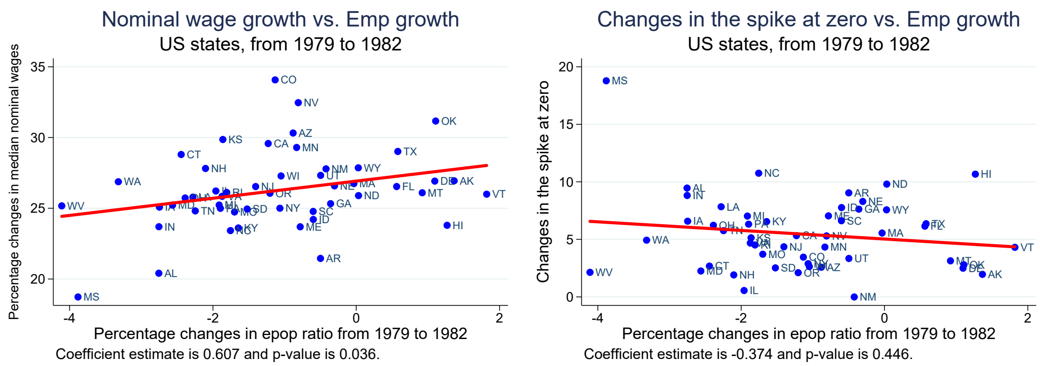

Figure 4: Nominal wage growth and changes in the spike at zero vs. employment growth from 1979 to 1982

Data source: CPS and author's calcuation. The left panel shows the median nominal wage growth with respect to employment growth rates from 1979 to 1982 across states. The right panel shows the change in the spike at zero with respect to employment growth from 1979 to 1982 across states. From 1979 to 1982, the average of annualized inflation rate was 9.5 percent and the cumulative inflation was 28.5 percent.

where Δe_i is the difference in the employment to population ratio from 2007 to 2010 in a state i. Table 8 shows regression results based on the equation (3). A 1 percentage point decrease in employment in a state is associated with 1) an increase in the size of the spike at zero by 0.7 percentage points, 2) an increase in the share of workers with wage cuts by 0.2 percentage points, and 3) a decrease in the fraction with raises by 0.9 percentage points. We again see that the responsiveness of the spike at zero is larger than the responsiveness of the share with wage cuts.

This result is still compatible with BHO's empirical findingshown in the last column of Table 8: the positive correlation with nominal wage growth rates and changes in employment. This is because a state with a larger decline in employment is likely to also have a higher increase in the share of workers with wage cuts, leading to an overall drop in nominal wage growth rates, presented in the left panel of Figure 3. However, this is also accompanied by a much larger increase in the spike at zero. Thus, I argue that the finding by BHO does not contradict the existence of downward nominal wage rigidity.

6.3 The recession of 1979 - 1982

The Great Recession of 2007 - 2010 was a period of relatively low inflation. Thus, it was a period in which downward nominal wage rigidity resulted in downward real wage rigidity and, hence, reallocative effects on employment. One way to check whether nominal wages, as opposed to real wages, are downwardly rigid is to perform the same analysis just performed for the low-inflation recession of 2007 - 2010 for a high-inflation recession. In what

Table 9: Changes in nominal wage distribution from 1979 to 1982 across states

	(1) Changes in Spike at zero $\Delta W = 0$	(2) Changes in Share of cuts $\Delta W < 0$	(3) Changes in Share of raises $\Delta W > 0$	(4) Changes in Spike at zero minus Share of cuts	(5) $\ln \frac{W_{s1982}}{W_{s1980}}$
Percent change in employment rate	-0.374	0.163	0.211	-0.537	0.607**
	(0.487)	(0.333)	(0.678)	(0.486)	(0.281)
Observations	50	50	50	50	50
Adjusted R^2	0.00407	-0.0148	-0.0166	0.00958	0.0715

Data source: CPS and author's calculation. Sample Period: 1979 - 1982. This table shows changes in nominal wage change distributions along with employment for each state from 1979 - 1982.* p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

follows, I will consider the recession of 1979 - 1982, because it was a deep recession – similar in size to the 2007 - 2010 recession, and inflation was high – the aggregate price level grew by 29 percent between 1979 and 1982. What we should see, then, under the hypothesis that nominal wages, as opposed to real wages, are downwardly rigid, is that there is no significant relationship in the cross-section of US states between employment changes and changes in the share of workers receiving a zero wage change.

The left panel of Figure 4 shows state-level median nominal wage growth rates with respect to changes in employment across states from 1979 to 1982, and the right panel of Figure 4 shows changes in the spike at zero versus employment growth rates across states for the same period. Although median nominal wage growth rates show strong positive relationships with employment growth rates shown in the right panel of Figure 4, we cannot find distinctive relationships between the changes in the spike at zero and changes in employment. Table 9 shows the regression results of changes in nominal wage change distributions on employment, confirming what we have seen from Figure 4, when the average inflation rate is high. This finding shows rigid nominal wages do not matter for the employment during the period of high inflation; it is about nominal wage rigidity, not real wage rigidity.

7 Heterogeneous agent models

In this section, I build heterogeneous agent models with both idiosyncratic and aggregate shocks, imposing 5 alternative wage-setting schemes - perfectly flexible, Calvo, long-term contracts, menu cost, and downward nominal wage rigidity. The basic setup of the model is from Erceg, Henderson, and Levin (2000).

7.1 Firm

Consider a representative firm that produces consumption goods using 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. The firm's profit maximization problem 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 $[\int [W_t(i)/q_t(i)]^{1-\theta} di]^{1/(1-\theta)}$.

7.2 Households

There is a continuum of households, indexed by $i \in [0,1]$, and each household chooses the consumption, saving, nominal wage, and labor supply to maximize lifetime 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. Each household chooses the $\{C_t(i), B_{t+1}(i), W_t(i), l_t(i)\}$ to maximize

$$\max_{\{C_t(i), B_{t+1}(i), W_t(i), l_t(i)\}} \mathbb{E}_t \Sigma_{t=0}^{\infty} \beta^t \left[\frac{C_t(i)^{1-\gamma}}{1-\gamma} - \frac{1}{1+\psi} l_t(i)^{1+\psi} \right] \tag{4}$$

subject to

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

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

7.3 Five wage-setting restrictions

As the household utility is additively separable, we can isolate the wage-relevant part of the household problem (4), which is is equivalent to choose the wage $W_t(i)$ and labor supply $l_t(i)$ to maximize

$$\max_{\{W_t(i),l_t(i)\}} \mathbb{E}_t \Sigma_{t=0}^{\infty} \beta^t \left\{ \lambda_t(i) W_t(i) l_t(i) - \omega \frac{l_t(i)^{1+\psi}}{1+\psi} \right\} \text{ (s.t.) } \underbrace{l_t^d(i) = q_t(i)^{\theta-1} (\frac{W_t(i)}{W_t})^{-\theta} L_t}_{\text{Wage setting constraint}} \tag{5}$$

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

Second, Calvo wage rigidity is considered, assuming that only a constant fraction of workers can optimize wages every year. This is the most commonly used wage-setting mechanism for nominal rigidity.[21] Followed by Calvo (1983), wage setters cannot optimize their wages with the constant probability of μ^{Calvo}, regardless of the state of the economy. The Calvo wage-setting constraint can be rewritten as follows:

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

where $W_t^*(i)$ is the optimal wage, the nominal wage that maximizes the equation (5) in the absence of wage-setting constraint in a period t.

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

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

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

, where s is the probability of renewing the contract.

Fourth, consider the symmetric menu cost model of wage rigidity, motivated by the empirical evidence that changes in nominal wage change distribution are state dependent. Wage setters must pay a menu cost 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 the random menu cost model in the price rigidity literature (Alvarez, Le Bihan, and Lippi (2016)), which explains small changes in prices. This model can be summarized as follows:

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

The fifth wage-setting scheme is the DNWR model. This paper introduces two types of DNWR: asymmetric menu cost and Calvo. In the asymmetric menu cost model, wage setters have to pay an extra fixed cost (K^D) with the probability of μ^{Menu} to lower their wages, whereas there are no fixed costs to raise their wages. When wage setters find that the optimal wage is lower than the previous wage, they have to compare between lowering their wages at the optimal level after paying the fixed cost and keeping wages at the previous level without incurring an additional cost. The wage-setting decision with asymmetric menu cost model can be described as follows:

$$W_t(i) = \begin{cases} \begin{cases} W_t^*(i) & \text{if } W_t^*(i) \geq W_{t-1}(i), \text{no cost} \\ W_t^*(i) & \text{if } W_t^*(i) < W_{t-1}(i), \text{pays cost } K^d \\ W_{t-1}(i) & \text{if } W_t^*(i) < W_{t-1}(i), \text{no cost} \end{cases} & \text{,with the prob } \mu^{\text{Menu}} \\ W_t^*(i) & \text{,with the prob (1-}\mu^{\text{Menu}}\text{)} \end{cases} .$$

In the DNWR model with asymmetric Calvo model, only a certain fraction of wage setters is able to lower their wages. If the optimal wage 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 is lower than the previous wage, then the 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 written, as follows:

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

7.4 Closing the market

The goods market clearing condition is $Y_t = C_t$. In the economy, nominal output equals the total wage payment in the economy, which is the same as the total money supply in the economy, as follows:

$$P_t Y_t = P_t C_t = W_t L_t = M_t,$$

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

$$\ln(M_{t+1}) = \mu + \ln(M_t) + \eta_{t+1} \quad \eta_{t+1} \sim \mathbb{N}(0, \sigma_\eta^2), \tag{6}$$

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

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

We can write down households' wage-setting problem in a recursive way. Bellman equation for each wage-setting scheme is provided in Appendix D.1.

8 Numerical results

As the model has both idiosyncratic shock and aggregate shock, I solve the model numerically. This section begins to explain solution methods and calibrated parameters. This section characterizes the stationary nominal wage change distribution and cyclical properties of nominal wage change distributions implied by each of the five alternative wage-setting schemes.

8.1 Solution methods

This paper solves the recursive problem numerically using the policy function iteration over the discretized state space. The wage-setter's problem is infinite dimensional as they have to take into account the entire wage and productivity distribution. Following Krusell and Smith (1998), this paper assumes that agents use only partial information, the first and second moments of the distribution, to predict the law of motion of the aggregate wage growth.Further details on solution methods are available in Appendix D.2.

Table 10 shows calibrated parameters. Parameters in the top panel are 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 that the steady-state annual real interest rate is 3 percent. ψ = 0.5 is the inverse of Frisch elasticity, which is withing a permissible range in the macro literature shown in Chetty, Guren, Manoli, and Weber (2011). The wage elasticity of labor demand, θ, varies from 1.67 to 21 from the previous literature.[22]

[22]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. Fagan and Messina (2009) used $\theta = \frac{11}{12}$.

Table 10: 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	Table 4
μ^{Calvo}	0.22	The frequency of no wage change	Matching the spike at zero, implied by DNWR model (asymmetric Calvo)
s	0.23	The probability of continuing contract	
$\mu^{\text{Menu cost}}$	0.8	The probability of facing menu cost	
K	0.002	Symmetric menu cost	
K^d	0.013	Asymmetric menu cost	

Time unit is a year.

This paper sets θ to be 3, which implies steady-state markup 1.5, in accordance with Smets and Wouters (2007).

The second panel of Table 10 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[23] to estimate the aggregate shock process given by the equation (6). I estimate the constant growth rate (μ) and the standard deviation from the growth rate of the total wage payment. 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.[24]

The last panel of Table 10 shows parameters governing the degree of wage rigidity. In the DNWR with asymmetric Calvo model, μ^{DNWR}, the probability that wages cannot be adjusted downwardly is calibrated to match cyclical properties of nominal wage change distribution, shown in Table 4. All parameters other than μ^{DNWR} – μ^{Calvo} from the Calvo model, s from the long-term contracts model, μ^{Menu} and K from the symmetric menu cost model, and K^d for the asymmetric menu cost model – are calibrated to have the same size of the spike at zero at the steady-state level of the spike at zero under DNWR.

