Aggregate Nominal Wage Adjustments: New Evidence from Administrative Payroll Data*

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Abstract

Using administrative payroll data from the largest U.S. payroll processing company, we document a series of new facts about nominal wage adjustments in the United States. The data contain administrative measures of the per-period contracted ("base") wages for over 20 million workers per month. Nominal base wage declines are much rarer than previously thought with only 2% of workers, who remain in continuous employment relationships, receiving a nominal base wage cut during a given year. However, accounting for shifts in nominal wages of job-changers and for changes in other forms of compensation, such as bonuses and employer-provided fringe benefits, imply that *aggregate* nominal worker compensation is much more flexible than the base nominal wages of job-stayers. In addition, nominal wage adjustments are state-dependent: aggregate nominal wage adjustments were much more downwardly flexible during the Great Recessions than in the subsequent recovery period, and these downward adjustments were concentrated in industries hit hardest by the recession. Finally, we provide evidence that new hire base wages are no more flexible than the wages of existing workers. Collectively, our results can be used to discipline models of worker nominal wage adjustments.

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1 Introduction

Nominal rigidities are an important component of many models of aggregate fluctuations. A large literature has developed using micro data to discipline the degree of nominal price rigidities.[1] However, the literature using micro data to document nominal wage rigidities is far less extensive. As a result, the nature of nominal wage stickiness remains a central question within both the macroeconomics and labor economics literatures. For example, at the 2014 Jackson Hole Symposium, Janet Yellen speculated that downward nominal wage rigidity was an important contributor both to why wages did not fall more during the Great Recession and why they did not increase at a faster rate during the subsequent recovery.

There are three reasons why the literature using micro data to measure nominal wage rigidities has remained underdeveloped. First, and most importantly, existing data sets are not well-suited to measure the extent of nominal wage rigidities. Household surveys often define the nominal wage by dividing self-reported earnings by self-reported hours. Any measurement error in either earnings, hours worked, or even self-reported hourly wages can result in a substantial upward bias in the volatility of individual level wage changes. Administrative datasets, on the other hand, have high quality panel data on quarterly or annual earnings but usually lack the measures of individual hours worked necessary to construct a wage.[2]

Second, the composition of compensation varies across workers and over time. For example, worker compensation includes their guaranteed contract earnings as well as commissions, tips, bonuses, performance pay, overtime premiums, and employer-provided fringe benefits. Existing household and administrative datasets do not decompose the different types of compensation into their components nor do they include measures of employer-provided fringe benefits. There are gains to understanding adjustment patterns of each form of compensation separately both because these forms of compensation may have differing degrees of flexibility and because the composition of compensation differs across workers and over time.

Finally, different models have different notions of nominal wage rigidities. Many models of frictional labor markets include separate measures of nominal wage adjustments for those who remain with the same employer and for those who switch employers. In some of these models, it is the flexibility of new hire wages that is important for aggregate employment

[1]See, for example, Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008) for important contributions.

[2]There are some exceptions. Barattieri et al. (2014) attempts to correct for measurement error in self-reported hourly wages among SIPP respondents when examining nominal wage adjustments. Kurmann and McEntarfer (2017) uses administrative data from Washington state which records measures of both earnings and hours to explore changes in earnings-per hour. Throughout the paper, we will discuss how having administrative data on actual worker wages contrasts with the results of these papers and other papers in the literature.

fluctuations. On the other hand, most New Keynesian models do not make a distinction between job-stayers and job-changers and instead require measure of aggregate nominal wage adjustments including both margins of adjustment. For example, in order to match aggregate employment and wage dynamics during and after the Great Recession, one would need measures of nominal wage changes inclusive of those who remain on the job and those who switch jobs. This variety of wage rigidity notions puts further requirements on data seeking to understand nominal adjustments.

In this paper, we use administrative data from ADP – one of the world's largest payroll processing companies – to produce a series of new facts about aggregate nominal wage adjustments in the U.S. over the last decade. Our data is unique in that it: (1) includes administrative records of worker's per-period nominal wage, (2) has a sample of about 20 million workers per month which are generally representative of the US population, (3) provides data for the universe of workers within a firm, (4) allows workers to be tracked both within and across firms over time, (5) includes administrative records on various other forms of compensation including bonuses and fringe benefits, and (6) spans multiple years so as to examine business cycle variation. The data allow us to compute measures of nominal wage adjustments separately for job-stayers and job-changers as well as making a composite aggregate measure including both stayers and changers. Additionally, we create measures of nominal wage adjustments inclusive of bonuses and employer-provided fringe benefits. Finally, we use the rich data to explore the cyclicality of new hire wages. Collectively, our results paint a relatively complete picture of nominal wage adjustments for workers and firms in the U.S. during the 2008-2016 period.

