Downward nominal wage rigidity in the United States*

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Abstract

This paper constructs distributions of individual workers' year-over-year changes in nominal hourly wages across time and across US states from two nationally representative household surveys, the Current Population Survey (1979-2017) and the Survey of Income and Program Participation (1984-2013). The novel result is that the share of workers with no wage changes, which accounts for the large spike at zero in the wage change distribution, is more countercyclical than the share of workers with wage cuts. A strand of related literature interpreted the empirical finding that US states with larger decreases in employment are also the states with lower average wage increases as a sign of wage flexibility. This paper overturns this interpretation by showing that the states with larger employment declines are also the states with greater increases in the share of workers with a zero wage change, suggesting wage rigidity instead. The paper then analyzes heterogeneous agent models with five alternative wage-setting schemes—perfectly flexible, Calvo, long-term contracts, menu costs, and downward nominal wage rigidity—and shows that only the model with downward nominal wage rigidity is consistent with the empirical findings regarding the shape and cyclicality of the wage change distribution documented in this paper.

JEL classification: E24, E32, J30.

Keywords: Downward nominal wage rigidity, Countercylicality, Employment

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1 Introduction

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

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

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

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

[1] Kahn (1997); Card and Hyslop (1996); Lebow, Sacks, and Anne (2003); Daly, Hobijn, and Lucking (2012); Barattieri, Basu, and Gottschalk (2014); Daly and Hobijn (2014); Elsby, Shin, and Solon (2016); Fallick, Lettau, and Wascher (2016)

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

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

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

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

With the national level data, I first show that, unsurprisingly, both employment and the share of workers with raises decline during recessions: a one percentage point decline in employment is associated with a 0.9 percentage point decline in the share of workers with raises, controlling for inflation. Mechanically, this decline in the share of workers with raises corresponds to the sum of the increases in the share of workers with no wage changes and in the share with wage cuts. I then examine which of these two shares shows a larger co-movement with employment, controlling for inflation. I find that a one percentage point decline in employment is associated with a 0.6 percentage point increase in the share of workers with no wage changes and a 0.3 percentage point increase of workers with a wage cut. That is, as employment falls during recessions, the share of workers with no wage changes increases a lot more than the share of workers with wage cuts.

This pattern I identify at the national level across time also holds in the cross-sectional analysis of the data at the 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 workers with no wage changes compared to that of workers with wage cuts.

At first sight, this appears to contradict the recent finding by Beraja, Hurst, and Ospina (2016), which shows a positive correlation between state-level changes in nominal wages and employment during the Great Recession. Based on this finding, these authors argue wages were "fairly flexible", as lower employment growth was associated with lower wage growth. However, also using the state-level data for the 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. I conclude, contrary to Beraja, Hurst, and Ospina (2016), that nominal wages were "fairly rigid" during the Great Recession.

My empirical analysis suggests that the shape and cyclical properties of the nominal wage change distribution are consistent with DNWR. The findings are established using both the CPS and the SIPP data, both at the national and state level.[3] In summary, my empirical analysis presents three stylized facts about inflation, employment, and the nominal wage change distributions. 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 with 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 costs, and DNWR. The models feature not only idiosyncratic uncertainty but also aggregate uncertainty. Using numerical methods, I characterize the year-over-year wage change distributions implied by each model and study how they change with aggregate employment.

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

The remainder of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the data sets: the CPS and the SIPP. Section 4 discusses the shape of nominal year-over-year hourly wage change distributions. Section 5 examines the cyclical properties of the nominal wage change distribution: as employment declines, the share of workers with no wage changes increases more than the share with wage cuts. The state-level analysis of this finding

[3]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.

is presented in section 6. Section 7 builds heterogeneous agent models with 5 alternative wage-setting schemes, equipped with both aggregate and idiosyncratic shocks. Section 8 compares numerical predictions from 5 those wage-setting schemes to the empirical findings. Section 9 concludes and discusses future work.

2 Related literature

This paper is related to 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) use 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 share of workers with no wage changes, the spike at zero, and employment. My conjecture is that this is because in her sample period, the average inflation was very high at 6.1 percent per year. Card and Hyslop (1996) use both PSID and CPS data from 1979 to 1993, a period during which the average inflation rate was about 5.3 percent per year. They argue that inflation can grease the wheels of the labor market by showing that the share of workers with no wage changes 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) studies the period of low inflation, 1986 - 2014, when the average 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. The spike at zero from Daly and Hobijn (2014) is available from the Wage Rigidity Meter, published by the Federal Reserve Bank of San Francisco.[4] In contrast to Daly and Hobijn (2014), Elsby, Shin, and Solon (2016) argue that the spike at zero has been acyclical since 1998. Elsby, Shin, and Solon (2016) use the CPS data with biannual job-tenure supplements from 1980 to 2017. They show that the spike at zero has increased since 1998. They argue that the increase in the spike at zero is secular rather than cyclical in nature and is the consequence of a secular decline in inflation.

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

In the studies mentioned above, wage change is defined to equal zero only when data show an exact zero, that is, when a worker reports the exact same hourly wage rate in the interviews one year apart. Reported wages suffer from measurement error, which can over- or understate

[4]The Wage Rigidity Meter shows the percentage of workers with no wage change within the subgroups of the labor force by type of pay, education, and industry using the CPS, which is available from here.
Atlanta Fed's Wage Growth Tracker (here) also reports the percent of individuals with zero wage changes.

the size of the spike at zero wage changes. 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 taking into account measurement error. They argue that correcting for measurement error leads to a larger estimate of the size of the spike at zero and a decline in the estimate of the share of workers experiencing a wage cut.

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

Unlike the previous studies mentioned thus far, Beraja, Hurst, and Ospina (2016) use state variations of wages and employment to argue that wages were fairly flexible during the Great Recession. They use nominal wage data from the 2007-2010 American Community Survey (ACS), which does not have a panel structure. To avoid composition bias, they use the residual wages, taking out variations in wages depending on observable worker characteristics. They argue that wages were "fairly flexible", since they find a positive correlation between state-level changes in nominal wages and employment during the Great Recession. However, as described in detail in section 6.3, I argue that their finding still can be consistent with the existence of DNWR since I find a negative association between the share of workers with zero wage changes and employment at the state level.

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

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 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: a spike at zero and fewer wage cuts than wage increases. Their model has only idiosyncratic shocks. To generate the stationary distribution similar to the empirical distribution, they impose 3 different menu-costs: one for raises, one for cuts, and one for when wage growth rate is smaller than inflation.

Daly and Hobijn (2014) build a heterogeneous agent model with either perfectly flexible wages or DNWR, and they compare the stationary distributions implied by the two models. After a one-time negative aggregate shock, they also find the spike at zero increases for the model with DNWR. However, they do not consider the share of workers with wage cuts but only focus on the size of the spike at zero. Mineyama (2018) presents a heterogeneous agent model with DNWR, equipped with both idiosyncratic and aggregate shocks. The model by Mineyama (2018) generates the countercyclical spike at zero; however, this paper also does not consider the changes in the share of wage cuts. Mineyama (2018) argues that DNWR is helpful for explaining the observed flattening of the Philips curve during the Great Recession.

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; (3) 5 alternative wage-setting schemes - perfectly flexible, Calvo, long-term contracts, menu costs, 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 analysis.

3 Data

This paper uses two nationally representative household panel data sets, the CPS and the SIPP, in the United States, which have individual-level wage data. It is important to use disaggregated data to avoid the composition bias embedded in aggregate time series of wages. Solon, Barsky, and Parker (1994) show that the composition of employed workers changes over the business cycle, which gives more weight to low-skilled workers during booms compared to recessions. Because the wages of low-skilled workers tend to be lower than those of high-skilled workers, such cyclical changes in the composition of the workers can lead to aggregate wages appearing not to fall during recessions, spuriously suggesting wage rigidity. To avoid this composition bias, the present paper uses panel data.

3.1 Current Population Survey

The Current Population Survey (CPS)[5] is jointly collected by the United States Census Bureau and the Bureau of Labor Statistics (BLS). The purpose of this survey is mainly to construct nationally representative labor force related statistics, such as unemployment rates and median weekly earnings in the United States. Almost 60,000 households are interviewed monthly. The sample period starts in 1979 and ends in 2017.

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,

[5] CPS monthly microdata are available from http://www.nber.org/data/cps_basic.html .

households are out of the sample for 8 months and are interviewed 4 times again in the following 4 months. Table 1 shows the sampling design of the CPS. Among the 8 interviews, only when households are in the Outgoing Rotation Group (Earner Study) - the fourth and eighth interview of the survey - do they respond to earnings-related questions: usual earnings, hours worked last week, union coverage, and so on. Thus, each individual in the survey reports wages at most two times in a year apart, in the month in sample (MIS) in 4 and 8.

Table 1: CPS sampling design

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

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

Knowing the special sampling design of the CPS, the monthly CPS could be exploited as panel data. However, CPS microdata do not provide unique individual identifiers within the households. Instead, Integrated Public Use Microdata Series - CPS (IPUMS-CPS)[6] provides the unique individual identifiers to link individuals across monthly CPS based on Drew, Flood, and Warren (2014).[7] 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.[8] 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 United States, about 58 percent of workers are hourly-rated in 2014.[9] Workers paid hourly both in the previous and the current year represent about 50 percent of all workers.

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 imputed since 1996.[10] Hirsch and Schumacher (2004) and Bollinger and Hirsch (2006) show that including imputed wages in the analysis may cause bias due to imperfect matching of donors with

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

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

[8]When respondents are in the Outgoing Rotation Group (MIS4 or MIS8), they report their earnings in the easiest way: hourly, weekly, annually, or some other basis. Those who reported that the easiest way to report their wage is hourly are considered 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.

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

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

nonrespondents. Therefore, it is essential to exclude imputed wages. Although IPUMS-CPS provides individually linked CPS data, the IPUMS-CPS does not provide allocation flags for wage variables, that indicate whether wage variables are imputed or not. Therefore, I merge the IPUMS-CPS data with the monthly CPS, merged with the Outgoing Rotation Group. In this way, this paper exploits the longitudinal feature of the CPS after excluding imputed wages.

One disadvantage of the CPS is that it is difficult to define job stayers and job switchers. Although the CPS provides the variable to inform whether the respondent is employed by the same employer from the last month since 1994, this variable is missing in the MIS5 after 8 months break of the interview. Thus, it is difficult to define job stayers in the CPS. For example, if the respondent has switched jobs during the 8-month break period, for example in the 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 a job switcher. Therefore, this paper does not distinguish job stayers from job switchers for the empirical analysis using the CPS.

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

3.2 Survey of Income and Program Participation

The SIPP[11] is a U.S. household survey conducted by the U.S. Census Bureau. Each panel consists of approximately 14,000 to 52,000 households, and the interview is conducted every 4 months over 3 or 4 years. Longitudinal weights provided by the SIPP are used to aggregate data at the national level. This paper uses thirteen panels: 1984, 1985, 1986, 1987, 1988, 1990, 1991, 1992, 1993, 1996, 2001, 2004, and 2008. The sample period is from 1984 to 2012.

The main objective is the annual hourly wage growth rate for each hourly rated worker. Although wages for each worker are available from the SIPP at a monthly frequency[12], this paper studies the annual hourly wage growth rate since the hazard of a nominal wage change is highest at 12 months after a wage change (Barattieri, Basu, and Gottschalk (2014)). Similar to the CPS, this paper focuses on hourly rated workers who report the hourly rate directly to the survey in order to eliminate errors from the imputation of the hourly pay rate for salaried workers.[13]

There are advantages of using the SIPP. First, the SIPP provides the unique individual identifiers so we can match individuals across waves without an additional process. Second,

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

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

[13]The SIPP uses a specific questionnaire to ask whether survey respondents are paid by the hour for the main jobs. For workers who are paid by the hour, the SIPP questions for the regular hourly pay rate at that job from the specific employer. SIPP has introduced the dependent interviewing procedure to improve data quality since 2004 (Moore (2006)). That is, if respondents indicated the hourly wage is "the same as the last interview", the hourly wage at the current interview is filled by the one from the last interview.

the SIPP keeps track of movers, while the address-based CPS does not follow movers in the sample. Third, the SIPP provides the unique and consistent job IDs across waves for each job that the respondent had, whereas the CPS does not offer them. Since job IDs are allocated based on a respondent's employer information in the SIPP, I define job stayers as employer stayers.[14] Job switchers are the ones who reported to work for the different employers in any given year, regardless of jobless spell between employer switching. One disadvantage of SIPP data is that the time series data are discontinuous because of gaps between the panels. Thus, state-level analysis is more reliable than the aggregate time series analysis in the SIPP.

The average number of observations in the SIPP is 13,937 per year, which is smaller but comparable to the CPS sample size.[15] In the SIPP, 55 percent of workers are hourly rated. On average, 71 percent of them are job stayers. The time series number of observations is available from Table A13, and the number of job stayers and job switchers are available from Table A14 in the appendix.

4 Asymmetric nominal wage change distribution

This section examines year-over-year nominal hourly wage change distribution for each year from 1979 to 2017 using the CPS (section 4.1) and from 1984 to 2013 using the SIPP (section 4.2). Nominal wage change distributions show a large spike at zero, that is, a large share of workers experience exact zero wage changes in a given year. In addition, these distributions are highly asymmetric: there are fewer wage cuts than raises. This is consistent with the findings in a strand of earlier literature that argues for the existence of DNWR; Kahn (1997); Card and Hyslop (1996); Lebow, Sacks, and Anne (2003); Barattieri, Basu, and Gottschalk (2014); Elsby, Shin, and Solon (2016); Fallick, Lettau, and Wascher (2016).

4.1 Nominal wage change distribution: CPS

I plot the distribution of log nominal hourly wage changes of hourly rated workers for each year from 1979 to 2017 using the CPS data. The following characteristics appear common to all nominal wage change distributions: 1) there is a large spike at zero, and 2) there are fewer wage cuts than raises. As an example, Figure 1 shows the distribution for the year, 2009-2010. We can clearly observe an apparent spike at zero, which is shown in red, defined as the percentage of hourly rated workers whose annual hourly wage growth rate is exactly zero. In other words, the spike at zero represents the share of hourly workers who report the exact same hourly wages in interviews

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

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

one year apart. The width of all the blue bins is 0.02, except for the two bins at the very ends. From the smaller sizes of the blue bins to the left of zero, it is clear that the distribution contains fewer wage cuts than raises.