Mineyama (2018) used θ at 9, which results in a steady-state wage markup of 12.5 percent. A recent paper by De Loecker and Eeckhout (2017) reported that the average markup in 1980 was 1.18, after which it began to rise and reached 1.67 in 2014.

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

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

8.2 Stationary wage change distribution

Figure 5 shows the stationary nominal wage change distributions generated from 5 alternative wage-setting schemes. The red bar represents the fraction of workers with exact zero wage changes. The top left panel shows the stationary wage change distribution under the perfectly flexible case. It is symmetric around the median and there is no spike at zero. Other models than the case of the perfectly flexible model are calibrated to have the same size of the spike at zero across models.

The Calvo model generates the spike at zero but the symmetric stationary wage change distribution around the median, shown in the top right panel of Figure 5. The frequency of wage adjustment from the Calvo model determines the level of the spike at zero. 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. If we further allow wage indexation for those workers not able to re-optimize their wages as in Christiano, Eichenbaum, and Evans (2005), stationary wage change distribution has a spike at the indexed wage inflation rate, not at zero.

The long-term contract wage setting also generates the spike at zero but symmetric stationary wage change distribution. The second left panel of Figure 5 shows the remitted wage change distribution from the long-term contract under perfect foresight. Allocated wages come from the perfectly flexible model, so its implications for employment should be the same as those of the perfectly flexible model. However, the stationary wage distribution has the spike at zero and is symmetric around the median, which is again inconsistent with empirical findings.

Symmetric menu cost of wage adjustment generates the spike at zero, but there is no discontinuous drop in the stationary distribution approaching zero from the left compared to that from the right, shown in the second right panel of Figure 5. As wage setters must pay an additional fixed cost for any changes in wages, wage setters decide to change their wages only when the current wages are significantly different from the optimal wages. Hence, the size of wage change is large and there are few small wage changes compared to the size of wage change from the Calvo model. Under positive inflation, the optimal nominal wage change distribution always has higher densities above zero than below zero. Therefore, a greater portion of the spike at zero comes from the right of the zero than from the left of zero, which leads to the lack of raises compared to wage cuts. This pattern is inconsistent with empirical nominal wage change distribution.

The DNWR wage restriction generates a spike at zero and a sudden drop in below zero

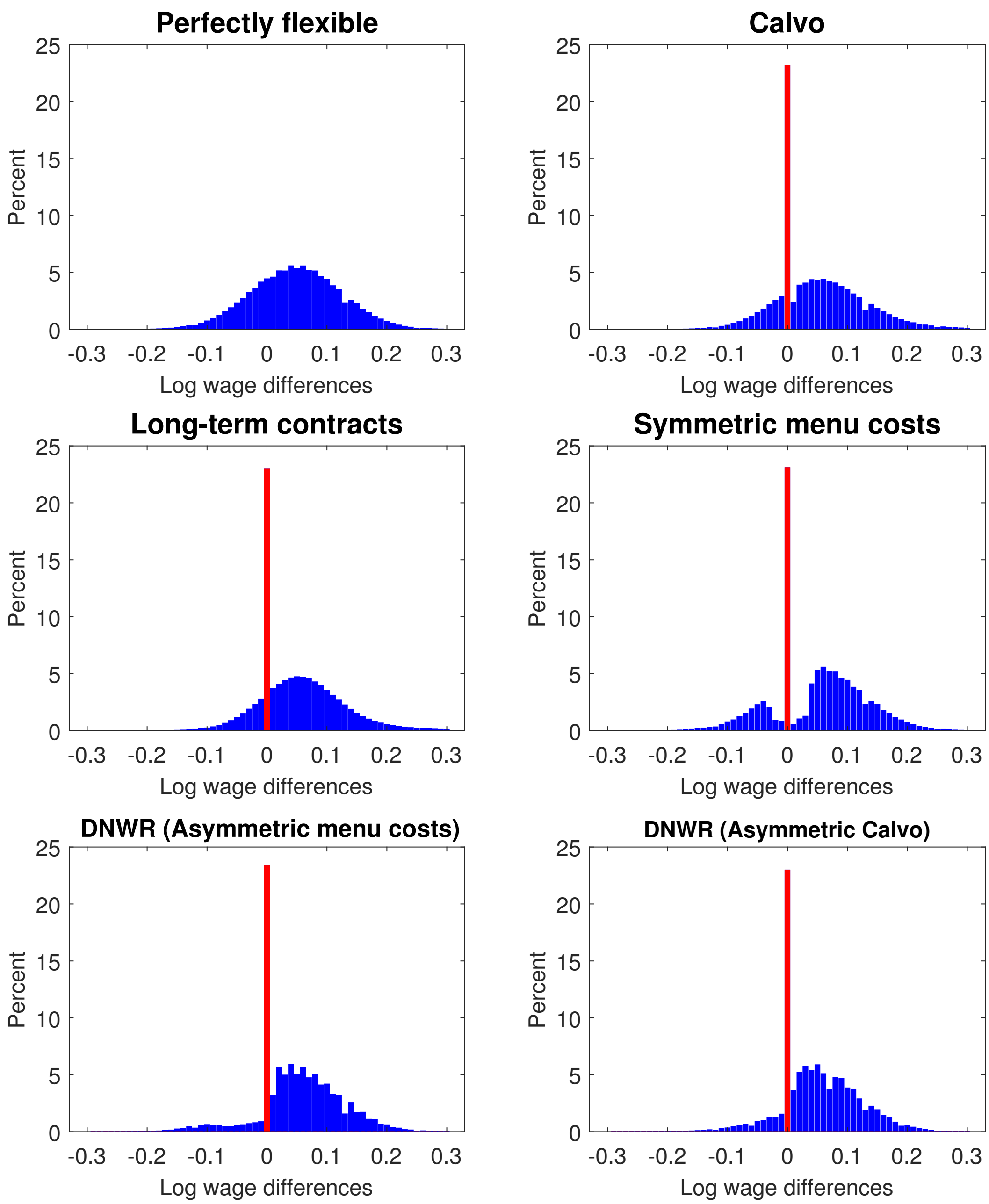

Figure 5: Staionary wage change distribution from 5 different wage-setting schemes

This figure shows stationary distribution implied by 5 alternative wage-setting schemes: perfectly flexible (top left), Calvo (top right), long-term contract (second-row left), symmetric menu cost (second-row right), asymmetric menu cost (bottom left), and asymmetric Calvo (bottom right). The red bar represents the percentage of workers with no wage change and the width of the blue bin is 0.01.

compared to above zero from the stationary nominal wage change distribution. The bottom panel of Figure 5 displays the stationary nominal wage change distribution under the DNWR model. Furthermore, it is asymmetric, fewer wage cuts than raises, and there is a sudden drop in below zero compared to above zero. Therefore, we can conclude that only DNWR among 5 wage-setting schemes generates stationary distribution, consistent with empirical findings.

8.3 The cyclicality of wage change distribution

Table 11: The predicted spike at zero, the fraction of wage cuts, and raises along the business cycle from each model

	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 $\Delta W > 0$
	Data					
Employment	-0.616	-0.305	0.921			
Inflation	-1.181	-0.674	1.855			
	Perfectly flexible			Calvo		
Employment	-0.042	-0.414	0.456	0.089	-0.553	0.465
Inflation	-0.042	-4.476	4.519	-0.192	-3.919	4.111
	Long-term contracts			Symmetric menu costs		
Employment	0.005	-0.424	0.419	-0.187	-0.329	0.516
Inflation	-0.018	-4.207	4.225	-1.623	-3.452	5.074
	DNWR (Asymmetric menu costs)			DNWR (Asymmetric Calvo)		
Employment	-0.539	-0.213	0.752	-0.712	-0.329	1.041
Inflation	-3.185	-2.078	5.263	-3.699	-1.772	5.470

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). The inflation rate is calculated from CPI-U. The first panel is from data, last three columns of table 4. This table (from the row 2 to row 4) shows the regression results based on the equation (1) using simulated data series under 5 alternative wage-setting schemes.

This section runs the main regression (1) using simulated data from the 5 alternative wage-setting schemes to determine which model has consistent implications for cyclical patterns of nominal wage change distributions: 1) the spike at zero increases when employment declines, and 2) the increase in the spike at zero is higher than the increase in the fraction of wage cuts when employment declines, shown in the first panel of Table 11. The second panel of Table 11 shows cyclical properties of wage change distributions implied by each model: perfectly flexible (second row left), Calvo (second row right), long-term contracts (third row left), symmetric menu cost (third row right), asymmetric menu cost (bottom left), and asymmetric Calvo (bottom right).

Nominal wage change distributions shift left or right along the business cycle under a perfectly flexible wage model. After controlling for inflation, we can see that the increase in

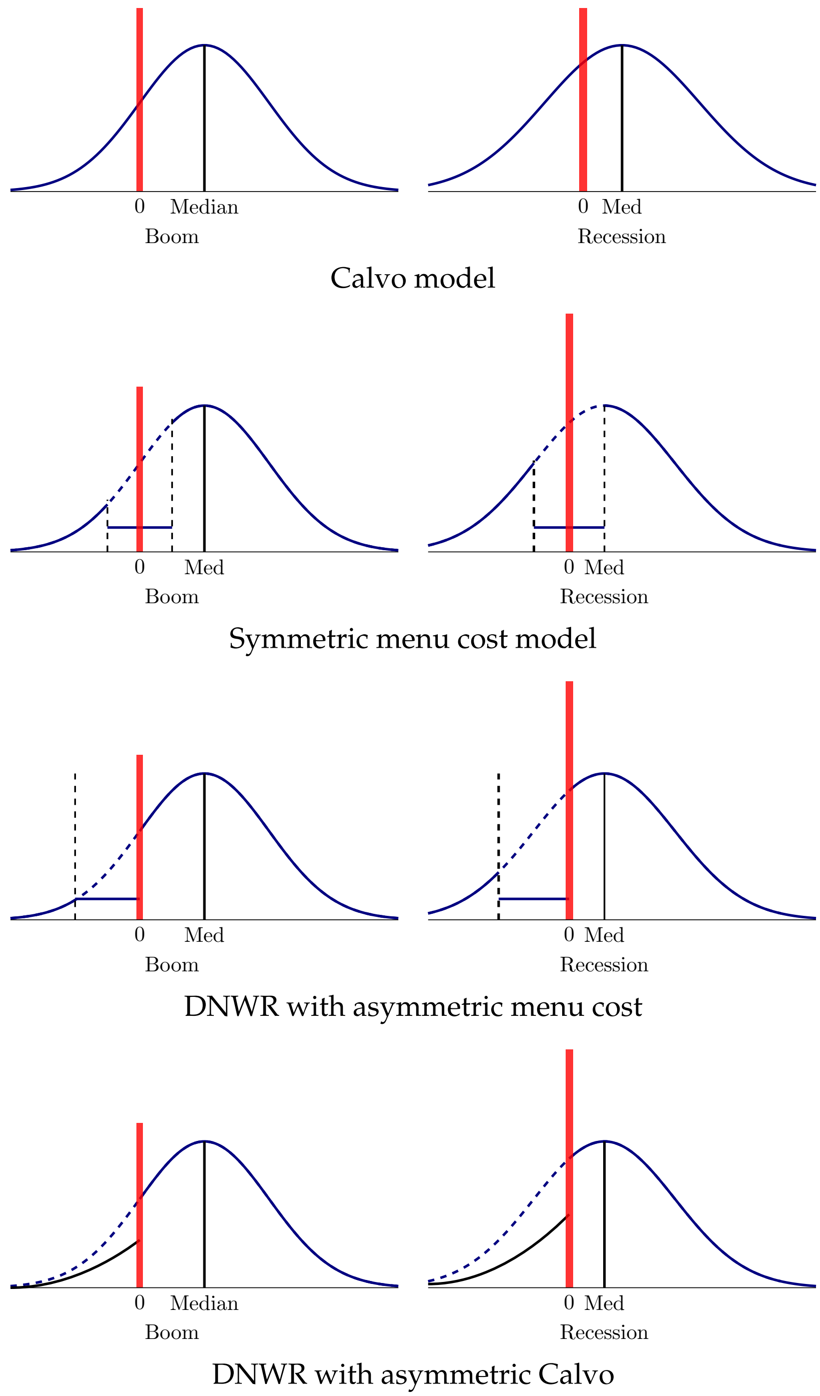

Figure 6: Conceptual wage change distributions

This figure shows conceptual nominal wage change distributions along the business cycles under symmetric wage rigidity models (Calvo and symmetric menu cost model) and asymmetric wage rigidity models (asymmetric menu cost and Calvo).