We begin the paper by describing the compensation composition of workers. For most workers, essentially all of their annual earnings (excluding employer-provided fringe benefits) comes from what we term a worker's annual "base earnings". For a worker who is paid hourly, this is their hourly wage times the number of hours they worked. For a worker who is salaried, this is simply their annual contracted salary. However, for some workers, bonuses, commissions, performance pay and overtime premiums are also important. For about ten percent of workers, 20% of their annual earnings comes from sources other than their base earnings. We document that the share of earnings accruing from bonuses are monotonically increasing in individual base wages. For individuals in the bottom forty percentiles of the base wage distribution, hardly any of their annual earnings comes in the form of annual bonuses. However, for the median household, the 80th percentile, the 95th percentile and the 99th percentile of the base wage distribution, about 3 percent, 5 percent, 10 percent and 16 percent of their annual earnings, respectively, comes in the form of bonuses.

We also measure a worker's total annual compensation inclusive of employer-provided health and retirement fringe benefits. The share of annual fringe benefits out of total annual compensation is hump-shaped in individual base wages. For households between the 0 and 20th percentile of the base wage distribution, the fringe benefit share rises from about 5 percent to about 12 percent. The fringe benefit share is relatively constant at about 12 percent between the 20th and 90th percentile of the worker wage distribution and then declines to about 8 percent for the top percentile. The reason for the decline appears to be the result of the fact that fringe benefits are not paid on bonus income. As bonus earnings rises sharply for individuals at the top of the income distribution, the fringe share of total compensation falls sharply.

The results in the first part of the paper show that to measure adjustments in a worker's total nominal wages, we need to examine wages accruing from base earnings, bonus earnings, and fringe benefits. In the second part of the paper, we measure how various components of nominal wages adjust. Like most of the literature, we begin by focusing on a measure of nominal wages excluding bonuses, fringe benefits and other irregular forms of compensation for a sample of workers who remain continuously employed with the same firm. We refer to this sample as our "job-stayer" sample. We measure a worker's "base wage" as either their hourly wage (for workers paid hourly) or their per pay-period contracted compensation (for salaried workers). A worker's per pay-period contracted compensation is their contractually obligated annual salary divided by the annual number of pay-periods during the year. For essentially all salaried workers this is their contractually obligated weekly, bi-weekly or monthly earnings.[3]

Our first main result is that nominal base wage cuts are exceedingly rare. During our entire sample period, only about 2.5% of all workers received a nominal base wage cut during a year. The number was slightly higher for salaried workers compared to workers paid hourly (3.6% vs. 1.8%). On average, about one-third of both hourly and salaried workers who remain on the job received no nominal wage adjustment during a given year. Therefore, about two-thirds of both hourly and salaried workers receive a positive nominal base wage increase during a given year. We also document a missing mass of small positive changes with many more workers receiving a nominal wage increase of 2 to 4 percent than from 0.1 to 2 percent. The patterns are similar regardless of whether or not the worker receives an annual bonus, whether or not the worker receives frequent commission/tips, and whether or not the worker's hours fluctuate substantively during a given year. Our results imply a duration of nominal base wages for the typical worker who remains continuously employed on the same job of about 6 quarters.

[3]Note that this need not be the worker's actual earnings because actual earnings can include, among other things, bonuses, overtime premiums, commissions, tips, and performance pay.

Second, we show that for job-stayers, annual bonuses vary substantively from year to year. The additional variation means a measure of a worker's wages including both base pay and bonuses varies more than a workers base pay. However, even with this broader measure of compensation, nominal wage declines are rare in the data (only 16 percent who receive a nominal wage decline vs 75 percent who receive a nominal wage increase during a given year). The average duration of nominal wages inclusive of both base wages and bonuses is about 4.2 quarters. We further document that the additional flexibility in terms of nominal wage adjustments provided by bonuses differs markedly throughout the base wage distribution. For those in the bottom quartile of the base wage distribution, bonuses are not important at all. However, for those at the top of the base wage distribution, variation in annual bonuses is larger in magnitude than the variation in annual base earnings. Finally, we show that fringe benefits also provide an additional form of nominal wage adjustment for the average worker but again, downward nominal wage adjustments are far less common than increases and there is still a large mass of workers whose total compensation remains unchanged from year to year.