I provide some context for Figure 1. In 2010, the unemployment rate was highest at 9.7 percent after the onset of the Great Recession, and the inflation rate was 1.6 percent. Even with massive excess labor supply in the economy, 21.1 percent of the hourly rated workers experienced zero wage changes from 2009 to 2010, represented as the large spike at zero. The median hourly wage growth rate was 1.7 percent, and more than half of the hourly rated workers had raises higher than the inflation rate. Overall, 54.2 percent of hourly rated workers had raises, and only 24.6 percent of the hourly rated workers had wage cuts; that is, there were many more raises than wage cuts in 2010 despite high unemployment and low inflation.

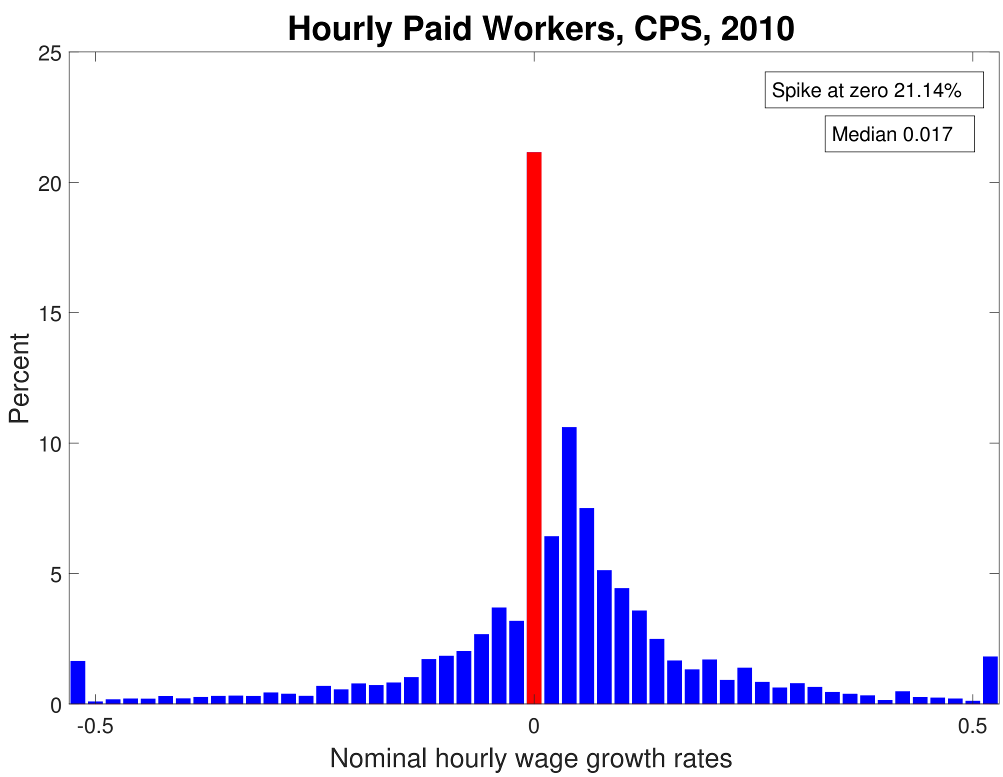


Figure 1: Year-over-year nominal hourly wage growth rates in 2010

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

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 right next 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 been also interpreted as being consistent with the existence of DNWR.

Figure A1 and A2 in the appendix show similar distributions for each year from 1979 to 2017. Similarly to the figure for 2010, all nominal wage change distributions have large spikes at zero and more raises than cuts for the entire sample period. This suggests that nominal wage change distributions are consistent with existence of DNWR for the entire sample period, 1979 - 2017.

To further exploit cyclical properties of nominal wage change distributions, I focus on three statistics from the distributions: the spike at zero (the share of workers with no wage changes), the share with wage cuts, and the share with raises. Table 2 reports the averages of these three statistics across the sample years. 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[16] only has a marginal effect on these average estimates.

Table 2: Descriptive statistics by worker charcteristic, CPS

	% of all workers	% of hourly workers	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
Hourly paid workers			15.25	21.13	63.63
Exc. Minimum wage workers			15.10	20.64	64.26
Male	52.17	49.25	15.17	22.15	62.69
Female	47.83	50.75	15.32	20.09	64.59
16 <= age <40	47.39	53.13	13.95	20.83	65.22
40 <= age <64	49.01	42.98	15.94	21.68	62.38
White	84.48	85.13	15.36	20.57	64.07
Non-white	15.52	14.87	14.62	24.39	60.99
High School or less	44.24	58.50	15.75	21.49	62.76
College or more	55.76	41.50	14.46	20.65	64.88
No union coverage	81.72	80.31	16.84	21.42	61.74
Union coverage	18.28	19.69	11.73	22.19	66.07

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

Nominal hourly wage change distributions do not show significant heterogeneity by worker characteristics. Table 2 reports descriptive statistics by worker characteristics. As I only focus 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

[16]Workers whose hourly wages are lower than the state's minimum wage in either previous or current year are dropped. Vaghul and Zipperer (2016) document the monthly state-level minimum wage from 1973 to 2016. To extend the data set to 2017, I use https://www.dol.gov/whd/state/stateMinWageHis.htm.

for different subsets of workers results in similar estimates.

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

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

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

On the contrary, nominal hourly wage change distributions exhibits heterogeneity by hourly wage level and industry. Table 3 reports the averages for the same three statistics 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 A3 in the appendix reports the averages calculated separately for the workers in each 2-digit NAICS industry code. The rows are sorted by the average size the spike at zero. The average size of the spike at zero varies from 11 percent to 23 percent. The biggest industry in terms of the number of hourly workers is manufacturing, and the average size of the spike at zero for manufacturing is around 14 percent, which is comparable to the national average.

4.2 Nominal wage change distribution: SIPP

Conducting the above analysis with the SIPP data from 1984 to 2013 results in very similar findings. Figure A4 in the appendix shows nominal hourly wage change distributions for hourly workers for each year in the sample period.[17] All the distributions are asymmetric with a large spike at zero.

Table 4 is similar to Table 2, reporting sample averages for the fractions of workers with zero wage changes, wage cuts, and raises. Again, these estimates do not show heterogeneity by worker characteristics such as gender and education - common to both the CPS and the SIPP.

In particular, the SIPP data allows 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 the other. [18]

[17] Note that the years 1990, 1996, 2001, 2004, and 2008 are missing from the sample due to the SIPP having gaps between panels

[18] Table A15 in the appendix shows the average of the spike at zero and the share of wage cuts and raises by reasons

Table 4: Descriptive statistics by worker characteristics, SIPP

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

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

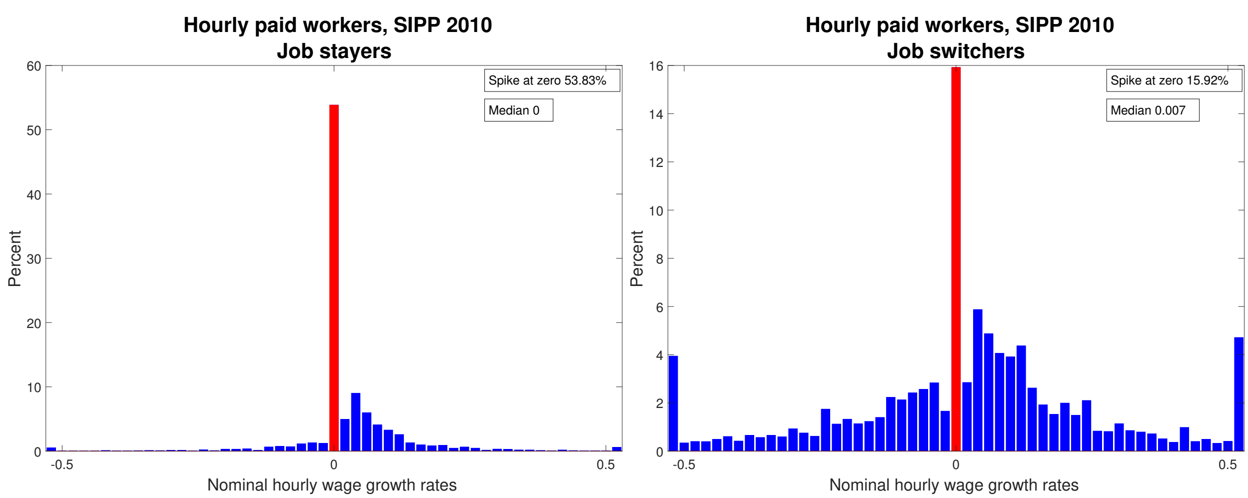


Figure 2: Nominal hourly wage distribution in 2010: job stayers vs. job switchers

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. Other than the red bin, bin size is 0.02. The spike at zero for job stayers is 54 percent and the spike at zero for job switchers is 16 percent.

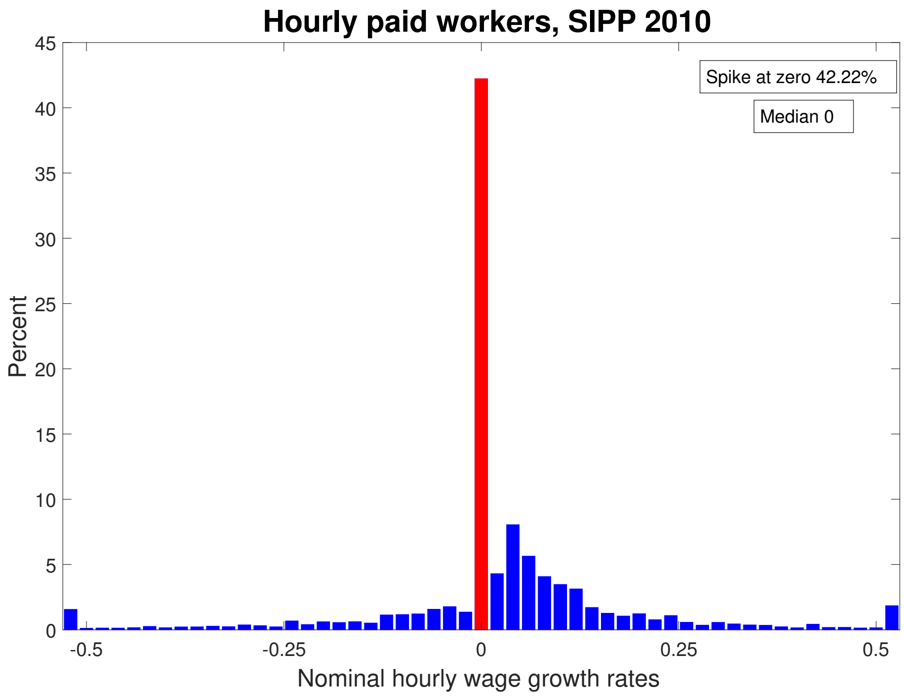


Figure 3: Nominal hourly wage growth rate distribution in 2010

Data source: SIPP and author's calculation. The red bin shows the spike at zero, which represents the percentage of workers whose hourly wage growth rate is exactly zero from 2009 to 2010. Other than red bin, bin size is 0.02. The spike at zero in 2010 is 42.2 percent and the median nominal hourly wage growth rate in 2010 is 0 percent. 16 percents of hourly workers had wage cuts and 41 percent of workers had raises.

Similarly, Table 4 shows that for job stayers, the average size of the spike is larger, whereas the average share of workers with wage cuts is smaller.[19] The median size of wage growth rates for job switchers is also much larger than that for job stayers, as shown in Table 5.[20] These comparisons between job stayers and switchers appear overall consistent with the findings by Bils (1985) and Shin (1994), who argue that wages are more flexible for job switchers than job stayers. However, my findings suggest 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 workers such as Figure 3 exhibit strong asymmetry and a large spike at zero. This is also comparable to Figure 1, nominal hourly wage change distributions in 2010 using the CPS, which also includes both job stayers and job switchers, with the former being a large share.

Table 5: Median size of wage change, SIPP

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

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

5 The cyclicality of the aggregate nominal wage change distributions

This section contains the main empirical results of the paper, namely that the spike at zero shows greater countercyclical fluctuations compared to the share of workers with wage cuts. Section 5.1 documents this pattern in the CPS data for the period 1979 to 2017 and section 5.2 in the SIPP data for the period 1984 to 2013. 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 A2 of appendix A reports these time series 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.

why hourly workers switched their employer in a given year. Contingent workers or temporary employed workers, workers on layoff, and injured or ill workers show the high average spike at zero among job switchers.

[19] 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 A14 shows time series spike at zero, the share of wage cuts and increases for both job stayers and job switchers.

[20] Nominal hourly wage change distributions for job stayers and job switchers for the entire sample period is available in Figure A5 and Figure A6. In addition, Table A12 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.

5.1 Aggregate analysis: CPS

To explore the cyclicality of the nominal wage change distributions, we could think about the following three regression equations:

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

where e_t 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 this 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 6: The spike at zero, the fraction of wage cuts, and raises along the business cycles

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

Standard errors in parentheses

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

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). Inflation rate is calculated from CPI-U. This table shows regression results from regressing the spike at zero, the fraction of workers with wage cuts, and raises on 1-epop ratio without and with controlling for inflation. Controlling for inflation, the spike at zero exhibits greater fluctuations compared to the share of workers with wage cuts.

Table 6 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. On the other hand, during periods of low inflation, nominal wage rigidity could potentially have a substantial effect on employment. During my sample period, 1979 - 2017, inflation varies 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 6 where I do not control for inflation, I do not find a statistically significant relationships between the dependent variables and employment.

By contrast, when I control for inflation, I find a statistically significant relationships between the dependent variables and employment. In particular, column (4) shows that the spike at zero increases when employment declines. The negative correlation between the spike at zero and employment, controlling for inflation, is consistent with the findings by Kahn (1997); Card and Hyslop (1996) and Daly and Hobijn (2014). [21] The countercyclicality of the spike at zero can also be seen from the figure 4, which plots the spike at zero against $1 - e_t$. We observe that the spike at zero has a countercyclical movement in the period of low inflation.

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 such 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. [22]

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 downwards. 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 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 consistent with the implication of DNWR.

Regarding the regressions above, one may be concerned about error of self-reported hourly wages (Bound and Krueger (1991)); however, measurement error on the dependent variables,

[21] Card and Hyslop (1996) use the sample period of high inflation from 1979 to 1993 and conclude that the spike at zero is negatively correlated with inflation, leading them to conclude that inflation can grease the wheels of the labor market. Daly and Hobijn (2014) use the sample period of low inflation from 1986 to 2014 and argue that the spike at zero is positively related to the unemployment rate. Different from the previous literature, this paper explores the cyclicality of the spike at zero as well as the share of workers with wage cuts and raises.

[22] Section A.2 from the appendix shows that there are no asymmetric responses of nominal hourly wage change distributions to employment increases compared to decreases.