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 findings.

The Calvo model presents a constant spike at zero along the business cycle. The spike at zero barely responds to employment because the Calvo wage adjustment assumes that the spike at zero, the frequency of no wage change, does not respond to the business cycle. The conceptual diagram of changes in wage distributions under the Calvo model is shown in the first panel of Figure 6. 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 impact on the spike at zero. This pattern is inconsistent with the empirical finding that the spike at zero is countercyclical.

The long-term contracts model also shows the constant spike at zero along the business cycle, similar to the Calvo 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. This is again inconsistent with empirical findings.

The spike at zero implied by menu costs model responds to the employment, as the menu costs model is state dependent. Intuitively, nominal wage distribution in the absence of rigidity shifts to the left in a recession, shown in the second panel of Figure 6. Then, as long as inflation is positive, there are greater densities around zero, that is, there are greater densities in the inaction region in a recession, 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 μ^{Menu}. While the entire optimal wage change distribution shifts to the left during a recession, only a certain fraction of worker's wages in the inaction region, whose optimal wages are close enough to the previous wages, do not change, which adds the size of the spike at zero. This leads to higher responsiveness of the share of workers with wage cuts compared to the spike at zero, which is inconsistent with empirical findings: greater responsiveness of the spike at zero than the share of workers with wage cuts.[25]

The DNWR model, both asymmetric menu cost and Calvo, predicts a countercyclical spike at zero and greater fluctuation of the spike at zero than the share of workers with wage cuts, consistent with the empirical findings. In a recession, nominal wage change distribution in the absence of wage rigidity shifts to the left as shown in the third and fourth

[25]In the menu cost model, two parameters, μ^{Menu} and the fixed cost,κ, are calibrated to match the average spike at zero implied by the DNWR model. Thus, we cannot uniquely pin down these parameters. Holding the average spike at zero fixed, Table E1 in Appendix D.3.1 shows that menu cost model implies higher responsiveness of the share of workers with wage cuts than the spike at zero by varying μ^{Menu} from 0.3 to 1. As μ^{Menu} increases, the fixed cost, κ, decreases, as does the inaction region. In the random menu cost model, the spike at zero is the proportion of the inaction region. The proportion is determined by μ^{Menu} , and the size of inaction region is determined by κ.

panels of Figure 6. In asymmetric menu-cost model, there are greater densities in the asymmetric inaction region, leading to the greater increase in the spike at zero than the increase in the share of workers with wage cuts. In the asymmetric Calvo model, 67 percent ($= \mu^{\text{DNWR}}$) of workers whose optimal wages are lower than the previous wages experience no wage changes, while the other 37 percent of worker cut their wages. In a recession, there are more workers whose optimal wages are lower than the previous wages, and this induces an increase in the spike at zero greater than the increase in the fraction of workers with wage cuts.

8.4 Implications on moments

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. Thus, Table 12 in presents the relevant moments implied by 5 alternative wage-setting schemes. To compare moments across the models, wage rigidity parameters are calibrated to have a similar level of the spike at zero, the frequency of no wage change.

I first compare moments generated by the Calvo model, the long-term contracts model, and the symmetric menu cost model, shown in Table 12. The average spike at zero and the fraction of wage cuts and raises are comparable, and that are 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, measuring the degree of monetary non-neutrality, is almost double that from the long-term contracts or menu cost model. The standard deviation of employment growth rates from the long-term contracts model is much smaller than that from the Calvo model because allocative wages from the perfectly flexible model determine employment but not remitted wages.

Even if the fraction of wage adjustments from the menu cost model is similar to the one from the Calvo model, the standard deviation of employment growth from the symmetric menu cost model is much 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 cost model, only those workers whose current wages are far from the optimal wages would want to change their wages after paying an additional fixed cost incurred to change in wages. Those workers willing to pay a fixed cost to change their wages would want to change their wages by a large amount, which leads to a smaller effect on employment from aggregate uncertainty.

The average spike at zero from the DNWR model is similar to that of the other symmetric rigidity model. However, the fraction of workers with wage cuts is smaller and the fraction of workers with raises is higher than in other symmetric rigidity models as a result of the DNWR restriction. The standard deviation from the DNWR model is in between those from

Table 12: 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	-	-	-
			Symmetric menu costs		
Mean	4.374	0.000	23.085	17.332	59.583
SD	2.069	0.503	3.625	7.351	10.616
Skewness	0.073	-0.019	-	-	-
			DNWR (Asymmetric menu cost)		
Mean	4.379	0.000	23.340	9.289	67.371
SD	1.795	0.749	6.266	3.987	10.052
Skewness	0.113	-0.006	-	-	-
			DNWR (Asymmetric Calvo)		
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.

the Calvo and symmetric menu cost models. 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 raises. As wage adjustment is asymmetric in the DNWR model, it has an asymmetric implication on employment. Although the DNWR model does not explain the entire left skewness of employment growth rate, only the DNWR model with asymmetric Calvo can explain the left skewness of employment growth, consistent with Dupraz, Nakamura, and Steinsson (2017).

9 Conclusion

This paper investigates which type of nominal wage rigidity model in the existing literature has the most consistent implications with micro-wage data in the US. To answer this question, this paper first documents cyclical properties of nominal wage change distributions using two nationally representative US household surveys: the CPS and the SIPP. I find that 1) the spike at zero increases when employment declines, controlling for inflation; 2) the share of workers with wage cuts also increases when employment declines, controlling for inflation; and 3) the increase in the spike at zero is much higher than the increase in the share of wage cuts when employment declines, controlling for inflation.

To differentiate each wage-setting model's predictions, this paper builds heterogeneous agent models with 5 alternative wage-setting schemes – perfectly flexible, the Calvo, long-term contracts, menu cost model, and DNWR - and characterizes the stationary distribution and its cyclical properties. This paper concludes that the model with DNWR (both asymmetric menu cost and Calvo model) has the most consistent empirical implications with empirical findings documented in the first part of the paper. This finding is suggestive of the allocative consequences of DNWR for employment.

References

Alvarez, F., H. Le Bihan, and F. Lippi (2016). "The Real Effects of Monetary Shocks in Sticky Price Models: A Sufficient Statistic Approach". *American Economic Review 106*(10), 2817–51.

Barattieri, A., S. Basu, and P. Gottschalk (2014). "Some Evidence on the Importance of Sticky Wages". *American Economic Journal: Macroeconomics 6*(1), 70–101.

Barro, R. (1977). "Long-term contracting, sticky prices, and monetary policy". *Journal of Monetary Economics 3*(3), 305–316.

Basu, S. and C. House (2016). "Allocative and Remitted Wages: New Facts and Challenges for Keynesian Models". *NBER Working Paper 22279*.

Beraja, M., E. Hurst, and J. Ospina (2016). "The Aggregate Implications of Regional Business Cycles". *NBER Working Paper 21956*.

Bils, M. (1985). "Real Wages over the Business Cycle: Evidence from Panel Data". *Journal of Political Economy 93*(4), 666–89.

Borjas, G. (1980). "The Relationship between Wages and Weekly Hours of Work: The Role of Division Bias". *Journal of Human Resources 15*(3), 409–423.

Bound, J. and A. Krueger (1991). "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?". *Journal of Labor Economics 9*(1), 1–24.

Calvo, G. (1983). "Staggered prices in a utility-maximizing framework". *Journal of Monetary Economics 12*(3), 383–398.

Caplin, A. S. and D. Spulber (1987). "Menu Costs and the Neutrality of Money". *The Quarterly Journal of Economics 102*(4), 703–725.

Card, D. and D. Hyslop (1996). "Does Inflation "Grease the Wheels of the Labor Market"?". *NBER Working Paper* (5538), 71–122.

Chetty, R., A. Guren, D. Manoli, and A. Weber (2011). "Are Micro and Macro Labor Supply Elasticities Consistent? A Review of Evidence on the Intensive and Extensive Margins". *American Economic Review 101*(3), 471–75.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005). "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy". *Journal of Political Economy 113*(1), 1–45.

Daly, M. C. and B. Hobijn (2014). "Downward Nominal Wage Rigidities Bend the Phillips Curve". *Journal of Money, Credit and Banking 46*(S2), 51–93.

De Loecker, J. and J. Eeckhout (2017). "The Rise of Market Power and the Macroeconomic Implications". *NBER Working Paper 23687*.

Den Haan, W. J. (2010). "Assessing the accuracy of the aggregate law of motion in models with heterogeneous agents". *Journal of Economic Dynamics and Control 34*(1), 79–99.

Dupraz, S., E. Nakamura, and J. Steinsson (2017). "A Plucking Model of Business Cycles". *Working paper*.

Elsby, M. W. L., D. Shin, and G. Solon (2016). "Wage Adjustment in the Great Recession and Other Downturns: Evidence from the United States and Great Britain". *Journal of Labor Economics 34*(S1), S249 – S291.

Erceg, C., D. Henderson, and A. Levin (2000). "Optimal monetary policy with staggered wage and price contracts". *Journal of Monetary Economics 46*(2), 281–313.

Fagan, G. and J. Messina (2009). "Downward Wage Rigidity and Optimal Steady-State Inflation". *ECB Working Paper 1048*.

Fallick, B. C., M. Lettau, and W. L. Wascher (2016). "Downward Nominal Wage Rigidity in the United States during and after the Great Recession". *Finance and Economics Discussion Series Washington: Board of Governors of the Federal Reserve System 2016-001*.

Fujita, S. and G. Moscarini (2017). "Recall and Unemployment". *American Economic Review 107*(12), 3875–3916.

Golosov, M. and R. Lucas (2007). "Menu Costs and Phillips Curves". *Journal of Political Economy 115*, 171–199.

Grigsby, J., E. Hurst, and A. Yildirmaz (2019). "Aggregate Nominal Wage Adjustments: New Evidence from Administrative Payroll Data". *NBER Working Paper 25628*.

Guvenen, F. (2009). "An Empirical Investigation of Labor Income Processes". *Review of Economic Dynamics 12*(1), 58–79.

Heer, B. and A. Maussner (2009). *Dynamic General Equilibrium Modeling: Computational Methods and Applications* (2 ed.). Springer-Verlag Berlin Heidelberg.

Hirsch, B. and E. J. Schumacher (2004). " Match bias in wage gap estimates due to earnings imputation.". *Journal of Labor Economics 22*(3), 689–722.

Jardim, E. S., G. Solon, and J. L. Vigdor (2019, January). "How Prevalent Is Downward Rigidity in Nominal Wages? Evidence from Payroll Records in Washington State". *NBER Working Paper 25470*.

Kahn, S. (1997). "Evidence of Nominal Wage Stickiness from Microdata". *American Economic Review 87*(5), 993–1008.

Krusell, P. and A. J. Smith (1998). "Income and Wealth Heterogeneity in the Macroeconomy". *Journal of Political Economy 106*(5), 867–896.

Kurmann, A. and E. McEntarfer (2018). "Downward Wage Rigidity in the United States: New Evidence from Worker-Firm Linked Data". *Working Paper*.

Lebow, D. E., R. Sacks, and W. B. Anne (2003). "Downward Nominal Wage Rigidity: Evidence from the Employment Cost Index". *The B.E. Journal of Macroeconomics 3*(1), 1–30.