We next turn to the measurement of wage adjustments for the aggregate economy including data on both job-stayers and job-changers. Almost all workers that transition across jobs experience a nominal base wage change. Furthermore, 38% of job-changers experience a decline in the nominal base wage. Given that job switchers are a non-trivial share of the economy, we create a broader measure of nominal base wage flexibility pooling together both job-stayers and job-changers. Doing so, we find that roughly 24 percent of all workers experience a base wage change during a given quarter and 71 percent experience a base wage change during a given year. Including both the job-stayers and job-changers, 8.5 percent of workers experience a nominal base wage decline with essentially all of the declines being driven by job-changers. Furthermore, incorporating bonuses and fringe benefits only enhances aggregate nominal wage flexibility.

That the aggregate economy, including job switchers, exhibits a substantially higher degree of base wage flexibility than the sample of job-stayers is another key insight of this paper. Models seeking to understand the muted fluctuations in mean nominal wages over the cycle must reckon with this finding that aggregate wages are made more flexible on the downside by the presence of job-changers and bonuses. In addition, models without realistic job search components should be cautious about using wage rigidity estimates from job-stayer samples, as is standard in the literature, for doing so will result in overstating the degree of rigidity in the economy as a whole. Including both job-stayers and job-changers and accounting for other forms of compensation yields an average duration of nominal wages (inclusive of base wages and bonuses) of about 4 quarters. However, there is still an asymmetry in adjustment with nominal wage increases being three times more likely than nominal wage cuts.

After documenting the difference between individual and aggregate wage rigidity, we examine the extent to which wages are able to adjust to shocks. We provide strong evidence that wage setting behavior is state dependent. Even though nominal base wage cuts are very rare for job-stayers over our entire sample period, roughly 6.6 percent of salaried workers and 2.8 percent of hourly workers received nominal base wage cuts during the Great Recession. Although the share of job-switchers, who are much more likely to see wage declines, fell during the recession, the aggregate propensity to receive a nominal base wage decline year-over-year was 10.4% during the recession, compared with 8.1% during the recovery. Indeed, the mean wage growth for a worker who remains continuously employed on a job rose from 2.7% during the recession to 5.2% during the recovery. This change was the result of both a decline in the share of workers receiving nominal wage cuts and an increase in the conditional mean size of wage increases in the post Great Recession period relative to the Great Recession. Both the propensity to receive a bonus and the size of the bonus is tied to aggregate business cycle conditions. The share of bonuses in aggregate earnings fell by about one and a half percentage points during the Great Recession relative to the post 2012 period. We also document that industries hit hardest during the Great Recession (including both manufacturing and construction) were much more likely to cut nominal base wages during the recession relative to other industries during the Great Recession, and relative to their propensities to cut in non-recessionary periods. These results suggests that any model with a constant fraction of wage adjustments will fail to match the wage setting patterns over a business cycle.

To complement our macro business cycle results, we explore another dimension of state dependence by examining cross-firm variation in wage setting in response to underlying firm-level shocks. We document that during the Great Recession firms with declining employment were much more likely to reduce the nominal wages of their workers relative to either firms with constant or increasing employment during the recession. Following the recession, however, this pattern became much more muted, as growing firms and shrinking firms were equally unlikely to cut wages. Instead, shrinking firms during the recovery were much less likely than growing firms to increase workers wages. However, even firms with sharply declining employment raise the wages of many of their employees, both during and after the recession. Likewise, even growing firms were much more likely to cut the nominal base wages of their workers during the Great Recession. The interaction between idiosyncratic and aggregate conditions for determining on-the-job base wage adjustment patterns suggests some state dependence in wage adjustments.