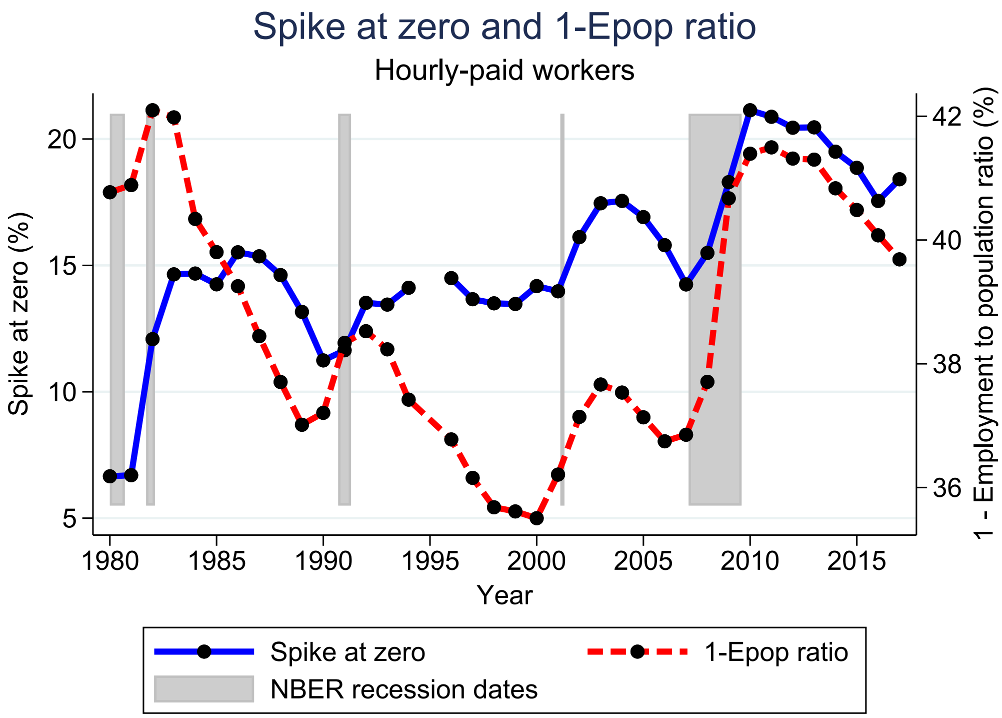


Figure 4: Time series of the spike at zero with 1-Epop ratio

Data source: CPS and author's calculation. Sample period: 1979 - 2017. This figure shows the spike at zero for each year (left axis) and the 1- employment to population ratio (right axis).

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, which is available from the last column of Table A1, 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.

In addition, my primary findings are robust to using the nominal hourly wage change distributions of salaried workers, instead of hourly wage workers. For salaried workers, we can compute hourly wages by dividing the usual weekly earnings by the usual weekly hours worked.[23] Table 7 shows regression results using imputed hourly wages for salaried workers. We

[23]This imputed hourly wage can be more volatile than the actual hourly wage due to measurement error in hours worked for salaried workers. The average of the spike at zero for salaried workers is 7.0 percent, the average of the share of workers with wage cut for salaried workers is 34.3 percent, and the average of the share of workers with wage increases for salaried workers is 58.8 percent.

Table 7: 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) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero $\Delta W = 0$	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$
1-Epop	0.429***	-0.0646	-0.364	0.471***	0.0535	-0.524**
$(1 - e_t)$	(0.0805)	(0.240)	(0.308)	(0.0539)	(0.165)	(0.196)
Inflation rate, π_t				-0.278***	-0.782***	1.060***
				(0.0322)	(0.122)	(0.132)
					0.472/0.524 = 0.9	
Observations	36	36	36	36	36	36
Adjusted R^2	0.416	-0.0269	0.0224	0.656	0.430	0.601

Standard errors in parentheses

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

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

can still see that the spike at zero is negatively associated with inflation and employment, jointly. 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.

The primary results are also robust to looking at subgroups of workers by worker characteristics such as gender, age, race, and education. These robustness checks are available in section A.2 of the appendix. For example, 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. 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. 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.[24] Table 8 shows that low-paid young workers still show a similar cyclical pattern of nominal wage change distribution as the overall sample. Controlling for inflation, I find that a 1 percentage point decline in employment is associated with 1) a 0.9 percentage point increase in the spike at zero; 2) a 0.8 percentage point increase in the share of workers with wage cuts; and 3) a 1.7 percentage point decrease in the share of workers with raises. This can be suggestive evidence that nominal wages are also rigid for those workers without a long-term contract.

[24]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 2017. Both of them are greater than the overall sample averages, 15.2 percent, and 21.1 percent, respectively.

Table 8: 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) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero $\Delta W = 0$	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$
1-Epop ratio	0.693*	0.772*	-1.465**	0.899***	0.844*	-1.743***
$(1 - e_t)$	(0.324)	(0.373)	(0.526)	(0.188)	(0.363)	(0.402)
Inflation rate, π_t				-1.325***	-0.468	1.794**
				(0.101)	(0.466)	(0.517)
				0.899/1.743 = 0.5		
Observations	37	37	37	37	37	37
Adjusted R^2	0.104	0.0892	0.159	0.739	0.121	0.516

Standard errors in parentheses

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

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

5.2 Aggregate analysis: SIPP

To analyze the cyclicality of nominal wage change distributions using the SIPP data, I construct the same three aggregate time series using three different samples: all workers, only job stayers and only job switchers. Table A13 in the appendix reports the spike at zero and the fraction of workers with wage cuts and raises for all hourly workers for each year. From this aggregate time series, we can see a sudden increase in the level of the spike at zero in 2005 and accordingly sudden decreases in the share of workers with wage cuts and raises. This is due to the introduction of the new survey design to 2004 panel and after – the dependent interviewing procedure. That is, if hourly workers mention that s/he is paid by the same as the last interview, the hourly pay rate at the current interview is automatically filled by the one from the last interview. Table A14 reports the time series of the three statistics for job stayers and job switchers. Similarly, there is also a sudden jump in the level of the spike at zero for job stayers in 2005 for the same reason.

I replicate the analysis using the regression specification (1). Unlike the CPS, the SIPP does not have rotating panels and there are discontinuities between panels. To control for heterogeneity across panels, for instance, the change in the survey design, panel fixed effects are included.[25] In Table 9, the first three columns report results for all hourly workers, column (4) ~ (6) are for job stayers, and the last three columns are for job switchers.

The results from the first three columns of Table 9 show that the spike at zero increases when employment declines and the spike at zero fluctuates more than the fraction with wage cuts, which is consistent with the results using the CPS.

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

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

Standard errors in parentheses

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

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

The spike at zero of job stayers appears to respond to employment more than the spike at zero of job switchers does. However, I still find that the spike at zero of job switchers have countercyclical fluctuations. This implies that the cyclical property of nominal wage change distributions for all hourly workers are not solely driven by job stayers. If the greater association between the spike at zero and employment, compared to that of the share with wage cuts and employment, is due to DNWR, then this analysis with the SIPP suggests that nominal wages are still rigid for job switchers, and more rigid for job stayers.

This contrasts with some of the findings in previous literature. I compare my method with those in the earlier studies, and discuss the potential reasons for the differences in findings in section A.3 of appendix.

6 The cyclicality of state-level nominal wage change distributions

In this section, I validate the above results using the state-level data. This allows me to use more observations to examine the relationship between employment, inflation and nominal wage changes distribution, controlling for state and year fixed effects. To explore the cyclicality of state-level nominal hourly 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 the share of workers 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).

6.1 State-level analysis of the cyclicality of nominal wage change distribution: CPS

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

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

where e_{it} is the employment to population ratio for each state i ($i = 1, \cdots, 48$) 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 aggregate real activity or aggregate inflation. As shown in section 5, controlling for inflation is important for obtaining a statistically significant relationship between employment and the share of workers with zero year-over-year wage changes. I estimate these equations using data from 50 states for the years 1979-2017 (except 1985, 1986, 1995, and 1996).[26]

Table 10: The spike at zero, the fraction of wage cuts and raises across states

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

Standard errors in parentheses

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

Data source: CPS and author's calculation. Sample Period: 1980-2017 (except 1985, 1986, 1995, and 1996 due to small sample sizes). The sample consists of 50 states over 34 years. The state-level spike at zero, the share of workers with wage cuts and raies are regressed on the state-level 1-epop ratio with both state and time fixed effects.

Table 10 shows the regression results using the regression specification (1), exploiting state-level variations. It shows that a 1 percentage point decrease in employment is associated with 1) an increase in the spike at zero by 0.38 percentage point, 2) an increase in the share of

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

workers with a wage cut by 0.29 percentage point, and mechanically 3) a decrease in the share of workers with raises by 0.67 percentage point. 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 U.S. 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 U.S. 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. This 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.

6.2 State-level analysis: job stayers versus job switchers

Table 11: 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) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$	(7) Spike at zero	(8) Fraction of $\Delta W < 0$	(9) Fraction of $\Delta W > 0$
1 - Epop	0.407***	0.0989	-0.506***	0.489***	0.121	-0.610***	0.348***	0.124	-0.471**
$(1 - e_{it})$	(0.101)	(0.0767)	(0.111)	(0.123)	(0.0789)	(0.121)	(0.101)	(0.176)	(0.182)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	0.407/0.506=0.80			0.489/0.610=0.80			0.348/0.471= 0.74		
Observations	855	855	855	855	855	855	855	855	855
Adjusted R^2	0.842	0.341	0.783	0.871	0.499	0.814	0.171	0.0608	0.148

Standard errors in parentheses

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

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

Table 11 shows regression results based on the equation (2) using the SIPP, controlling for both time and state fixed effects. Time fixed effects control for aggregate factors common across states for each year such as the change in the survey design in 2004. The first three columns include all hourly workers, the next three columns include only job stayers, and the last three columns are for job switchers. State-level regression results using all hourly workers in the SIPP also show higher responsiveness of the spike at zero than the share of workers with wage cuts.

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. 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 in the aggregate analysis, but the wages of job switchers also exhibit patterns consistent with DNWR.

6.3 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 top panel of Figure 5, 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 3 of of BHO. The difference between the wage data used in the study of BHO and my study is these authors compute the composition adjusted average nominal wage for each state every year using the American Community Survey (ACS), as the ACS does not have a panel structure.[27] The figure shows that a state with a higher fall in employment also has a lower wage growth rate. Based on this, BHO argue that wages were fairly flexible since nominal wage growth rates were responding to changes in employment.

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

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

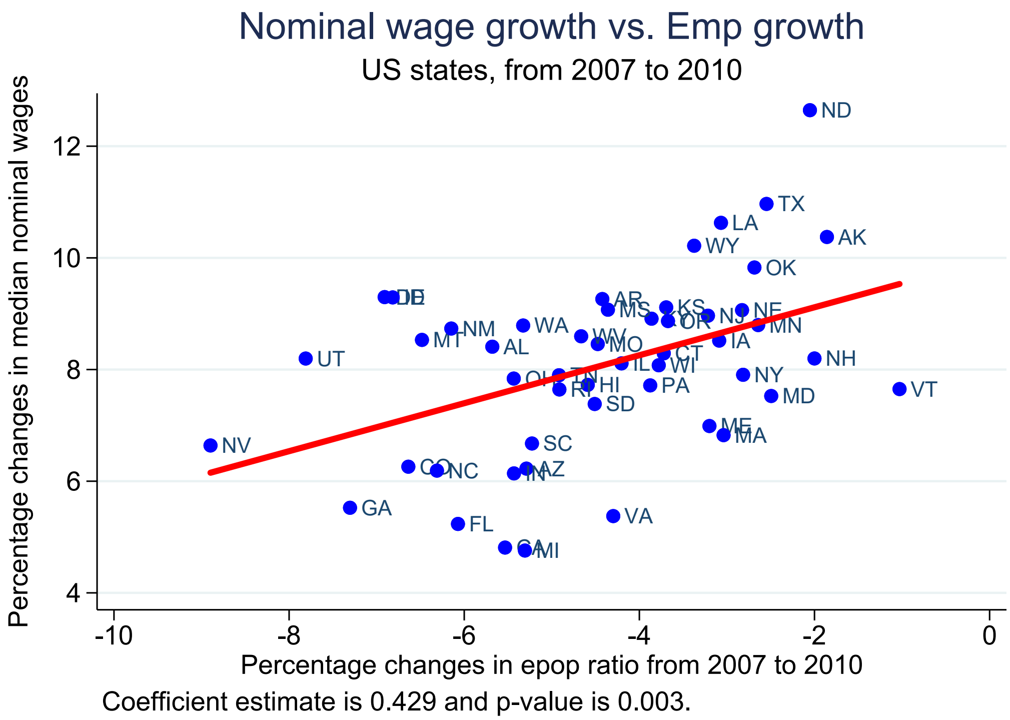
Standard errors in parentheses

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

Data source: CPS and author's calculation. Sample Period: 2007 - 2010. This table shows changes in nominal wage change distributions along with employment for each state from 2007 - 2010.

In the bottom panel of Figure 5, I present a similar plot, but using 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

[27] The sample consists of men between the ages of 21 and 55 with a strong attachment to the labor market only.



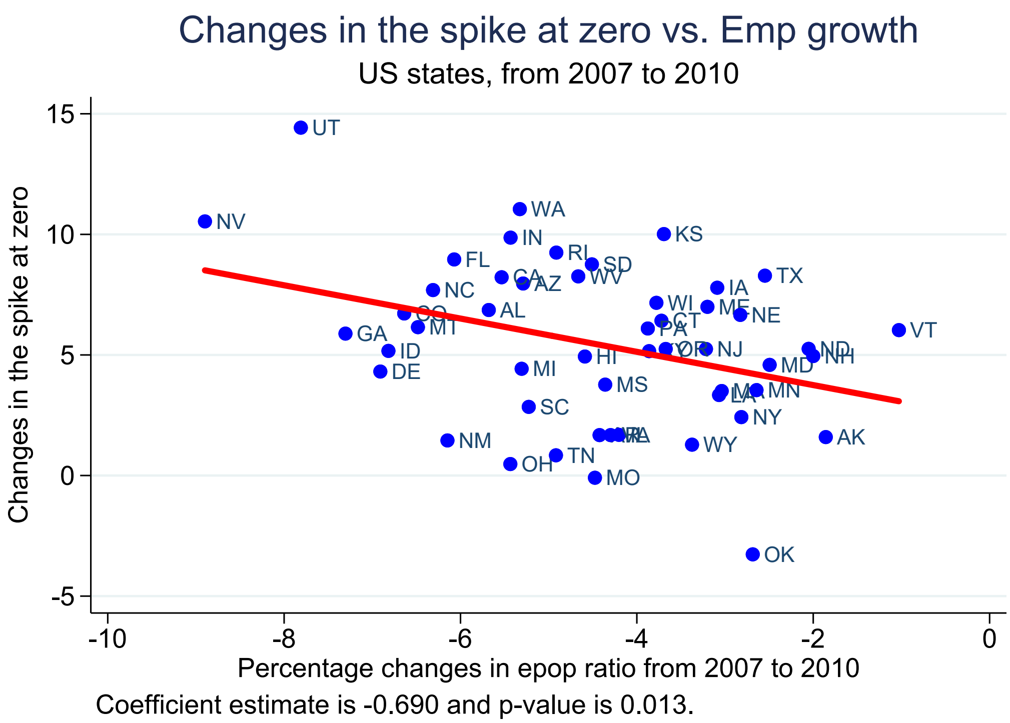


Figure 5: Nominal wage growth rates and changes in the spike at zero vs. employment growth from 2007 to 2010

Data source: CPS and author's calculation. The top panel shows the median nominal wage growth versus employment growth rates from 2007 to 2010 across states. The bottom 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.