Mineyama, T. (2018). "Downward Nominal Wage Rigidity and Inflation Dynamics during and after the Great Recession". *Working Paper*.

Nakamura, E. and J. Steinsson (2008). "Five Facts about Prices: A Reevaluation of Menu Cost Models". *The Quarterly Journal of Economics 123*(4), 1415–1464.

Sarah Flood, Miriam King, Steven Ruggles, and J. Robert Warren (2018). "Integrated Public Use Microdata Series, Current Population Survey: Version 6.0. [dataset].". *Minneapolis: University of Minnesota*.

Schmitt-Grohé, S. and M. Uribe (2016). "Downward Nominal Wage Rigidity, Currency Pegs, and Involuntary Unemployment". *Journal of Political Economy 124*, 1466–1514.

Schmitt-Grohé, S. and M. Uribe (2017). "Liquidity Traps and Jobless Recoveries". *American Economic Journal: Macroeconomics 9*(1), 165–204.

Smets, F. and R. Wouters (2007). "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach". *American Economic Review 97*(3), 586–606.

Vaghul, K. and B. Zipperer (2016). "Historical state and sub-state minimum wage data". *Washington Center for Equitable Growth Working Paper*.

Appendix

A Comparisons to the previous literature

Table A1 compares the average of spike at zero, the share of workers with raises and the share of worker with wage cuts from previous literature and this paper. Since these statistics respond to the business cycles, as shown in this paper, we have to compare sample averages, conditioned on the same sample periods.

There are also a few other aspects than cyclicality that determine the level of average statistics. First, using wages as earnings divided by hours tends to produce a lower spike at zero and a higher share of workers with wage cuts. This is because any reporting errors on hours worked makes earnings divided hours excessively volatile, known as division bias (Borjas (1980)). Second, job stayers have a smaller spike at zero than job switchers. Third, measurement error matters for the level of spike at zero and the share of workers with wage cuts. Barattieri et al. (2014) find a higher spike at zero after correcting for measurement errors. Grigsby et al. (2019) use ADP data, which are free of measurement errors, and they find a higher spike at zero and a lower share of workers with wage cuts. This finding implies that measurement errors in household surveys tend to underestimate the extent of downward nominal wage rigidity.

Since papers using the CPS have longer sample periods than others, Figure A1 plots the spike at zero from the previous papers using the CPS. When the present paper constructs the spike at zero from nominal wage change distributions using the CPS, it includes all hourly workers including both job stayers and job switchers, while the previous literature focuses only on job stayers. Card and Hyslop (1996) use the CPS of the sample period from 1979 to 1993 to construct the share of workers with no wage change among hourly rated job stayers. Elsby, Shin, and Solon (2016) use the CPS from 1980 to 2012 and job tenure supplements to construct the share of workers with no wage change among hourly rated workers whose job tenure is more than one year. The San Francisco Federal Reserve Bank publishes the Wage Rigidity Meter using the CPS from 1980 to 2018 with some gaps, which shows the fraction of workers with a zero wage change among workers who have not changed their jobs.[26]

Based on the description, the spike at zero from Card and Hyslop (1996), Elsby, Shin, and Solon (2016), and the Wage Rigidity Meter should be similar; however, this is not the

[26]For a fair comparison, I used the percentage of hourly rated job stayers with a wage change of zero from SF - Wage Rigidity Meter (here). In addition to hourly workers, non-hourly workers and all workers' (including both hourly and non-hourly workers) Wage Rigidity Meter is also available. The Atlanta Fed's Wage Growth Tracker (here) also reports the percentage of individuals with zero wage changes. However, when they count individuals with zero wage changes, they include individuals with hourly wage growth rates from -0.5 percent to 0.5 percent, while this paper and SF - Wage Rigidity Meter count only workers with exact zero wage changes. Additionally, the Atlanta Fed's wage growth tracker includes both hourly workers and non-hourly workers, while this paper considers only hourly rated workers. They impute hourly wages for non-hourly workers by dividing usual weekly earnings by usual weekly hours worked or actual hours worked.

Table A1: The average spike at zero, the share of workers with raises and cuts

Paper	Data	Period	Wage measure	Pay type	Job stayers vs. Job switchers	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
Kahn (1997)	PSID	1970-1988	Hourly pay rate	Hourly	Job stayers	9.8	10.3	79.9
			Earnings/Hours	Salary	Job stayers	4.8	23.4	71.8
Card and Hyslop (1996)	CPS	1979-1983	Hourly wage	Hourly	Job stayers	14.8	17.3	67.9
Elsby, Shin, and Solon (2016)	CPS	1980-2012	Hourly wage	Hourly	Job stayers	15.5	18.1	66.4
	CPS	1980-2012	Earnings/Hours	Nonhourly	Job stayers	11.6	28.6	59.8
Wage rigidity meter (Daly and Hobijn (2014))	CPS	1980-2017	Hourly wage	Hourly	Job stayers	15.6	-	-
	CPS	1980-2017	Earnings/Hours	Nonhourly	Job stayers	7.7	-	-
Jo (2019)	CPS	1979-2017	Hourly wage	Hourly	Both	15.2	21.1	63.6
	CPS	1979-2017	Earnings/Hours	Hourly	Both	10.0	27.3	62.7
	CPS	1979-2017	Earnings/Hours	Nonhourly	Both	6.9	34.3	58.8
Barattieri, Basu, and Gottschalk (2014)[a]	SIPP	1996-2000	Hourly wage	Hourly	Job stayers	43.3	-	-
	SIPP	1996-2000	Hourly wage	Hourly	Both	33.5	-	-
Jo (2019)	SIPP	1996-2000	Hourly wage	Hourly	Both	15.7	16.8	67.5
	SIPP	1996-2000	Hourly wage	Hourly	Job stayers	18.2	12.7	69.1
	SIPP	1996-2000	Hourly wage	Hourly	Job switchers	10.5	25.3	64.3
Fallick, Lettau, and Wascher (2016)	ECI	1981-2014	Annual compensation/Annual hours	Hourly + Salary	Job stayers	16.2	-	-
Kurmann and McEntarfer (2018)	LEHD,Washington	2006	Quarterly earnings/Quarterly hours	Hourly + Salary	Job stayers	7.5[b]	20[c]	72.5[d]
	LEHD,Washington	2010	Quarterly earnings/Quarterly hours	Hourly + Nonhourly	Job stayers	16[b]	25.0[c]	59[d]
Jo (2019)	CPS,Washington	2006	Earnings/Hours	Hourly + Nonhourly	Both	10.2[b]	28.7[c]	61.1[d]
Jo (2019)	CPS,Washington	2010	Earnings/Hours	Hourly + Nonhourly	Both	13.1[b]	37.8[c]	49.1[d]
Jardim, Solon, and Vigdor (2019)	LEHD,Washington	2005-2015	Quarterly earnings/Quarterly hours	Hourly + Nonhourly	Job stayers	4.4	24.8	70.8
Jo (2019)	CPS,Washington	2005-2015	Earnings/Hours	Hourly + Nonhourly	Both	8.1	32.7	59.1
Grigsby, Hurst, and Yildirmaz (2019)	ADP	2008-2016	Hourly wage	Hourly	Job stayers	32.9	1.8	65.3
	ADP	2008-2016	Base wage	Hourly + Salary	Job switchers	5.2	38.0	56.8
	ADP	2008-2016	Base wage	Salary	Job stayers	34.8	3.6	61.6
	ADP	2008-2016	Base wage	Hourly + Salary	Both	28.6	8.7	62.7
Jo (2019)	CPS	2008-2016	Hourly wage	Hourly	Both	19.2	22.8	58.0

[a] Barattieri, Basu, and Gottschalk (2014) report quarterly frequency of wage adjustment so it is converted to annual frequency.
[b] Spike at zero contains log wage changes between -0.005 and 0.005.
[c] The fraction of workers with wage cuts contatins log wage changes less than -0.005.
[d] The fraction of workers with raises includes log wage changes greater than 0.005.

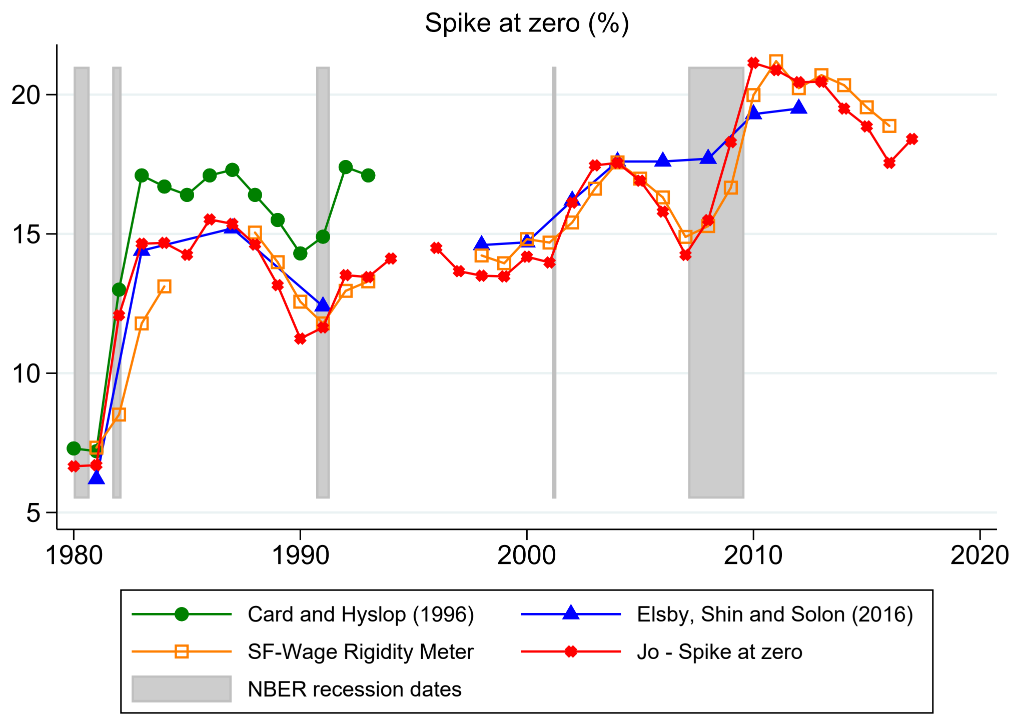

Figure A1: Comparisons of the spike at zero from the previous literature

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 - 2018, Job stayers only
Jo (2018) - Data: CPS, Sample Period: 1980 - 2018, Both job stayers and job switchers

case. Although they are highly correlated with each other, there are differences in the level of the spike at zero. The spike at zero from Card and Hyslop (1996) is higher than the that from Elsby, Shin, and Solon (2016) and the Wage Rigidity Meter. Instead, the spike at zero from Elsby, Shin, and Solon (2016) and the Wage Rigidity Meter closely follows the spike at zero from the present paper, 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 based on the SIPP data. This may imply that the spike at zero from Elsby, Shin, and Solon (2016) and the Wage Rigidity Meter do not solely come from job stayers.

Online Appendix to "Downward Nominal Wage Rigidity in the US"

Yoon J. Jo
Texas A&M University

Section B contains supplementary empirical results using the CPS, and Section C provides that using the SIPP. Section D explains additional numerical methods and results.

B Appendix: CPS

Table C1 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 C1 also shows the imputation ratio for usual weekly earnings and the hourly wage. After the major revision in the CPS in 1994, about 34 percent of hourly wages are imputed by the CPS. The CPS imputes unreported data items to fill gaps in based on the demographic characteristics and residential address.[27] Including imputed wages may amplify measurement error, and Hirsch and Schumacher (2004) show that including imputed wages in the analysis may lead to bias due to the imperfect matching of donors with nonrespondents. Thus, this paper drops imputed wages.

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

Table C2 shows the number of observations for hourly workers whose hourly wage growth rate is available. Table C2 also lists the time series of the national-level spike at zero and the fraction of hourly workers with wage cuts and raises.