We end the paper with a discussion of how the wages of new hires adjust over the business cycle. In many models of firm employment dynamics it is the flexibility of new hire wages that determine employment fluctuations. It is hard to measure the flexibility of new hire wages at business cycle frequencies given the importance of selection in who works over the business cycle.[4] Using our data, we can exploit how wages evolve for job-changers relative to job-stayers at business cycle frequencies. We perform two sets of analyses and both yield similar results. First, we segment job-changers by their initial wage at their originating firm. We then examine where those job-changers end up in the wage distribution of their new firm. Finally, we document that these patterns are invariant to business cycle conditions. If the wages of new hires are more flexible, we would expect to see job-changers entering at lower points in the firm wage distribution during recessions. The fact that we do not see such patterns provides evidence against the wages of new hires being more flexible. We complement these initial findings by benchmarking the job-changers who move from firm i to firm j between period $t-1$ and t to a similar worker in firm j in period $t-1$ based on their $t-1$ wages. We then document that the relative wages of the job-changer to their matched counterpart in t is also invariant to business cycle conditions. Collectively, these results suggest that new hire wages evolve similarly to incumbent workers within a firm at business cycle frequencies. These results complement the findings in Hazell and Taska (2018) which documents that posted wages for new hires display similar adjustment patterns as the base wage changes of existing workers.

There is a large literature on measuring nominal wage adjustments using either household surveys or administrative datasets. Instead of reviewing that literature collectively at this point, we discuss the relevant literature in relationship to the results we present. This allows us to contrast our specific results with those from the literature. While some of our findings are qualitatively similar to some results in the existing literature, they are often quantitatively different in magnitudes. As we discuss throughout, differences between the results in our paper using the ADP data and other results in the literature are consistent with substantial measurement error in nominal wages in household surveys and the lack of high quality hours measures in administrative datasets.

Overall, our results emphasize that there is an important conceptual difference between *compensation* flexibility and *contract* flexibility. If contracts specify a base wage per unit of labor, as well as a schedule of bonuses as a function of performance, then the striking absence of base wage declines and relative infrequency of wage changes more broadly suggest that contracts may be subject to adjustment frictions, even if measured compensation per hour appears flexible. What's more, the ability for workers to move across firms is a source of aggregate nominal wage flexibility, and represents a key conceptual difference between

[4]For the importance of selection in determining the wage cyclicality, see Solon et al. (1994), Basu and House (2016), and Gertler et al. (2016).

nominal wage adjustment and output price adjustments.

The paper proceeds as follows. Section 2 describes the ADP data in detail. Section 3 describes the allocation of worker compensation across base pay, bonuses and fringe benefits. Section 4 presents key facts about various measures of wage adjustments for job-stayers. Section 5 present wage change statistics for job-changers while Section 6 presents our measures of aggregate nominal wage adjustments. Sections 7 present evidence of state dependence at the aggregate and firm levels, respectively. Finally, Section 8 examines the cyclicality of new hire wages. Section 9 concludes.

2 Data and Variable Definitions

2.1 Overview of ADP Data

We use administrative individual panel data provided by the ADP Corporation. ADP is a large, international provider of human resources services including payroll processing, benefits management, tax services, and compliance. ADP has over 650,000 clients worldwide, and currently covers payroll for over 20 million individual workers in the United States per month. The data to which we have access starts in May 2008 and extends through December 2016. During that period, ADP processes payroll for approximately one-sixth of the American workforce.

The data to which we have access contains monthly aggregates of individual paycheck information, as well as all relevant pieces of information needed for human resources management. Crucially, we observe, without measurement error, the statutory per-period payment rate for all employees. For hourly workers, this payment rate is simply the worker's hourly wage. For salaried workers, this payment rate constitutes the pay that the worker is contractually obligated to receive each pay period (weekly, bi-weekly, or monthly). For much of our analysis, we consider hourly and salaried workers separately. Given the data is aggregated to the monthly level, the per-period payment rate is measured as of the last pay period of the month.

In addition to the administrative wage information, the data contain all other information that would appear on the worker's paycheck, such as the worker's gross earnings per pay period, taxes paid, and any taxable benefits provided by the firm. Additionally, the data contain other payroll information including whether the worker is paid hourly, the frequency at which the worker is paid and the number of hours worked during the month. For hourly workers, the exact number of hours worked is reported. For salaried workers, hours information is provided by the firm's HR administrator and often set to 40 hours. We also observe various additional worker characteristics including their zip code of residence, sex, and age, as well as details about the job, such as the start date of employment (and thus worker tenure), firm size, and industry. Selection into the ADP data is at the firm level. As a result, given unique firm identifiers, we can measure wage distributions within and across firms over time.[5] Finally, the presence of consistently-defined worker identifiers permits the careful study of individual worker dynamics across firms. The one caveat is that we are only able to track workers if they move to another ADP-covered firm. However, given our sample size, movements from one ADP firm to another ADP firm are quite common.