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:

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

where Δe_i is the difference in the employment to population ratio from 2007 to 2010 in a state i. Table 12 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 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, which is consistent with the findings reported earlier in table 6 for time series data and table 10 for cross-sectional data.

This result is still compatible with BHO's empirical finding, shown in the last column of Table 12: 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 a overall drop in nominal wage growth rates. 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 DNWR.

6.4 The recession of 1979 - 1982

Table 13: Changes in nominal wage distribution from 1979 to 1982 across states

	(1) Changes in Spike at zero $\Delta W = 0$	(2) Changes in Fraction of $\Delta W < 0$	(3) Changes in Fraction of $\Delta W > 0$	(4) $\ln \frac{W_{s1982}}{W_{s1979}}$
Percentage changes in the employment	-0.374	0.163	0.211	0.607**
	(0.487)	(0.333)	(0.678)	(0.281)
Observations	50	50	50	50
Adjusted R^2	0.00407	-0.0148	-0.0166	0.0715

Standard errors in parentheses

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

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.

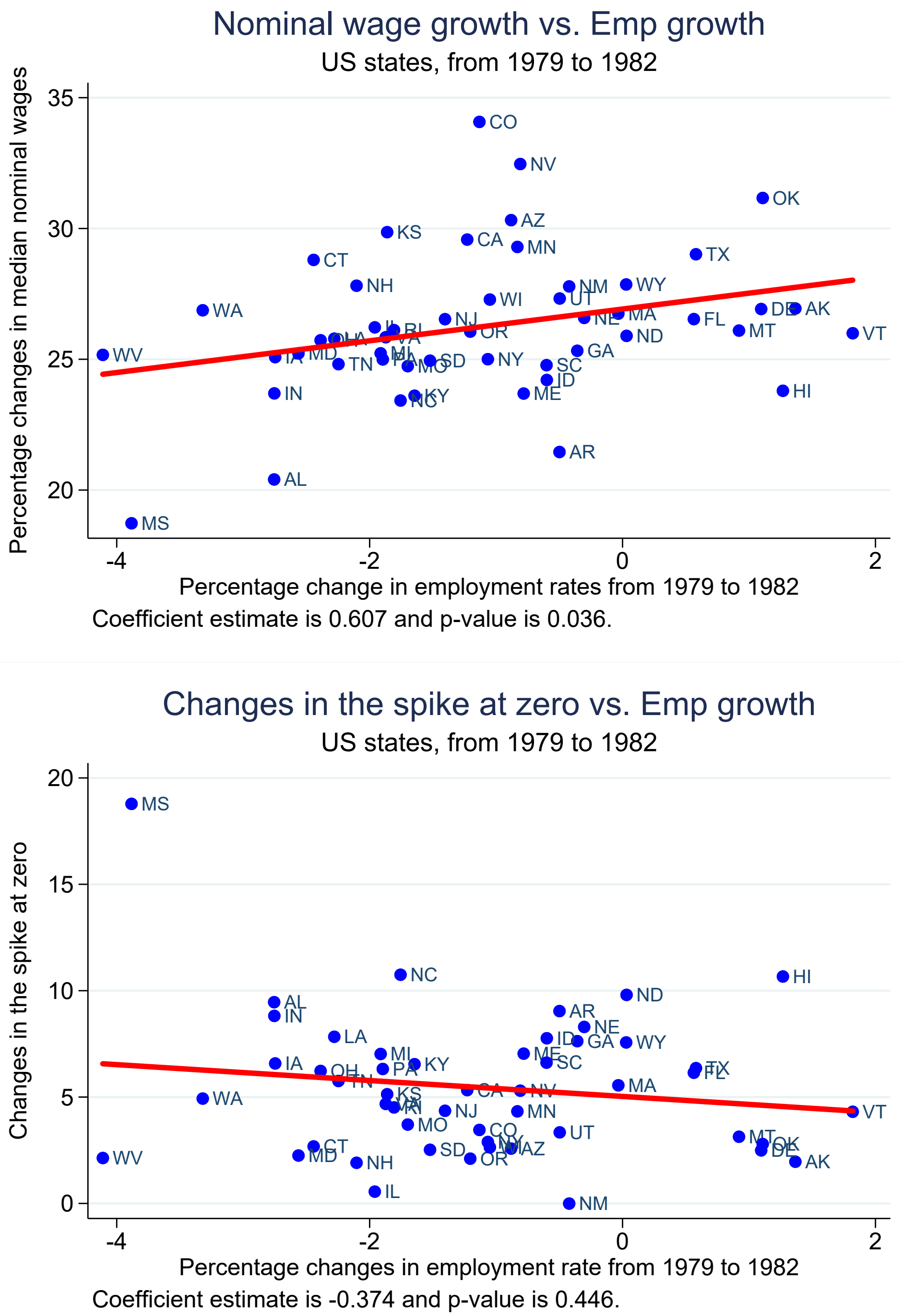


Figure 6: Nominal wage growth and changes in the spike at zero vs. employment growth from 1979 to 1982

Data source: CPS and author's calcuation. The top panel shows the median nominal wage growth with respect to employment growth rates from 1979 to 1982 across states. The bottom 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.

The Great Recession 2007 - 2010, was a period of relatively low inflation. Thus, it is 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 follows I will consider the recession of 1979 - 1982,[28] 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, in that there is no significant relationship in the cross-section of US states between employment changes and changes in the share of workers getting a zero wage change.

The top panel of Figure 6 shows state-level median nominal wage growth rates with respect to changes in employment across states from 1979 to 1982, and the bottom panel of Figure 6 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 relationship with employment growth rates shown in the top panel of Figure 6, we cannot find the distinctive relationships between the changes in the spike at zero and changes in employment. Table 13 shows the regression results of changes in nominal wage change distributions on employment, confirming what we have seen from Figure 6, when the average inflation rate is high. This 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 Five alternative models of wage rigidity with heterogeneous agents

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-costs, and downward wage rigidity model. A representative firm uses aggregate labor to produce output. The firm's profit maximization problem gives the labor demand function for each differenitated labor. Households supply heterogeneous labor determined by idiosyncratic labor productivity, and set nominal wages subject to labor demand and wage-setting constraints. The basic set up of the model is derived from Erceg, Henderson, and Levin (2000). Daly and Hobijn (2014); Mineyama (2018) introduce heterogeneous disutility of labor supply, and Fagan and Messina (2009) adds idiosyncratic labor productivity shocks to the basic model of Erceg, Henderson, and Levin (2000). The basic wage-setting mechanism of heterogeneous labor in this paper is derived from Fagan and Messina (2009).

[28] Based on NBER recession dates, there were two recessions: January 1980 - July 1980 and July 1981 - November 1982.

7.1 Firm

There is a representative firm, which 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 problem to maximize profits is equivalent to minimize the cost of labor. Hence, the firm chooses differentiated labor $l_t(i)$, indexed by $i \in [0, 1]$, to minimize the total production cost

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

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

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

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

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

7.2 Households

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

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

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

subject to

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

Wage setting constraint

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

The Lagrangian of the households problem is given by

$$
\begin{aligned}
\mathcal{L} = \mathbb{E}_t\Sigma_{t=0}^{\infty}\beta^t\Bigg\{\frac{C_t(i)^{1-\gamma}}{1-\gamma} - \frac{\omega}{\psi+1}l_t(i)^{1+\psi} + \lambda_t(i)[B_t(i) + W_t(i)l_t(i) + \Pi_t - P_tC_t(i) - Q_{t+1}B_{t+1}(i)] \\
+ \mu_t(i)[q_t(i)^{\theta-1}(\frac{W_t(i)}{W_t})^{-\theta}L_t - l_t(i)] \\
+ \theta_t(i)[\text{Wage-setting constraint}]\Bigg\}
\end{aligned}
\tag{4}
$$

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

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

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

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

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

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

7.3 Five wage-setting restrictions

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

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

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

Second, consider Calvo wage rigidity, assuming only a constant fraction of workers can optimize wages. This is the most commonly used wage-setting mechanism for nominal rigidity. [29] 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 following,

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

where $W_t^*(i)$ is the optimal wage, 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 to determine employment rather than the remitted wages or observed wages in each point of time. This is often called Barro's critique (Barro (1977)) or efficiency-wage theory. To address this concern by Barro (1977), Basu and House (2016) introduced long-term contracts in 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 one that the firm actually remits to the workers. Firms calculate allocative wages under the perfectly flexible case and find the remitted wages of which present discounted value is the same as the present discounted value of allocative wages over the contract. Following by Basu and House (2016), the remitted wages for each i type of labor, $x_t(i)$ can be determined as follows.

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

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

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

where s is the probability of renewing the contract.

Fourth, consider the menu-costs model of wage rigidity, motivated by the empirical evidence that changes in nominal wage change distribution is state-dependent. In the context of wage-setting model, we may imagine the cost involved in changes in wages. For example, whenever the wage setters want to change their wage, they have to pay an additional cost of bargaining to bring them to the bargaining table. Wage setters must pay menu-costs to change their wage with the probability of μ^{Menu}. With the other probability of $1-\mu^{\text{Menu}}$, wage setters can freely change their wage. The model with random menu-cost in the price rigidity literature (Alvarez, Le Bihan, and Lippi (2016)) to explain small changes in prices. This can be summarized as follows.

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

The fifth wage-setting scheme is the DNWR model. If the optimal wage in a period t, $W_t^*(i)$, maximizing the equation (5) in the absence of wage-setting constraint in a period t, is higher than the previous wage, $W_{t-1}(i)$, then the current wage can be the optimal wage, $W_t(i) = W_t^*(i)$. There is no explicit restriction to raise the current nominal wage. However, if the optimal wage in a period t , $W_t^*(i)$, is lower than the previous wage, $W_{t-1}(i)$, then wage setter cannot lower wage with the probability of μ^{DNWR}. With the other probability of $(1-\mu^{\text{DNWR}})$, wage setters can lower wages optimally. This wage-setting restriction can be summarized, as follows.

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

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

7.4 Closing the market

The goods market clearing condition is

$$Y_t = C_t.$$

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

$$P_tY_t = P_tC_t = W_tL_t = M_t,$$

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

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

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

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

7.5 Value function

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

Under 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:

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

where $C > \infty$ and

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

which can be derived from substituting labor demand into the current objective function in the equation, (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 to zero.

For the menu-costs model, wage setters have to pay an additional fixed cost, K, to adjust their wage with the probability of μ^{Menu}, when x_t equals to zero. With the other probability of $(1 - \mu^{\text{Menu}})$, wage setters can adjust wages without any cost. The recursive problem with menu costs can be written as follows:

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

Under the DNWR, wage setter's problem is

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

If the current 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 to 1, with the probability of $(1 - \mu^{\text{DNWR}})$.

8 Numerical results

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

8.1 Calibration

Table 14 shows calibrated parameters. Parameters in the top panel show parameters related to preference. The relative risk aversion parameter, γ, is 1, which implies the intertemporal elasticity of substitution as 1. The discount rate β is 0.97, which implies a steady-state annual real interest rate is 3 percent. ψ = 0.5 is the inverse of Frisch elasticity, which is in a permissible range of macro literature shown in Chetty, Guren, Manoli, and Weber (2011). Different from earlier parameters, there is no consensus regarding the wage elasticity of labor demand, θ. θ varies from 1.67 to 21 from the previous theory literature.[30] This paper sets θ to be 3, which implies steady state markup

[30] Erceg et al. (2000) set θ at 4. Christiano et al. (2005) set θ at 21. Smets and Wouters (2007) set wage markup at 1.5, which implies θ being 3. Daly and Hobijn (2014) set θ at 2.5. The model from the Daly and Hobijn (2014) has homogeneous differentiated labor but households have different disutility from the labor supply. Fagan and Messina (2009) used $\theta = \frac{11}{12}$. Mineyama (2018) used θ at 9, which makes the steady state wage mark up 12.5 percent

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

The second panel of Table 14 shows the parameters governing shock processes in the economy. Since the nominal output is total wage payment in the model, this paper uses total wage payment[31] to estimate the aggregate shock process, given by the equation (6). I estimated the constant growth rate (μ) and the standard deviation from the growth rate of the total wage payment. Parameters related to idiosyncratic productivity are from the Guvenen (2009). Guvenen (2009) decompose individual labor earnings into nonstationary and stationary components using more than 20 years of individual labor earnings data from PSID. For the individual labor productivity shock in this paper, I use the stationary process of labor earnings from Guvenen (2009), allowing heterogeneity growth rate of income.[32]

The last panel of Table 14 shows parameters governing the degree of wage rigidity. The probability that workers constrained not to adjust their wages downwardly, μ^{DNWR}, comes from Table 6, aggregate evidence using the CPS. Among households whose optimal wages are lower than the previous wages, only 37 percent of them can lower current wages at the optimal level. Other 67 percent of workers cannot lower wages if the optimal wages are below the previous wages. Therefore, μ sets to be 0.67. Other than DNWR wage-setting, $\mu^{\text{Calvo}}$from Calvo model, s from long-term contracts model, and μ^{Menu} and K from menu costs model, are set to have the same size of the spike at zero at the steady-state level of the spike at zero under the DNWR.

Table 14: Calibrated Parameters

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

Time unit is a year.

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

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

8.2 Solution methods

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

$$
\begin{aligned}
W_{t+1} &= H(W_t, M_{t+1}) \\
\ln(\frac{W_{t+1}}{W_t}) &= H(\ln(\frac{M_{t+1}}{W_t})) = \gamma_0 + \gamma_1 \ln\frac{M_{t+1}}{W_t} + \gamma_2(\ln\frac{M_{t+1}}{W_t})^2
\end{aligned} \tag{7}
$$

Parameters, γ_0, γ_1, and γ_2, are estimated by regressing the realized wage inflation on the aggregate state variables. Starting from the initial guess, the algorithm is iterated until the predicted wage inflation gets close enough to the realized wage inflation. The detailed algorithm is followed by Heer and Maussner (2009), which is available in the appendix D.1. 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 [33] and the maximum forecast error is less than 0.1 percent.