Figure C1 and Figure C2 show the nominal year-to-year hourly wage change distribution for each year from 1980-2018. The nominal hourly wage change distribution is highly asymmetric: there is an apparent spike at zero and fewer wage cuts compared to raises.

Table C3 reports the averages for the spike at zero, the share of workers with wage cuts and raises for the subsets of workers at different hourly wage quartiles. Workers in a lower hourly wage quartile tend to show a larger spike at zero and a larger share with wage cuts, compared to those in a higher hourly wage quartile. Table C4 presents the averages calculated separately for the workers in each 2-digit NAICS industry code. The rows are sorted by the average size of the spike at zero. The average size of the spike at zero varies from 11 percent to 23 percent across 2-digit NAICS industry codes. The largest industry in terms of the number of hourly workers is manufacturing, and the average size of the spike at zero for manufacturing is about 14 percent, which is comparable to the national average.

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

Table C1: The unweighted number of observation in the CPS and the imputation ratio

Year	Age ≥ 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	185,030	177,254	4.2	110,923	109,005	1.7
1991	1,341,040	822,621	179,560	171,214	4.6	108,093	105,956	2.0
1992	1,320,939	808,261	176,848	169,030	4.4	107,005	105,270	1.6
1993	1,302,955	798,202	174,595	165,972	4.9	105,602	103,921	1.6
1994	1,271,347	790,130	160,156			104,717	82,639	21.1
1995	1,251,928	784,129	159,310	39,792	75.0	104,848	25,973	75.2
1996	1,108,899	699,605	141,174	109,580	22.4	93,894	71,033	24.3
1997	1,114,451	708,705	143,973	111,196	22.8	95,476	72,171	24.4
1998	1,116,813	717,245	145,834	111,960	23.2	95,918	71,122	25.9
1999	1,123,666	723,156	147,696	107,912	26.9	96,442	67,733	29.8
2000	1,120,585	723,930	150,104	105,873	29.5	97,234	65,844	32.3
2001	1,236,870	793,912	157,442	110,464	29.8	102,311	68,661	32.9
2002	1,312,304	832,519	171,206	119,583	30.2	110,671	74,040	33.1
2003	1,302,483	818,795	167,375	114,274	31.7	108,836	70,930	34.8
2004	1,283,683	809,185	164,286	112,821	31.3	107,382	70,234	34.6
2005	1,279,052	810,893	165,503	114,618	30.7	108,562	71,481	34.2
2006	1,271,693	810,582	165,888	114,382	31.0	107,510	70,495	34.4
2007	1,260,380	801,226	165,231	115,212	30.3	104,829	70,235	33.0
2008	1,257,619	790,341	163,450	113,582	30.5	102,940	68,390	33.6
2009	1,273,634	766,660	158,320	110,577	30.2	99,912	66,768	33.2
2010	1,277,199	759,458	156,751	104,806	33.1	99,512	63,764	35.9
2011	1,265,607	749,778	155,621	102,347	34.2	98,814	62,310	36.9
2012	1,258,730	749,477	155,207	103,279	33.5	98,263	62,453	36.4
2013	1,253,663	745,840	155,464	99,956	35.7	97,500	60,157	38.3
2014	1,261,811	751,675	156,924	98,855	37.0	98,227	59,129	39.8
2015	1,245,862	739,222	155,718	94,663	39.2	97,012	56,362	41.9
2016	1,244,166	740,071	156,389	95,943	38.7	97,466	57,354	41.2
2017	1,227,127	731,896	154,793	94,628	38.9	95,871	56,350	41.2
2018	1,188,950	710,991	151,367	91,414	39.6	93,619	54,552	41.7
Mean	1,282,101	785,804	165,322	125,262	24.9	102,922	76,918	25.6

Data source: CPS and author's calculation. Sample period: 1979 - 2018. 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 C2: The unweighted number of observation in the CPS and the imputation ratio

	Unweighted count of		Spike at zero (%)		Share of cuts	Share of raises
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	28,898	3,282	11.36	11.29	23.44	65.27
1991	29,454	3,506	11.90	11.73	24.67	63.61
1992	29,247	4,009	13.71	13.62	25.37	61.01
1993	29,252	3,935	13.45	13.48	26.33	60.19
1994	22,971	3,253	14.16	14.11	23.89	62.00
1995						
1996	6,083	886	14.57	14.48	19.89	65.63
1997	18,057	2,533	14.03	13.66	19.56	66.78
1998	17,858	2,456	13.75	13.49	18.31	68.20
1999	16,876	2,346	13.90	13.47	18.95	67.58
2000	15,796	2,251	14.25	14.18	18.24	67.58
2001	14,719	2,062	14.01	13.98	18.64	67.38
2002	15,787	2,557	16.20	16.12	20.12	63.76
2003	17,333	2,932	16.92	17.46	21.08	61.46
2004	16,241	2,791	17.18	17.55	21.36	61.09
2005	14,991	2,466	16.45	16.91	20.63	62.46
2006	16,373	2,513	15.35	15.80	20.87	63.33
2007	16,245	2,309	14.21	14.25	20.43	65.32
2008	16,435	2,491	15.16	15.49	20.55	63.96
2009	16,069	2,906	18.08	18.30	23.59	58.10
2010	15,615	3,270	20.94	21.13	24.61	54.26
2011	14,774	3,030	20.51	20.88	24.30	54.81
2012	14,462	2,947	20.38	20.45	24.73	54.82
2013	14,463	2,896	20.02	20.46	23.07	56.48
2014	13,339	2,537	19.02	19.49	22.14	58.36
2015	10,752	1,975	18.37	18.86	21.58	59.56
2016	12,126	2,157	17.79	17.57	20.93	61.50
2017	12,674	2,322	18.32	18.41	20.26	61.33
2018	12,111	2,067	17.07	16.82	20.93	62.25
Mean	17,959	2,642	15.26	15.29	21.10	63.60

Source: CPS and author's calculation. Sample period: 1979 - 2018 (except 1995). 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 C3: Nominal hourly wage change distribution, CPS, by hourly wage quartiles

Hourly wage Quartiles	Spike at zero $\Delta W = 0$	Share of cut $\Delta W < 0$	Share of raises $\Delta W > 0$
25th below	20.88	31.61	47.50
25th to med	15.50	20.70	63.79
med to 75th	13.33	18.09	68.58
75th and above	12.90	16.68	70.42

Data source: CPS and author's calculation. Sample Period: 1979-2018 (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.

Table C4: The average of the spike at zero, the share of wage cuts and raises by industry, CPS

	% hourly workers	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$
Agriculture, Forestry, Fishing and Hunting	1.05	23.82	20.85	55.32
Other Services (except Public Administration)	3.70	22.09	22.04	55.87
Administrative and Support and Waste Management and Remediation Services	1.61	20.57	23.32	56.10
Real Estate and Rental and Leasing	0.96	18.48	20.35	61.17
Arts, Entertainment, and Recreation	1.87	18.31	22.78	58.91
Accommodation and Food Services	7.69	18.15	26.20	55.66
Construction	6.43	17.75	21.07	61.19
Professional, Scientific, and Technical Services	3.27	17.72	17.73	64.55
Wholesale Trade	3.07	16.28	19.52	64.20
Retail Trade	14.53	15.83	20.52	63.65
Educational Services	5.19	14.72	21.77	63.50
Mining, Quarrying, and Oil and Gas Extraction	0.71	14.34	23.82	61.85
Transportation and Warehousing	4.53	13.71	22.76	63.53
Manufacturing	20.70	13.66	20.78	65.56
Health Care and Social Assistance	15.12	13.32	19.59	67.09
Finance and Insurance	2.67	12.75	18.69	68.55
Information	1.42	12.14	20.48	67.38
Utilities	1.68	11.63	20.11	68.25
Public Administration	3.81	11.21	19.97	68.82

Data source: CPS and author's calculation. Sample Period: 1979-2018 (except 1995). This table shows the average of the spike at zero and the fraction of workers with wage cuts and raises over time by 2 digit NAICS industry classification.