We make two major sample restrictions for our analysis. First, we restrict attention to workers prime age workers between 21 and 60 years old, inclusive. Second, we only make use of data from ADP's "Autopay payment" product, which is marketed principally towards firms with over 50 employees. "Autopay" is ADP's primary payroll processing product. Therefore, our dataset is restricted to include only firms with more than 50 employees.[6]

The full dataset that includes over 50 million unique individuals and over 141 thousand firms. To reduce computational burden, we create three random subsamples of the full data. The first chooses one million unique employees, and follows them through their entire tenure in the sample across all firms which they work. This is the primary dataset for analysis. Second, we separately draw a sample of 1 million workers who change jobs during our sample period ("job-changers"). These are workers who show up in multiple firms during their time in the ADP database. This will allow us to explore fully the patterns of wage changes for workers who switch jobs (at least from one ADP firm to another). However, these two datasets are ill-suited to study questions at the firm level; we therefore construct a third subsample of three thousand unique ADP clients, drawing all workers from those firms in the process. This last sample will be useful when explore within firm wage changes as firms grow and contract. The random employee-level, job-changer and firm-level subsamples remain large, with roughly 25 million, 27 million, and 68 million unique employee-month observations, respectively.

[5] Strictly speaking, our definition of a firm is an ADP-provided client code. This will usually be an autonomous firm, rather than any individual establishment. One possible exception to this rule arises if large conglomerates have multiple subsidiaries, all of which separately hire ADP to handle their payroll. In this case, each subsidiary would count as a separate ADP client. As a result, our ADP firms are a combination of both Census notions of firms and establishments.

[6] There are a few workers in the Autopay database that work at firms with less than 50 employees. We exclude these few workers from our analysis.

2.2 Representativeness of ADP Data

There are two areas of concern with respect to the representativeness of the ADP data. First, as noted above, ADP has two separate products: one that it markets to firms with less than 50 employees and another that it markets to firms with more than 50 employees. We only have access to data from the product that they market to mid and large size firms. Therefore, the patterns we highlight in the paper apply only to firms with more than 50 employees. To the extent that the nature of nominal wage adjustments differs by firm size, the patterns we document within our sample may not be representative of the US economy as a whole. However, given that we show that there are only modest differences in nominal wage adjustments by firm size within our sample, we conjecture that any potential bias in our headline results from excluding firms with less than 50 employees is likely to be small.[7]

The second concern with the representativeness of our data is whether ADP clients are representative of firms with more than 50 employees. According to industry reports, roughly 50 percent of US firms in recent years report outsourcing their payroll services to payroll processing companies.[8] According to these same surveys, however, very large firms (firms with more than 10,000 employees) are less likely to outsource their payroll functions. As noted above, ADP processes payroll for about 20 million US workers per month: about one-sixth of U.S. workers. While ADP is the largest payroll processing company, the industry has many competing firms including Intuit, Workday, and Paychex.

Table 1 highlights the firm size distribution for employees in our employee sample (column 1) and employees in our firm sample (column 2). For the results in this table, we pool our data together over the entire 2008-2016 period. The table also shows the number of employees and the number of firms in each of our samples. By design, we randomly drew 1 million employees for our employee sample and 3,000 firms for our firm sample. Our employee sample includes roughly 91,500 distinct firms while our firm sample includes roughly 3.3 million distinct employees. The number of actual observations is much larger for each sample because we observe employees for multiple months. For our employee sample, we track employees across all months between 2008 and 2016 that they are employed at *any* ADP firm. For our firm sample, we track all employees in that firm across all months that they remain employed at that firm.

[7]Furthermore, for more recent periods, we also have access to ADP's data for firms with less than 50 employees. These data reinforce that any potential bias from excluding firms with less than 50 employees from the main results in our paper is likely to be small. We discuss these results in detail in the Data Appendix that accompanies the paper.