8.3 Stationary wage change distribution

Figure 7 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 and the width of the blue bar is 0.01. 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.

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

The long-term contract wage-setting generates the spike at zero but symmetric stationary

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

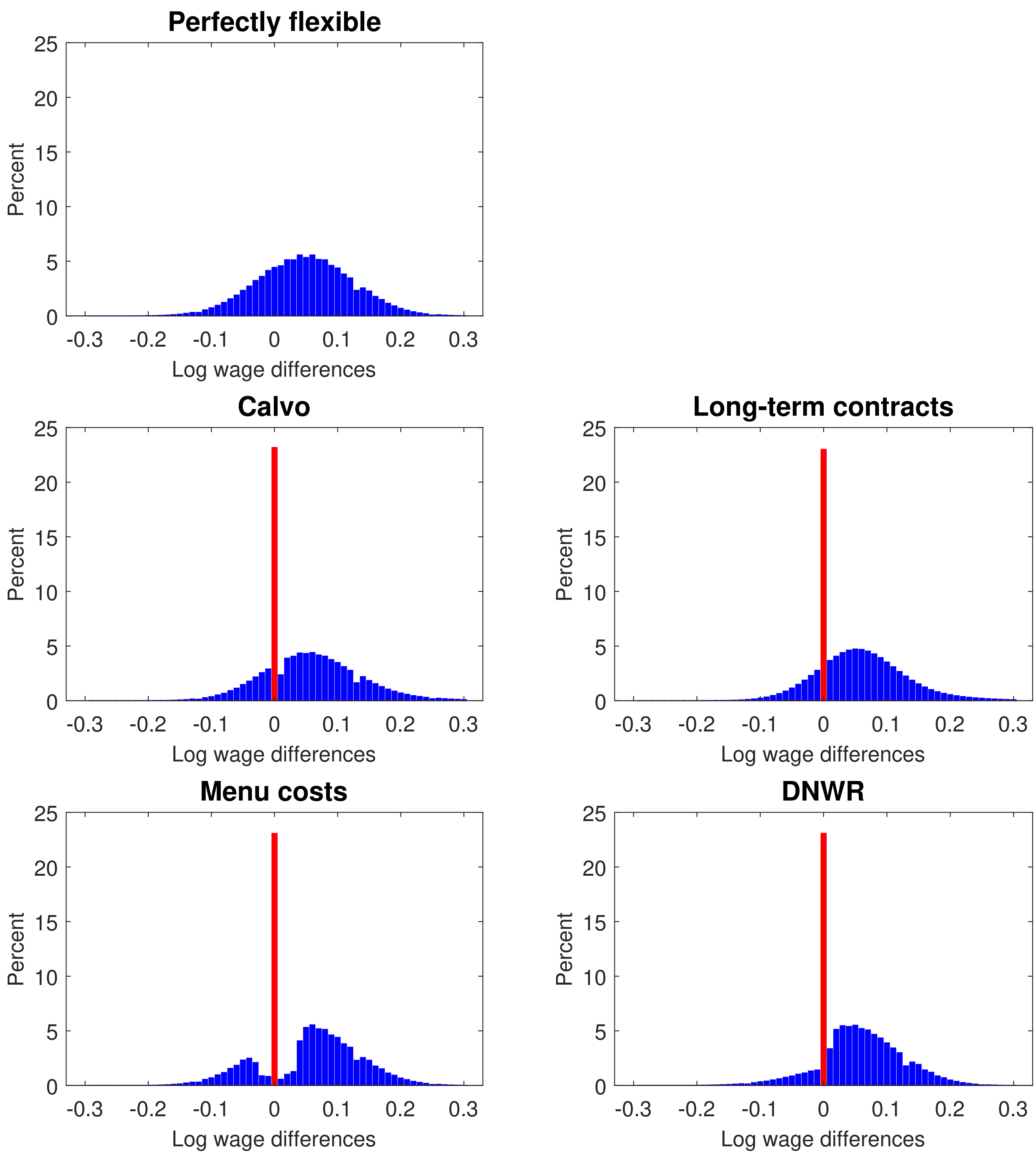


Figure 7: Staionary wage change distribution from 5 different wage-setting schemes

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

wage change distribution. The second right panel of Figure 7 shows the remitted wage change distribution from the long-term contract under the perfect foresight. Allocated wages come from the perfectly flexible model, so its implications on employment should be the same as the perfectly flexible model. However, the stationary wage distribution has the spike at zero and is symmetric around the median, which is similar to the one from the Calvo model, which is again inconsistent with empirical findings.

Menu-costs of wage adjustment generates the spike at zero, but there is no discontinuous drop in the stationary distribution approaching to zero from the left compared to approaching from the right. The stationary wage change distribution from the menu-costs model is shown at the bottom left panel of Figure 7. 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 big and there are not many small wage changes compared to the Calvo model. Under the positive inflation, the optimal nominal wage change distribution has always higher densities above zero than below zero. Therefore, more portion of the spike at zero comes from the right to the zero rather than the left to the zero, which leads to the lack of raises compared to wage cuts. This is inconsistent with empirical nominal wage change distribution, shown in the section 4.

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

8.4 The cyclicality of wage change distribution

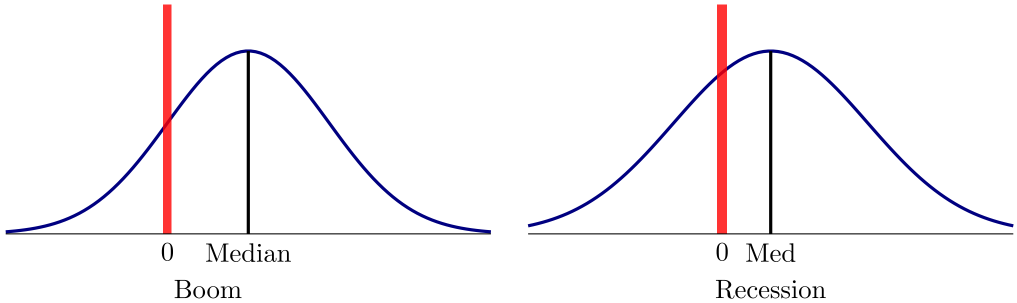
This section runs the main regression (1) using simulated data from 5 alternative wage-setting schemes to see which model has consistent implications on cyclicality patterns of nominal wage change distributions: 1) the spike at zero increases when employment declines and 2) the increase in the spike at zero is higher than the increase in the fraction of wage cuts when employment declines. Table 15 illustrates the regression results from the data and the models. The first panel of the table shows the cyclicality of nominal wage change distributions from national level analysis, which is shown at the last three columns of Table 6 from the section 5.1.

Nominal wage change distributions in the model shift left or right along the business cycle under a perfectly flexible wage model. The second panel of Table 6 shows regression results using simulated data series under the perfectly flexible wage setting. After controlling inflation, we can see that the increase in the fraction of workers with wage cuts is almost the same as the decrease in the fraction of workers with raises when employment declines without changing the spike at zero, which is inconsistent with the empirical findings.

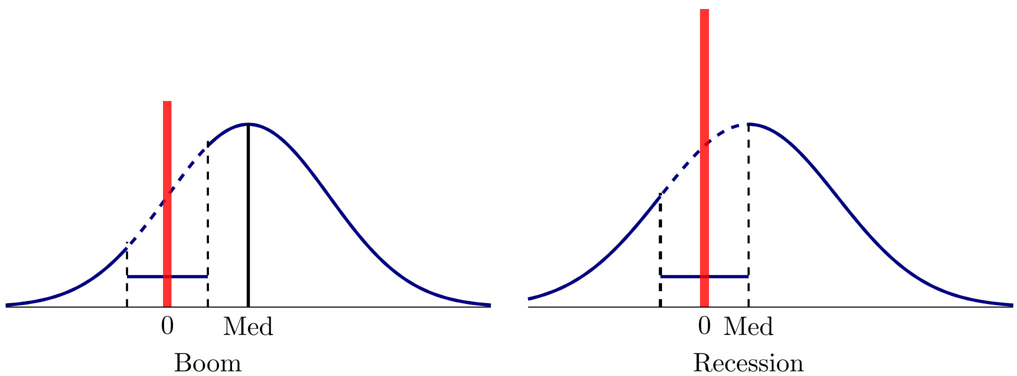
Table 15: The spike at zero, the fraction of wage cuts, and raises along business cycles

	(1) Spike at zero $\Delta W = 0$	(2) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$
		Data	
Employment	-0.616	-0.305	0.921
Inflation	-1.181	-0.674	1.855
		Perfectly flexible	
Employment	-0.042	-0.414	0.456
Inflation	-0.042	-4.476	4.519
		Calvo	
Employment	0.089	-0.553	0.465
Inflation	-0.192	-3.919	4.111
		Long-term contracts	
Employment	0.005	-0.424	0.419
Inflation	-0.018	-4.207	4.225
		Menu costs	
Employment	-0.187	-0.329	0.516
Inflation	-1.623	-3.452	5.074
		DNWR	
Employment	-0.712	-0.329	1.041
Inflation	-3.699	-1.772	5.470

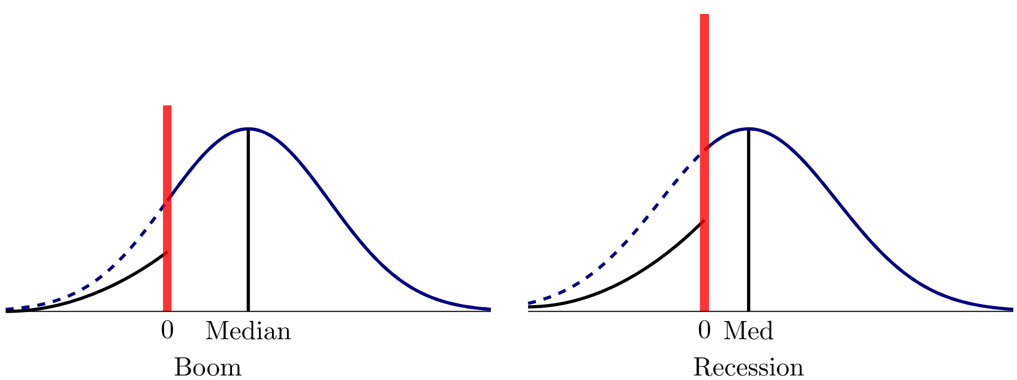
Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). The inflation rate is calculated from CPI-U. The first panel is from data, last three columns of table 6. This table (from the second panel to the last one) shows the regression results based on the equation (1) using simulated data series under 5 alternative wage-setting schemes.



Conceptual wage change distribution from the Calvo model



Conceptual wage change distribution from the menu costs model



Conceptual wage change distribution from the DNWR model

Figure 8: Conceptual wage change distribution from alternative wage-setting schemes

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

The Calvo model presents the constant spike at zero along the business cycle. The third panel of Table 6 shows regression results using simulated data under the Calvo model. The spike at zero barely responds to employment because the Calvo wage adjustment assumes the spike at zero, the frequency of no wage change, does not respond to the business cycle. Thus, we can observe a small coefficient of the spike at zero on employment. The conceptual diagram of changes in wage distributions under the Calvo model is shown at the first panel of Figure 8. Along the business cycle, the optimal nominal wage changes distribution shifts left or right. When employment declines, nominal wage change distribution shifts to the left and the fraction of workers with raises declines, leading to the increase in the fraction of workers with wage cuts to the same extent without any impact on the spike at zero. This is inconsistent with empirical findint that the spike at zero is countercyclical and the greater responsiveness of the spike at zero than the share of workers with wage cuts.

The long-term contracts model also shows the constant spike at zero along the business cycle similar to the Calvo model. The fourth panel of Table 6 shows regression results using simulated data implied by the long-term contracts model. The decrease in the fraction of workers with raises leads to the increase in the fraction of workers with wage cuts by the same magnitude when employment declines. 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. The fifth panel of Table 6 shows regression results using simulated data under the menu costs model. The spike at zero rises when employment declines. Intuitively, nominal wage distribution in the absence of rigidity will shift to the left in the recession, shown at the second panel of Figure 8. Then, there are more densities around the zero, that is, there are more densities in the inaction region, 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 whole 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 evidence.[34]

The DNWR model implies the spike at zero rises and the increase in the spike at zero is higher than the increase in the fraction of workers with wage cuts when employment declines, consistent with the empirical finding. The last panel of Table 6 shows regression results using simulated data under the DNWR model. In the DNWR model, when there is a decrease in employment by 1 percentage point, there is a decrease in the fraction of workers with raises by 1 percentage point. Out of 1 percentage point, 0.7 percentage point of workers have no wage change, and the other

[34] 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 DNWR model. Thus, we cannot uniquely pin down these parameters. Holding the average spike at zero fixed, Table A17 in the Appendix D.2.1 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, so does 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.

0.3 percentage point of workers have wage cuts, which is comparable to the first panel of Table 6. In the recession, nominal wage change distribution in the absence of wage rigidity shifts to the left as shown in the third panel of Figure 8. Under the DNWR wage-setting constraint, 67 percent ($= \mu^{\text{DNWR}}$) of workers whose optimal wages are lower than the previous wages experience no wage changes, and the other 37 percent of worker cut their wages. In the recession, there are more workers whose optimal wages are lower than the previous wages, and this leads to an increase in the spike at zero larger than the increase in the fraction of workers with wage cuts.

8.5 Data moments

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

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

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

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

The spike at zero from the DNWR model is similar to the other rigidity model. However, the fraction of wage cut is smaller and the fraction of raises is higher than other rigidity model as a result of the DNWR restriction. The standard deviation from the DNWR model is in between that the once from the Calvo and menu costs model. Compared to the Calvo model, the standard deviation of the DNWR model is lower because DNWR has restrictions only to lower wages but not to raise. However, the DNWR model shows many small wage changes below zero, which makes the standard deviation higher than the menu cost model. As wage adjustment is

Table 16: Data and model generated moments

	Wage growth rates	Employment growth rates	Spike at zero $\Delta W = 0$	Fraction of $\Delta W < 0$	Fraction of $\Delta W > 0$
			Data		
Mean	4.102	0.020	15.484	21.318	63.198
SD	1.539	0.792	3.059	2.436	4.686
Skewness	1.032	-1.492			
			Perfectly flexible		
Mean	4.374	0.000	1.822	27.013	71.165
SD	2.068	0.476	3.220	9.710	9.790
Skewness	0.094	-0.000	-	-	-
			Calvo		
Mean	4.378	0.000	23.171	17.626	59.203
SD	1.529	1.051	1.703	6.663	6.905
Skewness	0.006	0.032	-	-	-
			Long-term contracts		
Mean	4.363	0.001	22.994	15.944	61.062
SD	1.403	0.476	0.603	6.128	6.151
Skewness	0.051	-0.003	-	-	-
			Menu costs		
Mean	4.374	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		
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.