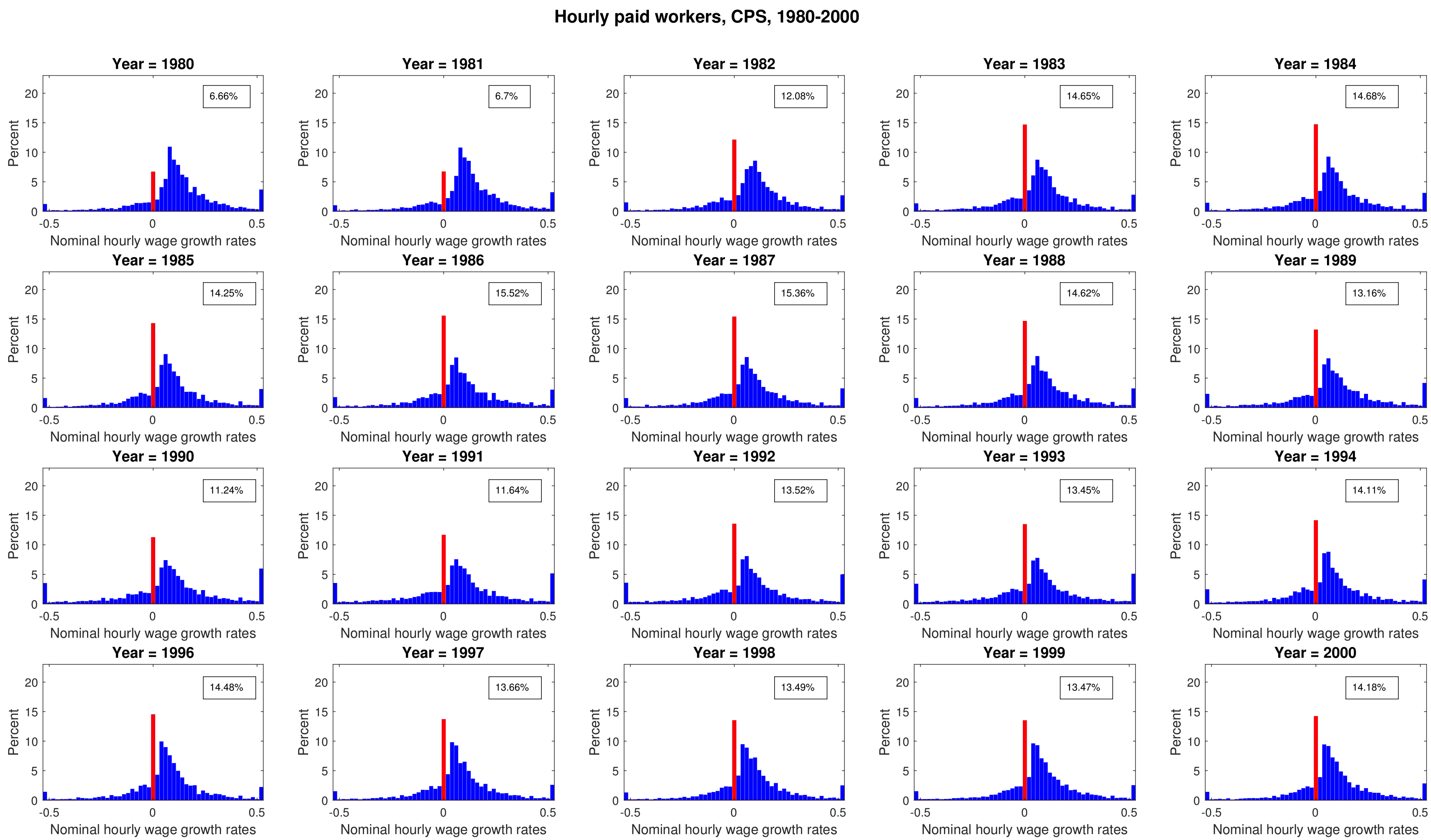

Figure C1: Nominal hourly wage growth rate distributions from 1980 to 2000

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

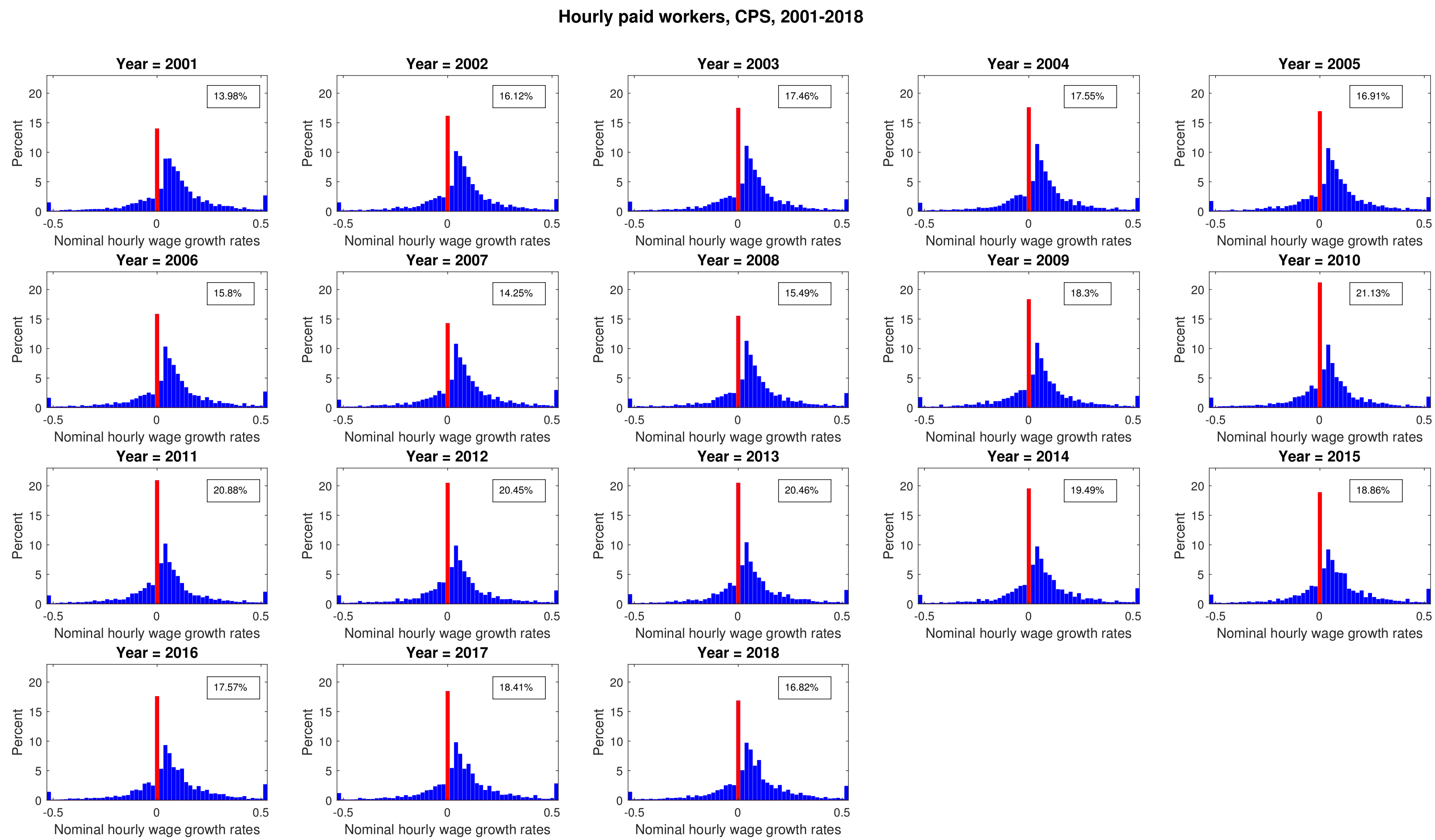

Figure C2: Nominal hourly wage growth rate distributions from 2001 to 2018

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

Table C5: The spike at zero, the share of wage cuts, and raises for salaried workers along business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts	(5) Spike at zero $\Delta W = 0$	(6) Share of cuts $\Delta W < 0$	(7) Share of raises $\Delta W > 0$	(8) Spike at zero minus Share of cuts
1-Epop ratio	0.432***	-0.0627	-0.369	0.495***	0.474***	0.0521	-0.526**	0.421***
$(1 - e_t)$	(0.0812)	(0.238)	(0.306)	(0.181)	(0.0553)	(0.163)	(0.195)	(0.145)
Inflation rate					-0.282***	-0.779***	1.061***	0.496***
(π_t)					(0.0337)	(0.120)	(0.132)	(0.117)
Observations	37	37	37	37	37	37	37	37
Adjusted R^2	0.413	-0.0263	0.0246	0.117	0.656	0.434	0.600	0.292

Data source: CPS and author's calculation. Sample Period: 1979-2018 (except 1994, 1995). Inflation rate is calculated from CPI-U. Hourly rate is calculated from usual weekly earning/usual hours worked per week. Controlling for inflation, the spike at zero exhibits countercylical fluctuations in employment while the share of workers with wage cuts does not respond to employment. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

B.2 Robustness checks for aggregate time series evidence

For salaried workers, we can compute hourly wages by dividing the usual weekly earnings by the usual weekly hours worked. Table C5 shows regression results using imputed hourly wages for salaried workers. We can still see that the spike at zero is negatively associated with both inflation and employment. The spike at zero shows greater association with employment than the share of workers with wage cuts, and in fact, the share of salaried workers with wage cuts is not significantly associated with employment.

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 employment, meaning that the response to the declining employment is different from the response to increasing employment. From the regression specification (7), γ captures the asymmetric response to declining employment. However, from Table C6, we can see that γ is not statistically different from zero, implying that there is no asymmetric response of nominal wage change distribution to employment.

$$\begin{aligned} [\text{Spike at zero}]_t &= \alpha_1 + \beta_1(1-e_t) + \gamma_1(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t) > 0] + \epsilon_{1t} \\ [\text{Fraction of wage cuts}]_t &= \alpha_2 + \beta_2(1-e_t) + \gamma_2(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t) > 0] + \epsilon_{2t} \\ [\text{Fraction of raises}]_t &= \alpha_3 + \beta_3(1-e_t) + \gamma_3(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t) > 0] + \epsilon_{3t} \end{aligned} \tag{7}$$

Table C7 shows regression results based on the regression equation (1), excluding minimum wage workers. Table C8 shows regression results based on (1) using only working age population from 16 to 64. The main results are robust even if we exclude minimum wage workers and we use only the working age population.

Table C9 shows regression results based on the regression equation (1), by varying the level of

Table C6: The spike at zero, the share of wage cuts, and raises for salaried workers along business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts
1-Epop ratio	0.624***	0.280*	-0.904***	0.344**
$(1 - e_t)$	(0.158)	(0.153)	(0.272)	(0.151)
$(1 - e_t) \cdot \mathbb{I}(\Delta(1 - e_t) > 0)$	-0.00762	0.0232	-0.0156	-0.0308
	(0.0167)	(0.0196)	(0.0266)	(0.0249)
Inflation rate	-1.175***	-0.691***	1.866***	-0.484***
(π_t)	(0.115)	(0.141)	(0.225)	(0.125)
Observations	38	38	38	38
Adjusted R^2	0.725	0.350	0.700	0.173

Data source: CPS and author's calculation. Sample Period: 1979-2018. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

education. Table C10, C11, C12, C13 show regression results based on the level of age, gender, race, and hourly wage 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, which also holds for different worker characteristics.

Table C7: Exluding minimum wage workers, the spike at zero, the fraction of wage cuts, and raises

	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts	(5) Spike at zero $\Delta W = 0$	(6) Share of cuts $\Delta W < 0$	(7) Share of raises $\Delta W > 0$	(8) Spike at zero minus Share of cuts
1-Epop ratio	0.369	0.197	-0.566	0.172	0.557***	0.300*	-0.856***	0.257
$(1 - e_t)$	(0.333)	(0.220)	(0.527)	(0.201)	(0.199)	(0.155)	(0.313)	(0.170)
Inflation rate					-1.239***	-0.675***	1.915***	-0.564***
(π_t)					(0.132)	(0.139)	(0.194)	(0.189)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.0172	-0.00489	0.0170	-0.0149	0.679	0.332	0.686	0.144

Data source: CPS and author's calculation. Sample Period: 1980-2018 (except 1995). Inflation rate is calculated from CPI-U. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table C8: The spike at zero, the fraction of wage cuts, and raises among prime-aged hourly workers along the business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts	(5) Spike at zero $\Delta W = 0$	(6) Share of cuts $\Delta W < 0$	(7) Share of raises $\Delta W > 0$	(8) Spike at zero minus Share of cuts
1-Epop ratio	0.608***	0.0336	-0.642***	0.575***	0.401***	-0.150	-0.251	0.551***
$(1 - e_t)$	(0.0794)	(0.122)	(0.180)	(0.101)	(0.0759)	(0.130)	(0.179)	(0.113)
Inflation rate					-0.841***	-0.744***	1.585***	-0.0966
(π_t)					(0.103)	(0.129)	(0.218)	(0.0823)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.501	-0.0254	0.204	0.537	0.799	0.299	0.616	0.528

Data source: Data source: CPS and author's calculation. Sample Period: 1979-2018 (except 1995). Inflation rate is calculated from CPI-U. The spike at zero, the share of wage cuts and raises are constructed among prime-aged hourly paid workers. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table C9: The spike at zero, the share of wage cuts, and raises by education

	High School or less				College or more			
	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts	(5) Spike at zero $\Delta W = 0$	(6) Share of cuts $\Delta W < 0$	(7) Share of raises $\Delta W > 0$	(8) Spike at zero minus Share of cuts
1-Epop	0.551***	0.296*	-0.847***	0.255	0.666***	0.324**	-0.989***	0.342**
	(0.167)	(0.167)	(0.295)	(0.156)	(0.178)	(0.147)	(0.288)	(0.152)
Inflation	-1.188***	-0.717***	1.906***	-0.471***	-1.235***	-0.628***	1.863***	-0.606***
	(0.123)	(0.145)	(0.226)	(0.145)	(0.139)	(0.126)	(0.201)	(0.174)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.699	0.353	0.688	0.112	0.713	0.315	0.696	0.197

Data: CPS and author's calculation. Inflation rate is calculated from CPI-U. Sample Period: 1979-2018 (except 1995). * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table C10: The spike at zero, the share of wage cuts, and raises by age

	16 <= age < 40				40 <= age < 64			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$	Spike at zero minus Share of cuts	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$	Spike at zero minus Share of cuts
1-Epop	0.578***	0.245	-0.823***	0.333***	0.616***	0.356*	-0.971***	0.260
	(0.150)	(0.150)	(0.275)	(0.118)	(0.160)	(0.176)	(0.283)	(0.180)
Inflation	-1.091***	-0.697***	1.788***	-0.393***	-1.181***	-0.609***	1.790***	-0.571***
	(0.109)	(0.124)	(0.200)	(0.119)	(0.127)	(0.173)	(0.237)	(0.190)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.738	0.391	0.675	0.185	0.716	0.214	0.680	0.0981

Data: CPS and author's calculation. Inflation rate is calculated from CPI-U. Sample Period: 1979-2018 (except 1995). * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table C11: The spike at zero, the share of wage cuts, and raises by gender

	Male				Female			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$	Spike at zero minus Share of cuts	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$	Spike at zero minus Share of cuts
1-Epop	0.515***	0.340**	-0.855***	0.175	0.716***	0.252	-0.968***	0.463***
	(0.176)	(0.161)	(0.285)	(0.181)	(0.149)	(0.168)	(0.291)	(0.127)
Inflation	-1.102***	-0.506***	1.608***	-0.596***	-1.264***	-0.878***	2.142***	-0.387***
	(0.116)	(0.169)	(0.213)	(0.197)	(0.133)	(0.130)	(0.239)	(0.110)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.674	0.190	0.622	0.138	0.758	0.463	0.735	0.162

Data: CPS and author's calculation. Inflation rate is calculated from CPI-U. Sample Period: 1979-2018 (except 1995). * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table C12: The spike at zero, the share of wage cuts, and raises by race

	White				Non-white			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$	Spike at zero minus Share of cuts	Spike at zero $\Delta W = 0$	Share of cuts $\Delta W < 0$	Share of raises $\Delta W > 0$	Spike at zero minus Share of cuts
1-Epop	0.632***	0.333**	-0.964***	0.299**	0.554***	0.0753	-0.629**	0.479*
	(0.164)	(0.147)	(0.281)	(0.135)	(0.153)	(0.205)	(0.272)	(0.238)
Inflation	-1.200***	-0.677***	1.877***	-0.523***	-1.077***	-0.589***	1.666***	-0.489*
	(0.119)	(0.135)	(0.213)	(0.139)	(0.145)	(0.197)	(0.244)	(0.245)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.739	0.368	0.710	0.182	0.615	0.149	0.623	0.0672

Data: CPS and author's calculation. Inflation rate is calculated from CPI-U. Sample Period: 1979-2018 (except 1995). * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table C13: The spike at zero, the share of wage cuts and raises by hourly wage quantiles

	25th below				From 25th to Median			
	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts	(5) Spike at zero $\Delta W = 0$	(6) Share of cuts $\Delta W < 0$	(7) Share of raises $\Delta W > 0$	(8) Spike at zero minus Share of cuts
1-Epop	0.972***	0.221	-1.193**	0.751***	0.622**	0.128	-0.750*	0.494**
	(0.271)	(0.246)	(0.453)	(0.251)	(0.231)	(0.213)	(0.390)	(0.216)
Inflation	-1.246***	-0.935***	2.181***	-0.310	-1.216***	-0.685***	1.900***	-0.531**
	(0.317)	(0.273)	(0.560)	(0.189)	(0.111)	(0.157)	(0.189)	(0.195)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.494	0.291	0.485	0.127	0.586	0.195	0.540	0.111
	Median to 75th				**Above 75th**			
	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts	(5) Spike at zero $\Delta W = 0$	(6) Share of cuts $\Delta W < 0$	(7) Share of raises $\Delta W > 0$	(8) Spike at zero minus Share of cuts
1-Epop	0.426*	0.381***	-0.807**	0.0453	0.552***	0.439***	-0.992***	0.113
	(0.225)	(0.139)	(0.321)	(0.193)	(0.191)	(0.152)	(0.298)	(0.175)
Inflation	-1.114***	-0.403***	1.517***	-0.711***	-1.150***	-0.703***	1.852***	-0.447**
	(0.179)	(0.123)	(0.249)	(0.180)	(0.130)	(0.133)	(0.186)	(0.186)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.537	0.193	0.533	0.205	0.661	0.428	0.718	0.0829

Data source: CPS and author's calculation. Sample Period: 1979-2018 (except 1995). This table shows the cyclicality of the spike at zero, the share of wage cuts and raises by hourly wage quantiles. Inflation rate is calculated from CPI-U. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

Table C14: The spike at zero, the fraction of wage cuts, and raises for low-paid young workers along the business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Share of cuts $\Delta W < 0$	(3) Share of raises $\Delta W > 0$	(4) Spike at zero minus Share of cuts	(5) Spike at zero $\Delta W = 0$	(6) Share of cuts $\Delta W < 0$	(7) Share of raises $\Delta W > 0$	(8) Spike at zero minus Share of cuts
1-Epop ratio	0.702**	0.806**	-1.508***	-0.104	0.899***	0.884**	-1.783***	0.0146
$(1 - e_t)$	(0.332)	(0.358)	(0.540)	(0.431)	(0.205)	(0.346)	(0.415)	(0.389)
Inflation rate					-1.298***	-0.513	1.811***	-0.784*
(π_t)					(0.117)	(0.449)	(0.477)	(0.449)
Observations	38	38	38	38	38	38	38	38
Adjusted R^2	0.105	0.0986	0.161	-0.0259	0.696	0.142	0.509	0.0918

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). Inflation rate is calculated from CPI-U. The spike at zero, the share of workers with raises and cuts come from the annual nominal hourly wage growth distribution of low-paid young workers, who are younger than the age of 30 and earn less than equal to the 25 percentile of hourly wages for each year and greater than the minimum wages. * p<0.10, ** p<0.05, ***p<0.01. Standard errors in parentheses.

C Appendix: SIPP

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

Table D1 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 D2 divides hourly workers into two categories - job stayers and job switchers - and shows the unweighted count of observations, the spike at zero, the share of wage cuts and raises for each group.

Figure D1 shows year-over-year hourly wage change distributions 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 the blue bin is 0.02. Figure D2 shows the year-over-year hourly wage change distribution for hourly job stayers and Figure D3 shows that for job switchers.

Table D3 reports sample averages for the fractions of workers with zero wage changes, wage cuts, and raises. These estimates do not show heterogeneity by worker characteristics such as gender and education - common to both the CPS and the SIPP. Table D4 shows the average spike at zero, the fraction of workers with wage cuts and raises by hourly wage quartile for both job stayers and job switchers. Table D5presents the aggregate cyclicality of nominal wage change distributions using the SIPP based on the regression specification (1) for all hourly workers, job stayers and job switchers.

Table D1: The spike at zero, the share of wage cuts, and raises in the SIPP

Year	Obs ΔW	Spike at zero (%) $\Delta W = 0$	Share of cuts (%) $\Delta W < 0$	Share of raises (%) $\Delta W > 0$
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
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
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
2002	13,727	16.12	21.85	62.04
2003	12,287	19.27	19.51	61.21
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
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
Mean	13,511	24.00	17.42	58.58

Data 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 D2: The spike at zero, the share of wage cuts, and raises in the SIPP by job stayers and job switchers

Year	Job stayers Obs ΔW	Job stayers Spike zero (%) $\Delta W = 0$	Job stayers Share of cuts(%) $\Delta W < 0$	Job stayers Share of raises(%) $\Delta W > 0$	Job switchers Obs ΔW	Job switchers Spike at zero (%) $\Delta W = 0$	Job switchers Share of cuts(%) $\Delta W < 0$	Job switchers Share of raises(%) $\Delta W > 0$
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
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
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
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
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
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
Mean	9,588	28.89	12.32	58.79	3,923	12.52	29.86	57.62

Data 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.

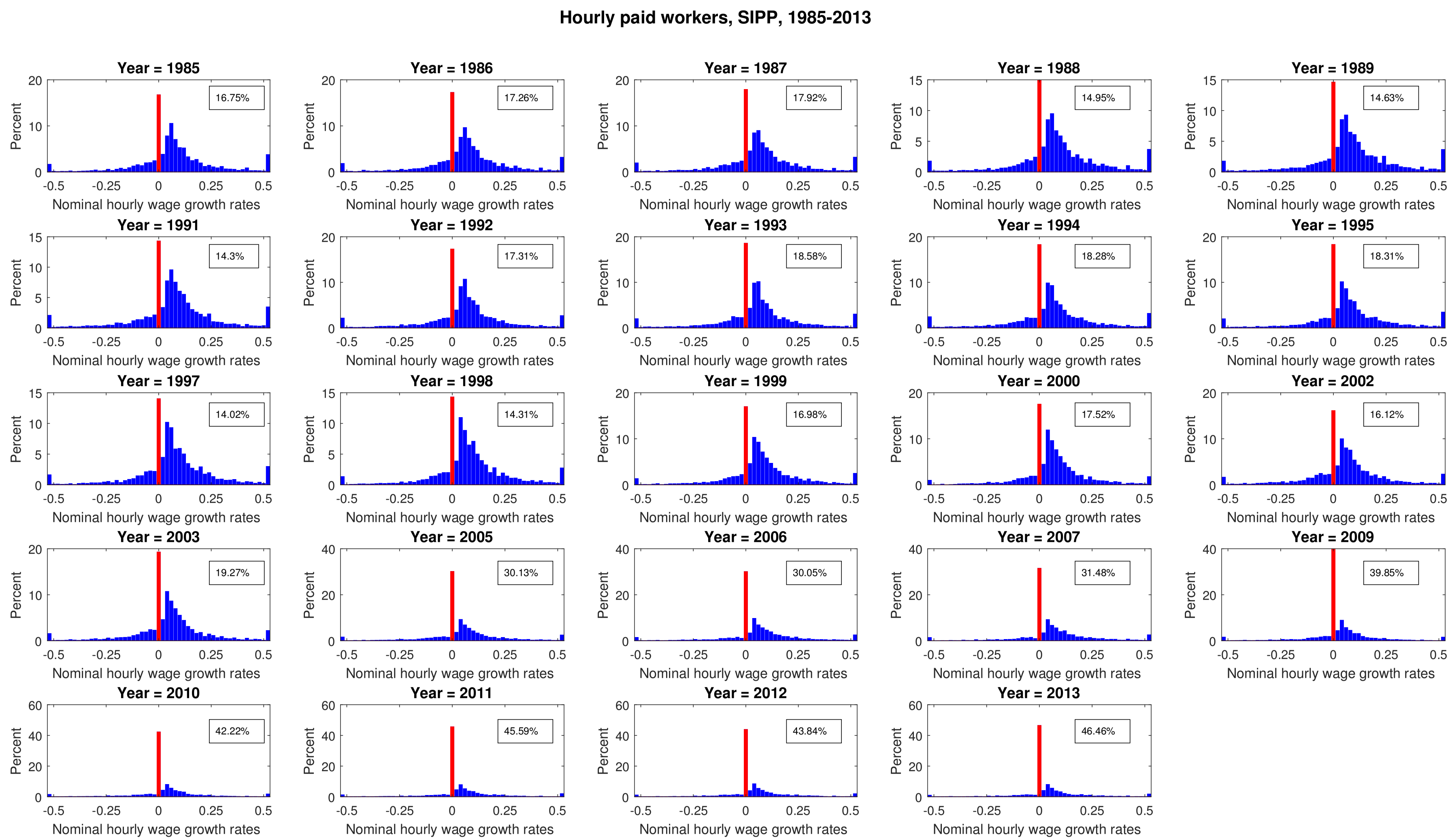

Figure D1: Nominal hourly wage growth rate distributions for 1985-2013

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, the width of the bin is 0.02.