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 can explain left skewness of employment growth, consistent with Dupraz, Nakamura, and Steinsson (2017).

9 Conclusion

This paper uses two nationally representative US household surveys, the CPS and the SIPP and establishes stylized facts regarding the cyclical variations in nominal wage change distributions for both aggregate-level and state-level: 1) the spike at zero increases when employment declines, controlling for inflation; 2) the share of workers with wage cuts 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. This paper shows among 5 widely used wage-setting schemes – perfectly flexible wage, the Calvo, long-term contracts, menu-costs model, and DNWR –, the only model with DNWR has consistent empirical implications with empirical findings. This paper shows cyclical properties of nominal wage change distribution, which is consistent with theories of DNWR. This can be suggestive evidence of allocative consequences of DNWR for employment.

The model with DNWR predicts a distribution of annual employment growth that is skewed to the left, which is consistent with data, whereas the standard model predicts a symmetric distribution. This has important implications for monetary policy since there is a potential welfare gain in pursuing high inflation targets to relax the DNWR constraint.

Appendix

A Appendix: CPS

Table A1 shows the unweighted number of population for age greater than 16 and the unweighted number of employed workers among the population greater than age 16. Table A1 also shows the imputation ratio for usual weekly earning and the hourly wage. Since the major revision in the CPS in 1994, about 34 percent of hourly wages are imputed by the CPS. The CPS imputes unreported data items to fill in based on the demographic characteristics and residential address.[35] Including imputed wages may amplify measurement error, so this paper drops imputed wages. Although IPUMS-CPS provides with the individual identifiers, they do not offer imputation flags for wage variables. Thus, this paper merges IPUMS - CPS data into CPS data to exclude imputed wages.

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

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

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

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

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

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

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

Table A2: Time series spike at zero, the share of wage cuts and raises for hourly workers in the CPS

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

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

Table A3: The average of the spike at zero, the share of wage cuts and raises by industry, CPS

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

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

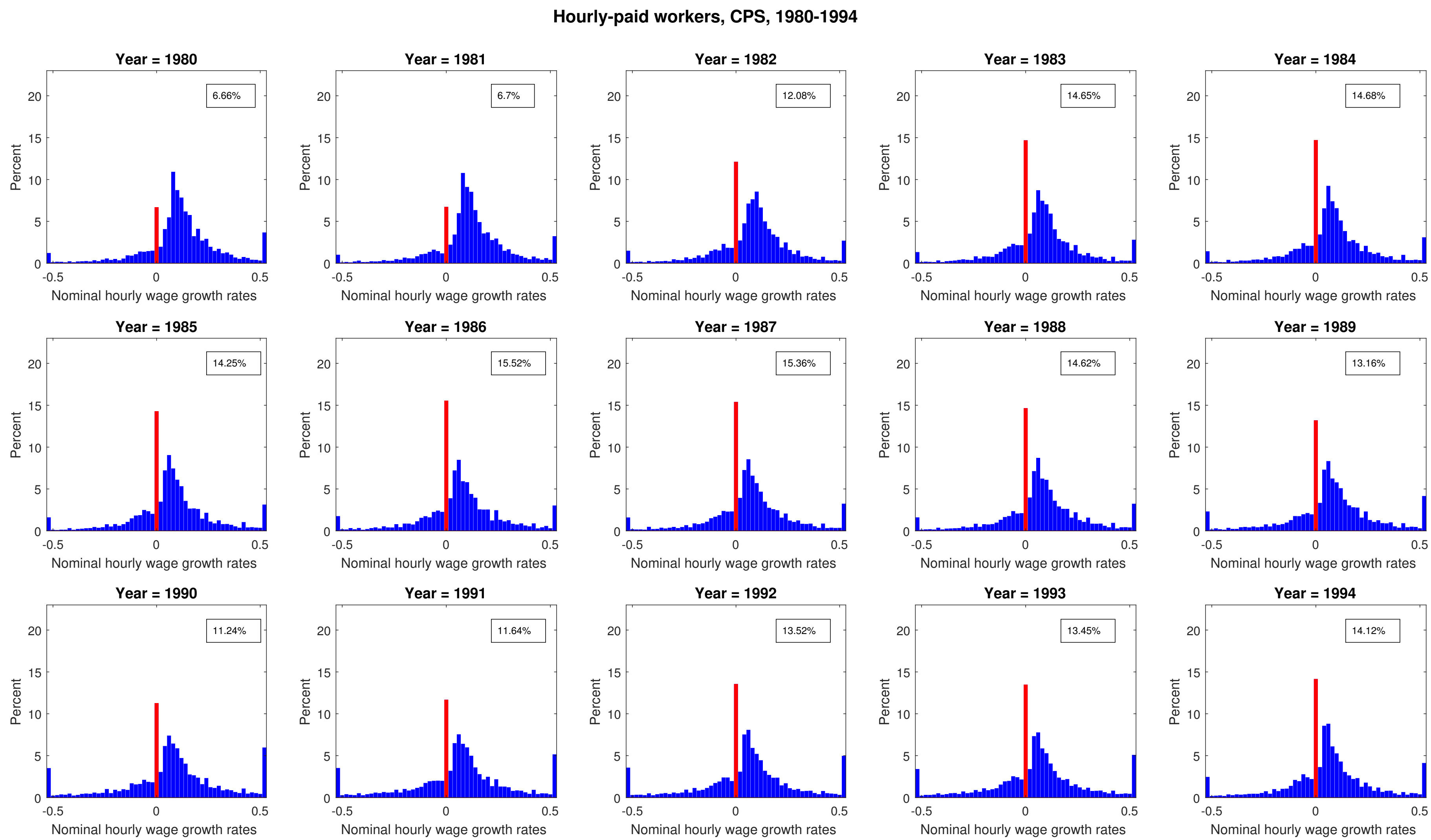


Figure A1: Nominal hourly wage growth rates distributions from 1980 to 1994

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.

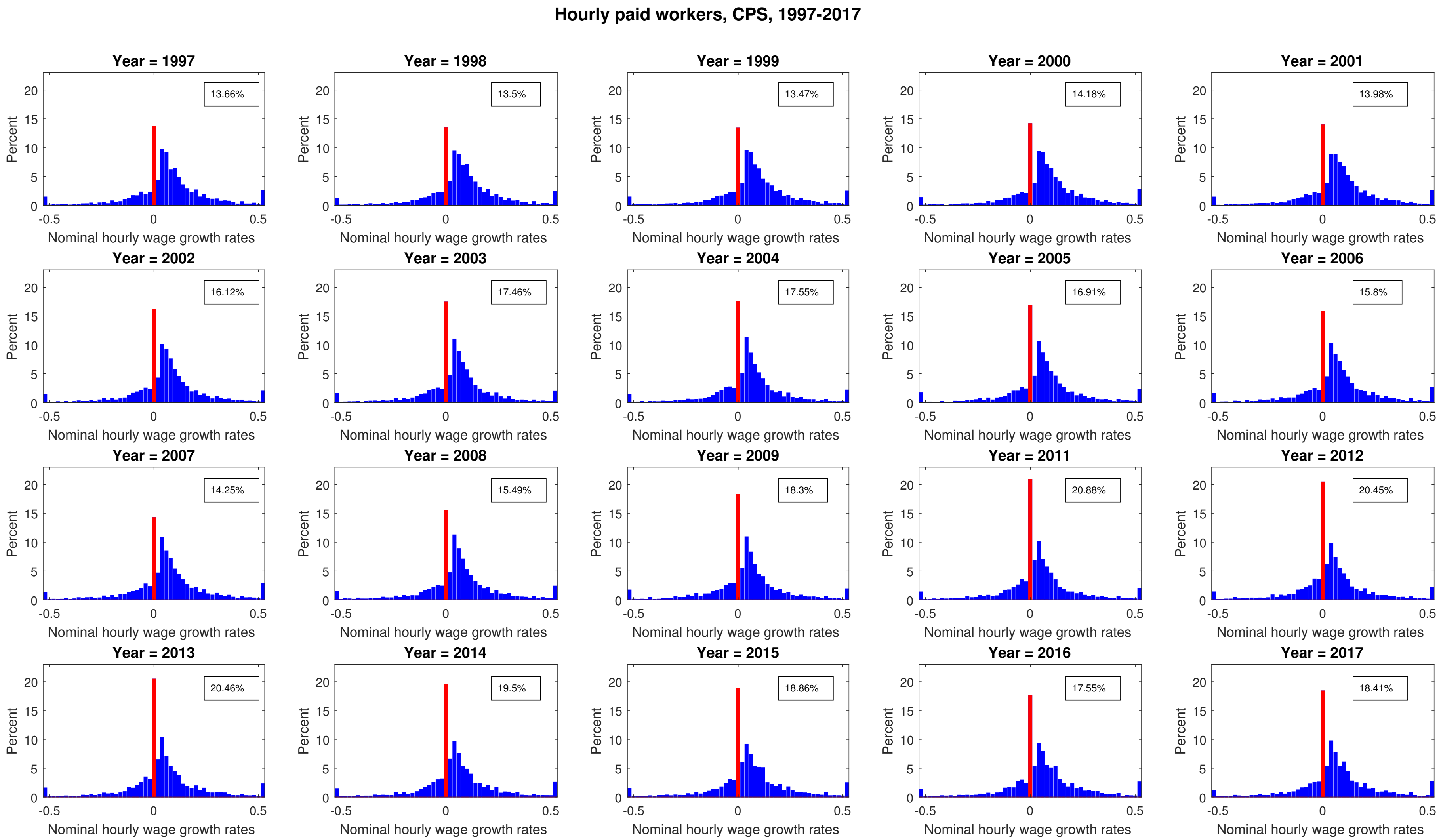


Figure A2: Nominal hourly wage growth rates distributions from 1997 to 2017

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.

A.2 Robustness checks for aggregate time series evidence

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

Table A6 shows regression results based on (1) by varying the level of education. Table A7, A8, A9, A10 show regression results based on the level of age, gender, race, and 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 also hold for different worker characteristics.

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

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

Standard errors in parentheses

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

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

There is no asymmetric response of nominal hourly wage change distribution to employment. Consider the specification, taking into account an asymmetric response of nominal wage change distribution to the employment, meaning that the response to the declining employment is different from the response to inclining employment. From the regression specification (8), γ captures asymmetric response to declining employment. However, from Table A11, we can see γ is not statistically different from zero, implying that there is no asymmetric response of nominal wage change distribution to employment.

$$\begin{aligned} [\text{Spike at zero}]_t &= \alpha_1 + \beta_1(1-e_t) + \gamma_1(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t)>0] + \epsilon_{1t} \\ [\text{Fraction of wage cuts}]_t &= \alpha_2 + \beta_2(1-e_t) + \gamma_2(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t)>0] + \epsilon_{2t} \\ [\text{Fraction of raises}]_t &= \alpha_3 + \beta_3(1-e_t) + \gamma_3(1-e_t)\cdot \mathbb{I}[\Delta(1-e_t)>0] + \epsilon_{3t} \end{aligned} \tag{8}$$

Table A5: 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) Fraction of $\Delta W < 0$	(3) Fraction of $\Delta W > 0$	(4) Spike at zero $\Delta W = 0$	(5) Fraction of $\Delta W < 0$	(6) Fraction of $\Delta W > 0$
1-Epop ratio	0.283	0.105	-0.388	0.507***	0.237*	-0.743***
	(0.270)	(0.210)	(0.463)	(0.145)	(0.140)	(0.253)
Inflation rate				-1.168***	-0.688***	1.856***
				(0.124)	(0.145)	(0.214)
				0.507/0.743 = 0.68		
Observations	37	37	37	37	37	37
Adjusted R^2	0.0184	-0.0192	0.00542	0.717	0.318	0.684

Standard errors in parentheses

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

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). Inflation rate is calculated from CPI-U. The spike at zero, the share of wage cuts and raises are constructed among prime-aged hourly paid workers.

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

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

Standard errors in parentheses

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

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

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

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

Standard errors in parentheses

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

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

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

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

Standard errors in parentheses

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

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

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

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

Standard errors in parentheses

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

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

Table A10: The spike at zero, the share of wage cuts and raises by hourly wage quantiles

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

Standard errors in parentheses

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

Data source: CPS and author's calculation. Sample Period: 1979-2017 (except 1995). This table shows the cyclicality of the spike at zero, the share of wage cuts and raises by hourly wage quantiles.

Table A11: The spike at zero, the fraction of wage cuts and raises along the business cycle

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

Standard errors in parentheses

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

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

A.3 Comparisons to the previous literature: CPS

Figure A3 compares the spike at zero from the previous literature using the CPS and the one that this paper constructed. When this paper constructs the spike at zero from nominal wage change distributions using the CPS, this paper 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 2017 with some gaps, which shows the fraction of works with a zero wage change among workers who have not changed their jobs.[36]

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

B Appendix: SIPP

Table A13 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 A14 divides hourly workers into two - job stayer and jobs switchers - and shows the unweighted count of observations, the spike at zero, the share of wage cuts and raises, respectively.

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

[36]For the fair comparison, I used the percent of hourly rated job stayers with a wage change of zero from SF - Wage Rigidity Meter (here). Other than hourly workers, non-hourly workers and all workers' (including both hourly and non-hourly workers) Wage Rigidity Meter is also available. Atlanta Fed's Wage Growth Tracker (here) also reports the percent 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. Also, 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. However, hourly wages calculated in this way tend to suffer from excess volatility, known as the division bias (Borjas (1980)).