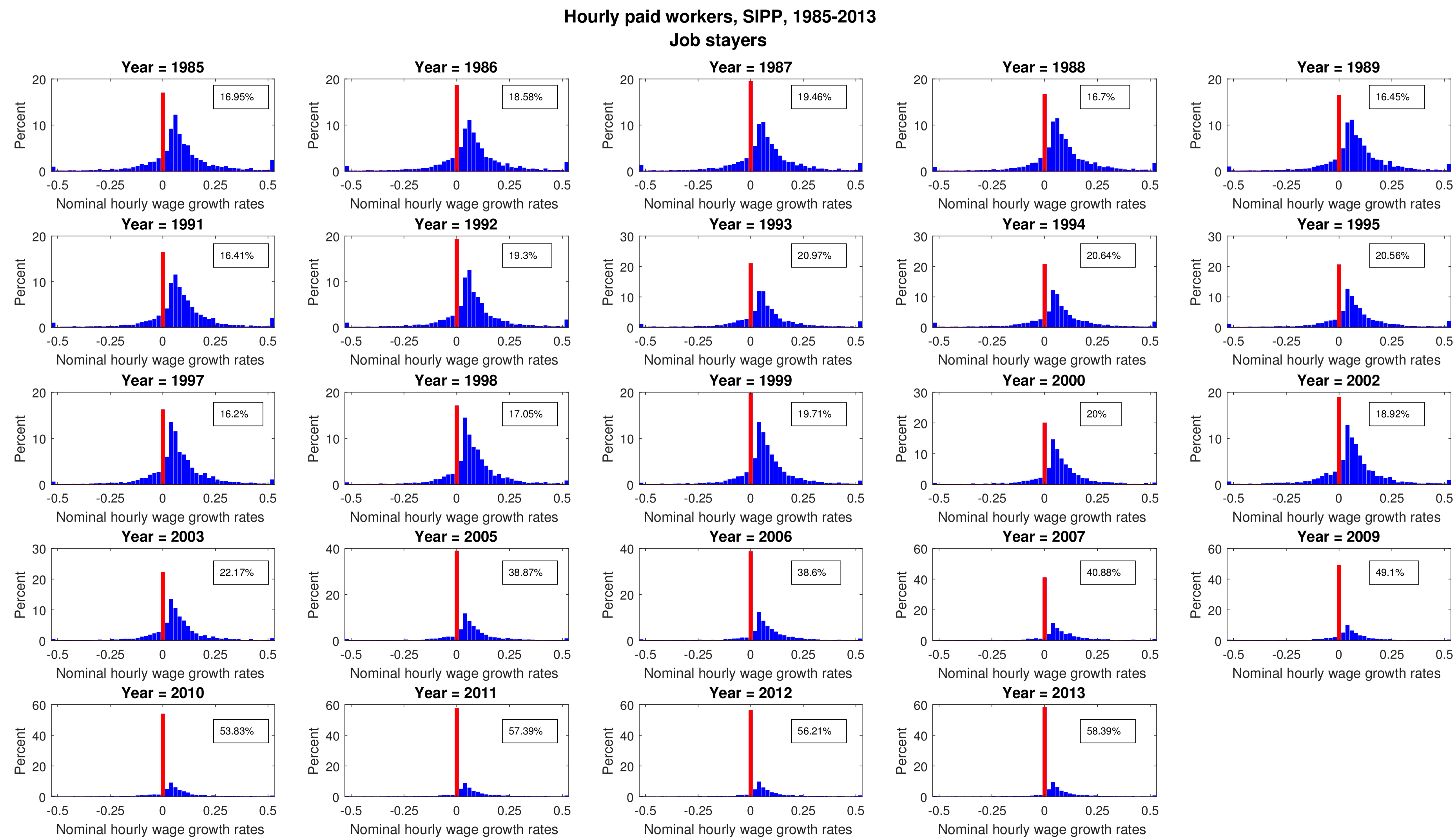

Figure D2: Nominal hourly wage growth rate distributions for 1985-2013 for job stayers

Data source: SIPP and author's calculation. For hourly rated 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, the width of blue bin is 0.02.

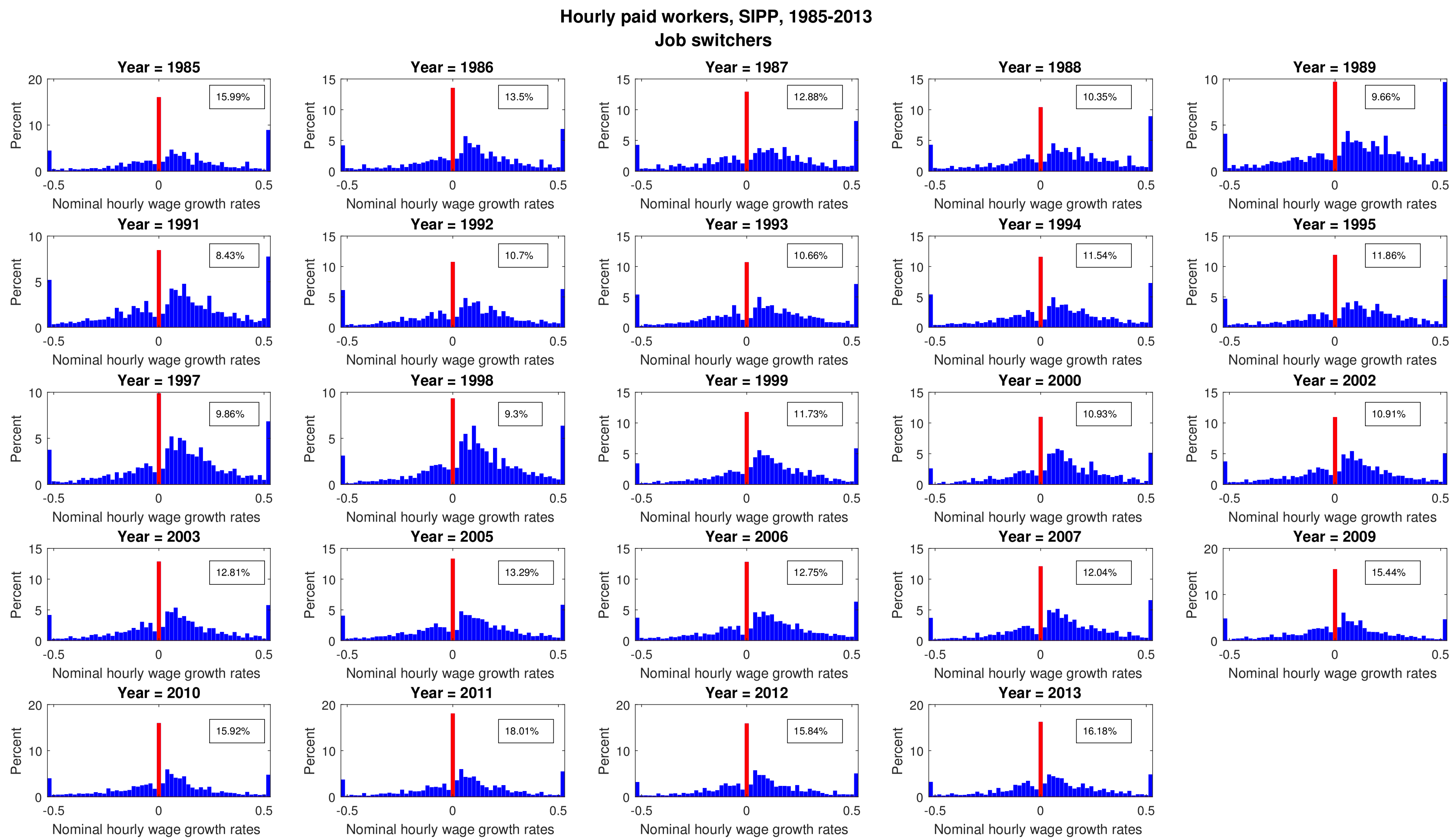

Figure D3: Nominal hourly wage growth rate distributions for 1985-2013 for job switchers

Data source: SIPP and author's calculation. For hourly rated 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, the width of blue bin is 0.02.

Table D3: 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
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 sample average of the spike at zero and the fraction of workers with wage cuts and raises over time by worker characteristics.

Table D4: 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.

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

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

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

Table D5: The spike at zero, the fraction of wage cuts and raises - job stayers vs. job switchers, SIPP

	All hourly paid workers			Job stayers			Job switchers		
	(1) Spike at zero	(2) Share of cuts	(3) Share of raises	(4) Spike at zero	(5) Share of cuts	(6) Share of raises	(7) Spike at zero	(8) Share of cuts	(9) Share of raises
1-Epop ratio	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 rate	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
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

Source: SIPP and author's calculation. Sample Period: 1984-2013 (except 1990, 1996, 2001, 2004, 2008). The first three columns include all hourly workers, columns 4-6 include only job stayers, and last 3 columns include only job switchers. The spike at zero shows greater association with employment than the share of workers with wage cuts for both job stayers and job switchers. Standard errors in parentheses.

Table D6: 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.

D Appendix: Model

D.1 Value function

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, following Nakamura and Steinsson (2008).

Under 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 reoptimze their wage. The recursive problem under the Calvo rigidity can be written as follows:

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

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, (5). When x_t is one, wage setters adjust nominal wages freely, whereas wage setters must pay infinite cost of wage adjustment when x_t equals zero.

For the menu cost 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:

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

The recursive problem of downward nominal wage rigidity with asymmetric menu costs model can be written as follows.

$$
\begin{aligned}
&V(q_t(i), L_t, \tfrac{W_{t-1}(i)}{W_t}, x_t) \\
&\quad = \max_{W_t(i)} \left[H(q_t(i), L_t, \tfrac{W_t(i)}{W_t}) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \tfrac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(x_t = 1) \\
&\qquad + \max_{W_t(i)} \left[H(q_t(i), L_t, \tfrac{W_t(i)}{W_t}) - K^d \mathbb{I}(W_t(i) < W_{t-1}(i)) \right. \\
&\qquad\qquad \left. + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \tfrac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(x_t = 0).
\end{aligned}
$$

Under the DNWR (asymmetric Calvo model), the wage setter's problem is

$$
\begin{aligned}
&V(q_t(i), L_t, \tfrac{W_{t-1}(i)}{W_t}, x_t) \\
&\quad = \max_{W_t(i)} \left[H(q_t(i), L_t, \tfrac{W_t(i)}{W_t}) \mathbb{I}(\tfrac{W_t(i)}{W_t} > \tfrac{W_{t-1}(i)}{W_t}) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \tfrac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \\
&\qquad + \max_{W_t(i)} \left[H(q_t(i), L_t, \tfrac{W_t(i)}{W_t}) \right. \\
&\qquad\qquad \left. + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \tfrac{W_t(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(\tfrac{W_t(i)}{W_t} \le \tfrac{W_{t-1}(i)}{W_t}) \mathbb{I}(x_t = 1) \\
&\qquad + \left[H(q_t(i), L_t, \tfrac{W_{t-1}(i)}{W_t}) + \beta \mathbb{E}(V(q_{t+1}(i), L_{t+1}, \tfrac{W_{t-1}(i)}{W_{t+1}}, x_{t+1})) \right] \mathbb{I}(\tfrac{W_t(i)}{W_t} \le \tfrac{W_{t-1}(i)}{W_t}) \mathbb{I}(x_t = 0).
\end{aligned}
$$

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

D.2 Solution Algorithm

This algorithm is basically from Heer and Maussner (2009).

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

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

- 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 cross-sectional distribution for finite households for T periods using the policy function obtained by step 2.

- Step 4 : Construct a time series for wage inflation. Burn first initial periods and estimate the parameters γ_0, γ_1, and γ_2.

– Calculate simulated wage inflation, $\ln(\frac{W_{t+1}^S}{W_t})$,

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

– Estimate parameters using the OLS

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

- Step 5: Update γ_0, γ_1, and γ_2 using the OLS. Iterate from Step 2 to Step 5 until the parameters converge.

- Step 6: Test the goodness of fit for H using R^2.

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,[28] and the maximum forecast error is less than 0.1 percent.

D.3 Sensitivity

D.3.1 Menu cost model

In the menu cost model, two parameters, the probability of facing the menu cost to change their wage (μ^{Menu}) and the fixed cost (κ) , are calibrated to match the average spike at zero. To keep the average spike at zero fixed, as μ^{Menu} increases, the fixed cost, κ, decreases, as does the inaction region. In the random menu cost model, the spike at zero is the proportion of the inaction region. Table E1 shows that the menu cost model implies greater responsiveness of the share of workers with wage cuts by varying μ^{Menu} from 0.3 to 1.

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

Table E1: The spike at zero, the fraction of wage cuts, and raises along the business cycles by varing menu cost, K, and μ^{Menu}

			The responsiveness to employment		
		The average Spike at zero	(1) Spike at zero	(2) Fraction of	(3) Fraction of
μ^{Menu}	K	(%)	$\Delta W = 0$	$\Delta W < 0$	$\Delta W > 0$
1	0.0010	23.200	-0.120	-0.336	0.456
0.9	0.0012	23.035	-0.165	-0.333	0.498
0.8	0.0015	23.085	-0.187	-0.329	0.516
0.7	0.0020	23.205	-0.210	-0.358	0.568
0.6	0.0003	23.100	-0.210	-0.292	0.502
0.5	0.0004	23.000	-0.142	-0.353	0.495
0.4	0.0075	23.100	-0.164	-0.391	0.555
0.3	0.0190	23.164	-0.037	-0.469	0.506

This table shows the responsiveness of the spike at zero, the share of workers with wage cuts, and raises by varing parameters of symmetric menu cost model, μ^{Menu} and K.