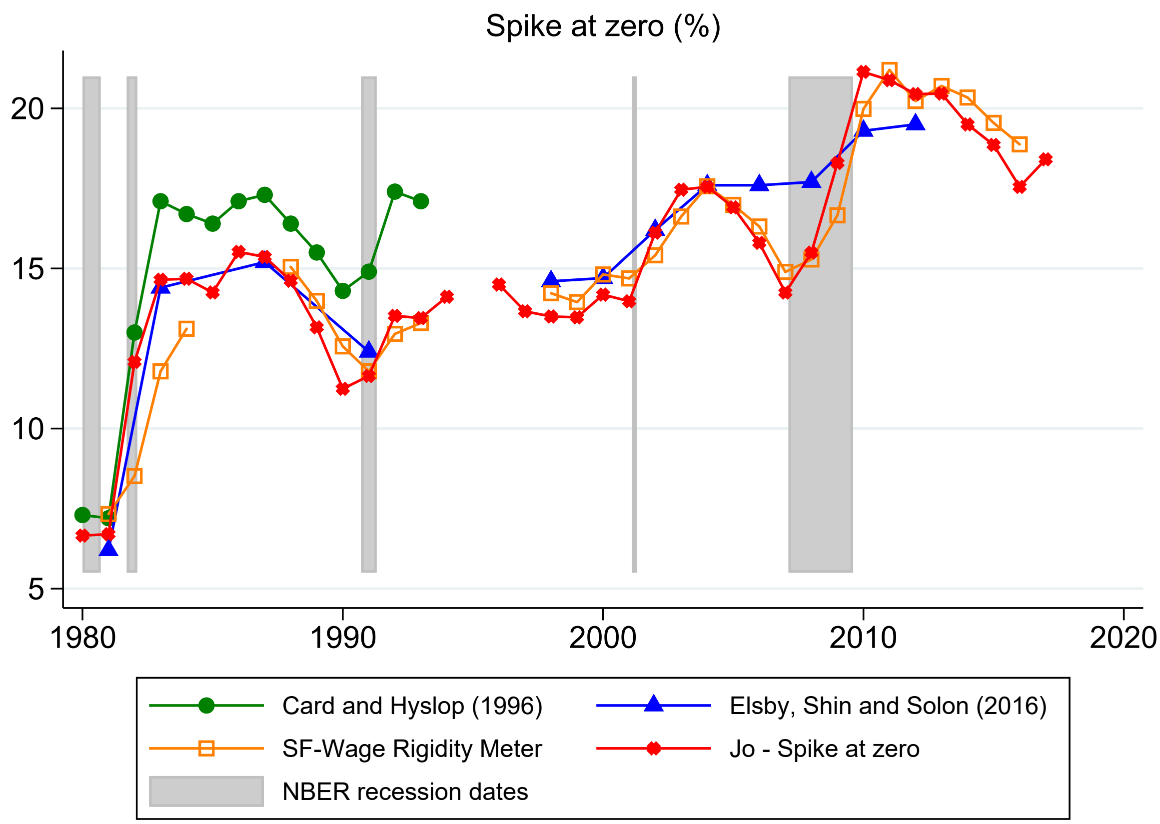


Figure A3: Comparisons of the spike at zero from the previous literature

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

is 0.02. Figure A5 shows year-over-year hourly wage change distribution for hourly job stayers and Figure A6 shows one for job switchers.

Table A12: 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.

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

Table A13: The spike at zero, the share of wage cuts, and raises in the SIPP

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

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

Table A14: The spike at zero, the share of wage cuts, and raises in the SIPP by job stayers and job switchers

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

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

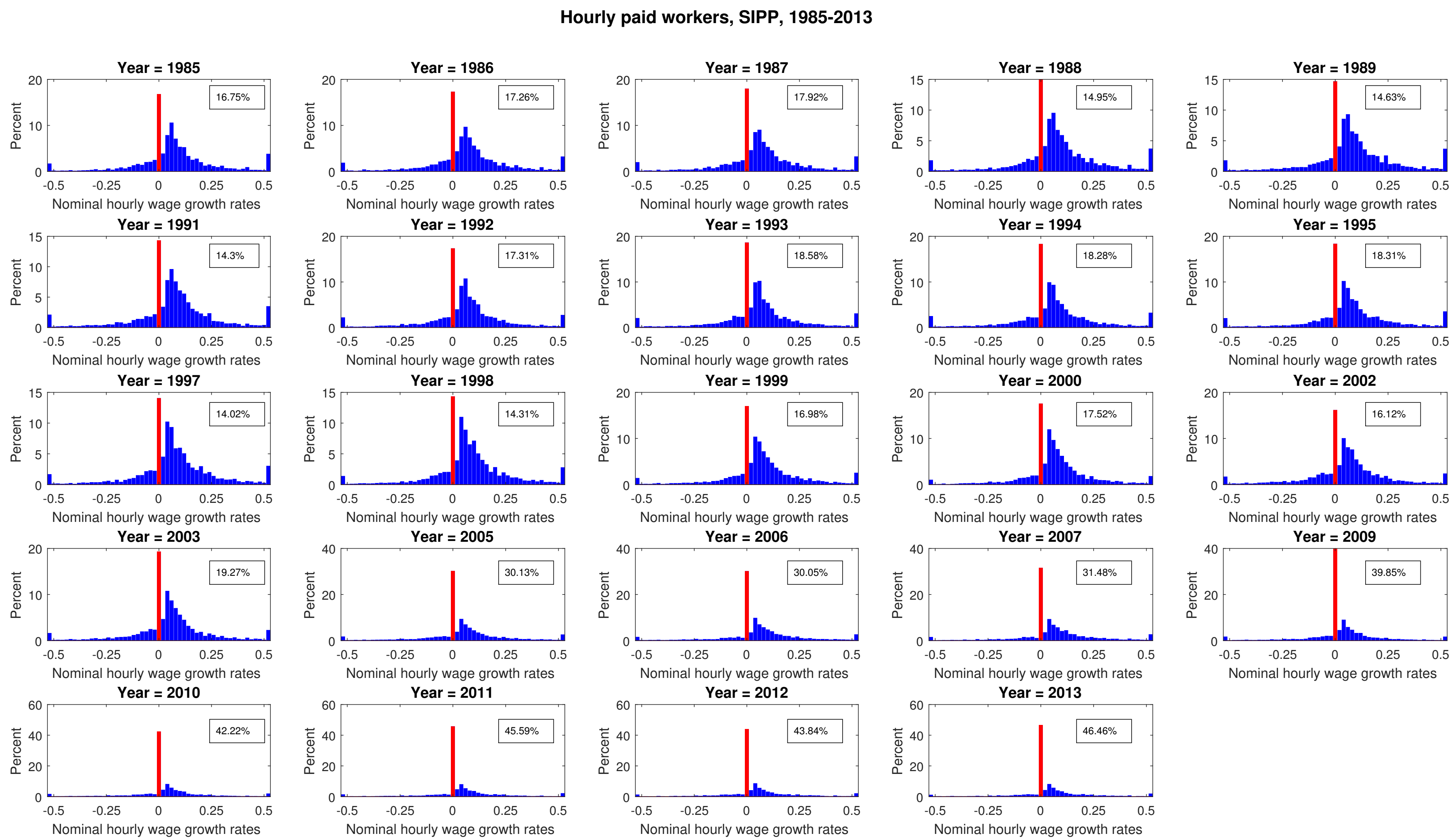


Figure A4: Nominal hourly wage growth rates 1985-2013

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

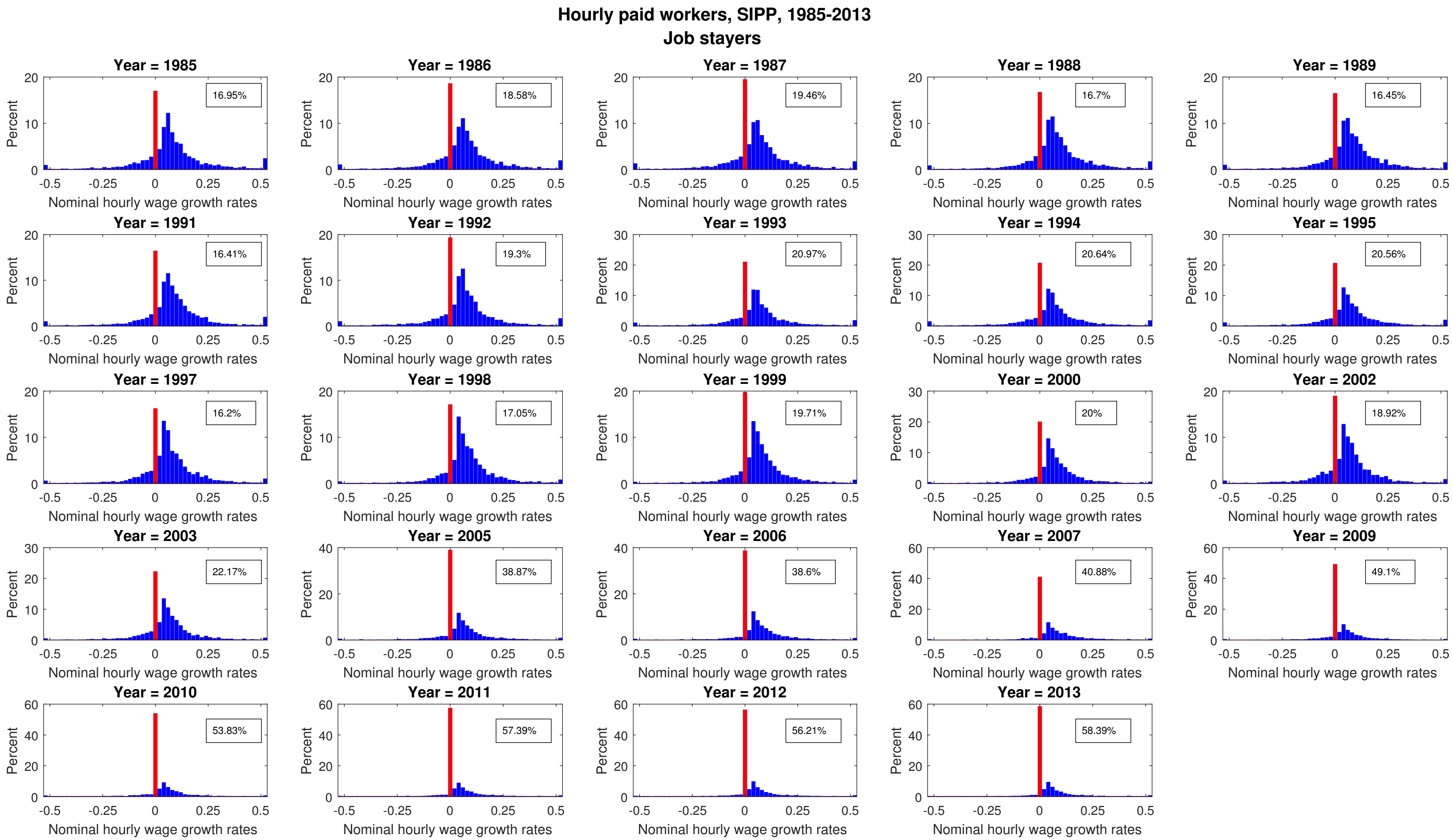


Figure A5: Nominal hourly wage growth rates 1985-2013 for job stayers

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.

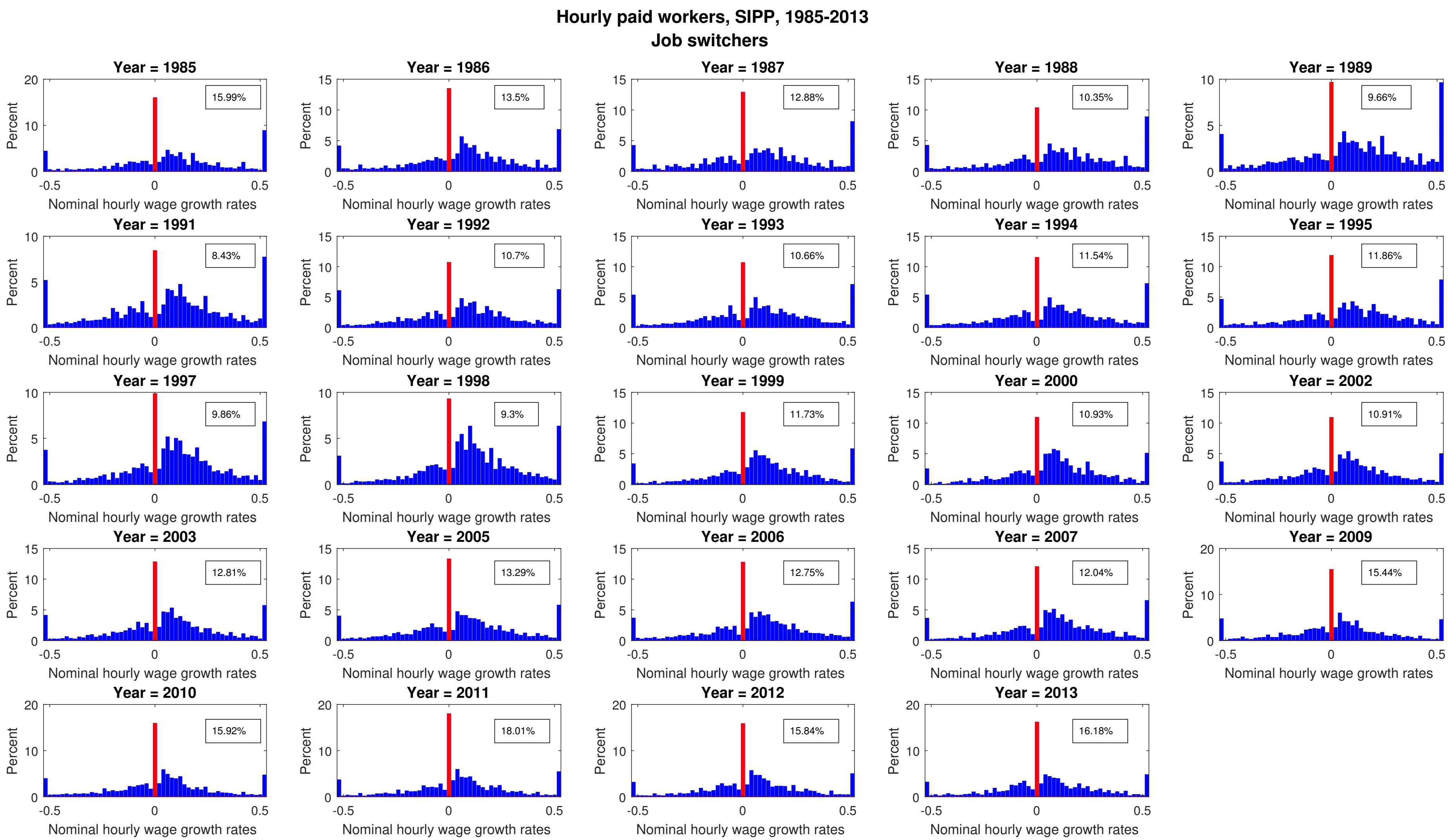


Figure A6: Nominal hourly wage growth rates 1985-2013 for job switchers

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.

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

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

Fired/Discharged workers presents the similar level of the spike at zero compared to workers who quit the job to take another jobs. However, workers who quit the job to take the another job tend to have higher fraction of raises and the less share of cuts. Fired or discharged workers tend to show the higher share of wage cuts. A15

Table A15: The spike at zero, the fraction of wage cuts, and raises for job-switchers by reasons of switching, SIPP

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

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

C Counterfactual analysis: Missing mass

Lack of nominal wage cuts compared to nominal wage increases is often suggested as the existence of DNWR. To measure how absent of nominal wage cuts in the nominal wage growth distribution, this paper introduces the concept of missing mass. This concept is often used to show the asymmetry of wage change distribution in the previous literature, Card and Hyslop (1996), Lebow et al. (2003), and Kurmann and McEntarfer (2017).

To define missing mass, let us assume that nominal wage growth rate distribution is symmetric around the median without any types of wage rigidity, which is shown as the left panel of Figure A7. However, instead of symmetric distribution around the median, what we can observe in the data is that an apparent peak at zero wage change and shortages of wage growth rates around the zero compared to nominal wage change distribution above median, displayed at the right panel

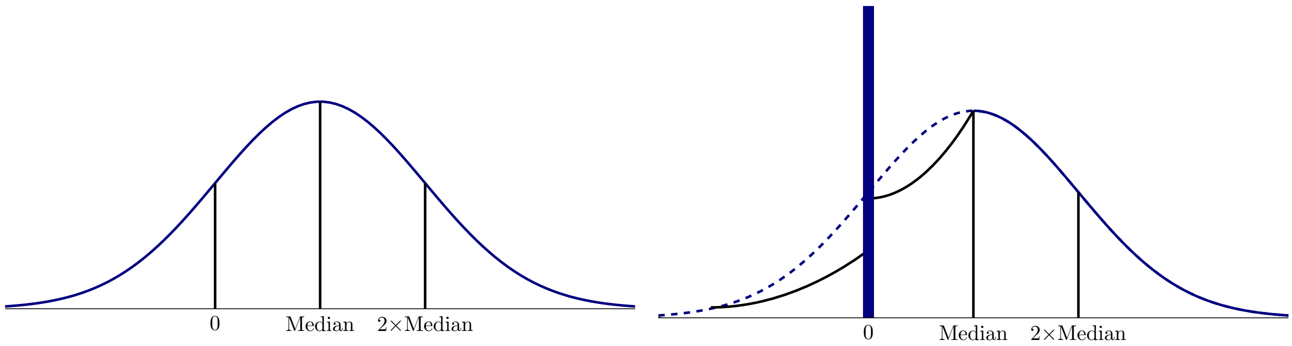


Figure A7: Conceptual diagram of nominal wage distribution

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

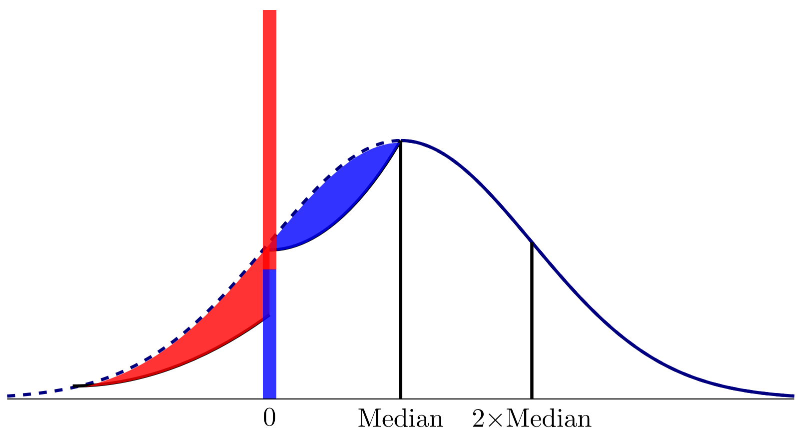


Figure A8: Missing mass left to the zero vs. missing mass right to the zero

of Figure A7.

An apparent peak at zero, referred as the spike at zero in this paper, can be decomposed into two: one is the share of workers with no wage change who would have otherwise wage cut without wage rigidity and the other is the share of workers with zero wage change who would have positive wage growth rate in the absence of wage rigidity. The red colored area left to the zero in Figure A8 shows the missing share of wage cuts due to wage rigidity, which becomes the part of the spike at zero. The blue colored area right to the zero in Figure A8 represents the lack of share of raises due to wage rigidity, which becomes part of the spike at zero. From now on, this paper refers the red shaded area as the missing mass left to the zero and the blue shaded area as the missing mass right to the zero.

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

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

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

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

Table A16 shows missing masses calculated using the equation 9 and 10. We can clearly see the most of missing mass comes from the left using the CPS and the SIPP. In the CPS, 85 percent of the spike at zero comes from the left to the zero. In the SIPP, 90 percent of the spike at zero for job stayers comes from the left to the zero and 87 percent of the spike at zero comes from the left to the zero for job switchers.

Table A16: Missing mass from left to the zero vs. right to the zero

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

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

D Appendix: Model

D.1 Solution Algorithm

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

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

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

- Step 3 : Simulate the dynamics of the 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.

D.2 Sensitiveness

D.2.1 Menu cost model

Table A17: The spike at zero, the fraction of wage cuts, and raises along the business cycles by varing menu cost, κ, and μ^{Menu}

			The responsiveness to employment		
		The average	(1)	(2)	(3)
		Spike at zero	Spike at zero	Fraction of	Fraction of
μ^{Menu}	κ	(%)	$\Delta W = 0$	$\Delta W < 0$	$\Delta W > 0$
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 menu-cost model, μ^{Menu} and κ.

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, so does inaction region. In the random menu cost model, the spike at zero is the proportion of the inaction region. Table A17 shows that menu cost model implies greater responsiveness of the share of workers with wage cuts by varying μ^{Menu} from 0.3 to 1.

D.2.2 DNWR model

As the parameter governing the degree of DNWR(μ^{DNWR}) increases, model predicts the higher degree of DNWR. When employment declines, the optimal nominal wage change distributions shift to the left. For those workers whose optimal wages are lower than the previous wages, μ^{DNWR} fraction of workers cannot change their wages and the other $(1 - \mu^{\text{DNWR}})$ fraction of workers would experience wage cuts. Thus, we can expect that as μ^{DNWR} increases, the average spike at zero increases and the average share of wage cuts decreases, which is shown at Table A19 and Figure A9. Similarly, the degree countercylicality of the spike at zero increases as μ^{DNWR} increases, which is shown at Table A18.

Lowering the persistence of idiosyncratic shock to $\rho_q = 0.3$ does not make changes in the average wage change distribution. The second panel of Table A21 shows the similar level of the average spike at zero and the share of workers with wage cuts and raises. On the contrary, increasing σ_q raises the level of spike at zero and the share of wage cuts, shown at Table A21. Table A20 shows that as long as μ^{DNWR} is the same, the degree of higher responsiveness of the spike at zero compared to the share of wage cut is the same, the ratio of two coefficients from the regression of the spike at zero on employment to the that of the share of wage cuts on employment.

By varying μ

By varying idiosyncratic shock

Table A18: The spike at zero, the fraction of wage cuts, and raises along the business cycle by varying μ^{DNWR}

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

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

Table A19: Data and model generated moments, varying μ^{DNWR}

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

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

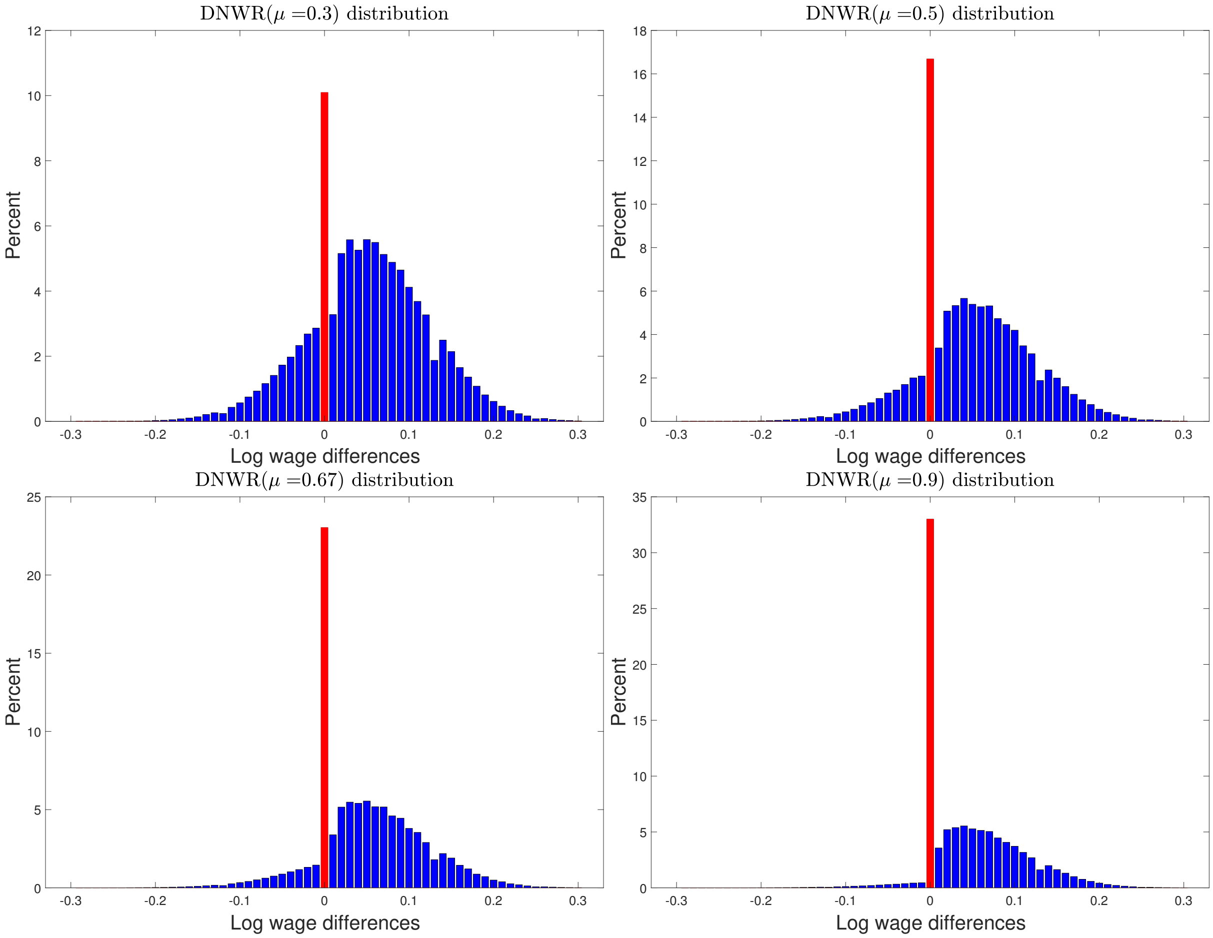


Figure A9: Staionary wage change distribution by varying μ^{DNWR}

Table A20: The spike at zero, the fraction of wage cuts, and raises along the business cycle by varying idiosyncratic shock

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

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

Table A21: Data and model generated moments by varying idiosyncratic shock

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

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

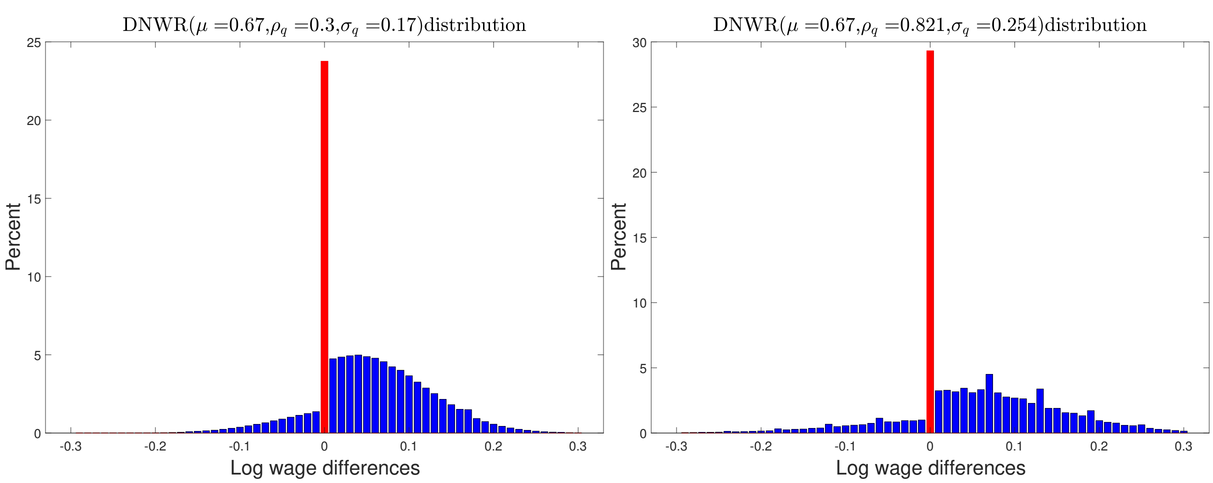


Figure A10: Staionary wage change distribution by varying idiosyncratic productivity shock

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.

Bollinger, C. and B. Hirsch (2006). "Match Bias from Earnings Imputation in the Current Population Survey: The Case of Imperfect Matching". *Journal of Labor Economics 24*(3), 483–520.

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.

Daly, M. C., B. Hobijn, and B. Lucking (2012). "Why Has Wage Growth Stayed Strong?". *FRBSF ECONOMIC LETTER*.

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.

Drew, J. A. R., S. Flood, and J. R. Warren (2014). "Making Full Use of the Longitudinal Design of the Current Population Survey: Methods for Linking Records Across 16 Months". *Journal of Economic and Social Measurement 39(3)*, 121–144.

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

Elsby, M. (2009). "Evaluating the economic significance of downward nominal wage rigidity". *Journal of Monetary Economics 56*(2), 154–169.

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.

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.

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 (2017). "Downward Wage Rigidity in the United States: New Evidence from Administrative 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.

Madrian, B. and L. J. Lefgren (1999). "A Note on Longitudinally Matching Current Population Survey (CPS) Respondents". *NBER Working Paper T0247*.

Mary C. Daly, Bart Hobijn, and Theodore S. Wiles (2011). "Aggregate real wages: macro fluctuations and micro drivers". *Working Paper Series 2011-23, Federal Reserve Bank of San Francisco.*.

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

Moore, J. C. (2006). "The Effects of Questionnaire Design Changes on General Income Amount Nonresponse in Waves 1 and 2 of the 2004 SIPP Panel.". Research report series(survey methodology 2006-4), Statistical Research Division, U.S. Census Bureau, Washington, DC.

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.

Shin, D. (1994). "Cyclicality of real wages among young men". *Economics Letters 46*(2), 137–142.

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

Solon, G., R. Barsky, and J. A. Parker (1994). "Measuring the Cyclicality of Real Wages: How Important is Composition Bias". *The Quarterly Journal of Economics 109*(1), 1–25.

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