[8]According to a 2014 survey of 1,600 CFOs by Robert Half, a professional staffing company, 48 percent of US firms reported outsourcing their payroll services. See Thompson and McDonald (2014). Deloitte performed a smaller survey in 2014 and found that 56 percent of North American mid and large size firms outsourced their payroll services.

Table 1: Firm Size Distribution in ADP Samples and the BDS, Pooled 2008-2014 Data

	Pooled 2008-2016		
	ADP Employee Sample	ADP Firm Sample	BDS Data
Number of Employees	1,000,000	3,296,701	.
Number of Firms	91,577	3,000	.
Number of Observations	24,831,244	68,267,166	.
% Firm Size: 50-499	37.8	31.3	29.5
% Firm Size: 500-999	13.6	13.9	7.3
% Firm Size: 1000-4999	25.1	22.2	17.5
% Firm Size: $\geq$ 5000	19.7	32.5	45.6

Note:

For comparison, column 3 of Table 1 includes the firm size distribution from the U.S. Census's Business Dynamics Statistics (BDS) over the same time period restricting our attention to only firms with more than 50 employees.[9] As seen from the table and consistent with industry surveys, ADP under-represents very large employers (those with at least 5,000 employees). According to BDS data, nearly 46 percent of all employment in firms with more than 50 employees is in firms with more than 5,000 employees. The ADP data only has about 20 percent of employment (in our employee sample) in firms with more than 5,000 employees.[10]

To account for the concern that the data do not perfectly represent the universe of all U.S. firms with at least 50 employees, all subsequent analyses in this paper have been weighted so as to match the BDS's firm size by industry mix of employment shares for firms with greater than 50 employees. We compute our weights for each year between 2008 and 2016. By re-weighting the data, we control for sample selection along these key observable dimensions. Although there may yet remain selection into the sample along unobservable dimensions, we consider these potential selection issues to be small once controlling for firm size and industrial mix.

Given this is the first paper using the ADP data, a deeper discussion of the representativeness of the ADP sample is warranted. We have relegated much of this discussion to the Online Appendix. In particular, we benchmark the demographic composition of the ADP

[9] According to BDS data, 72% of all U.S. employment during this time period is in firms with more than 50 employees.

[10] We also explore how the industry distribution of the ADP sample compares to the industry distribution in the BDS. We are unable to report ADP's precise industry distribution for disclosure reasons. The ADP sample has a slight over-representation amongst the manufacturing and broad service sectors, and a complementary underweight in retail trade, construction, and agriculture.

sample to that of the CPS along a variety of dimensions. Additionally, we compare annual earnings dynamics in our ADP sample for people who remain continuously employed with the same firm for two years to the earnings dynamics in Guvenen et al. (2014) for a similarly defined sample. Additionally, we compare both yearly levels and time series trends in the average hourly wage for workers paid hourly between our ADP sample and a similarly defined CPS sample. We also examine patterns in nominal wage adjustments by firm size to explore potential biases from our data being under-representative of both really small and really large firms. Finally, we show the unweighted results for many of the paper's key findings. After performing all of these benchmarking exercises, we are confident that the ADP data provides a fairly representative picture of nominal wage adjustments for U.S. workers over the 2008 to 2018 period.

3 The Nature of US Worker Compensation

In this section, we explore the nature of compensation for US workers. We start by defining the concept of a worker's "base wage" and "base earnings". This is determined by a worker's per period contract wage rate (e.g., a worker's hourly wage or their contracted guaranteed annual earnings). We show that for most workers, essentially all of their annual gross earnings comes from their base earnings. We then explore the importance of commissions, overtime payments and bonuses in determining a workers gross earnings. Finally, we explore a broader measure of compensation that includes worker earnings plus employer-provided fringe benefits.

3.1 Base Wages and Base Earnings

The ADP data includes many detailed administratively recorded measures of worker compensation. We primarily use three such measures in our analysis: (1) the worker's per-period contract rate, (2) the worker's total gross monthly earnings (excluding employer-provided fringe benefits), and (3) the worker's total monthly employer-provided fringe benefits. In this subsection, we discuss the first two measures. In subsection 3.3, we discuss our measures of employer-provided fringe benefits.

Employers participating in the ADP payroll services are required to report the contractually obligated per-period wage rate for each worker in a separate field from their monthly earnings. For workers who are paid hourly, this is the workers' hourly wage. For salaried workers, this is the workers' annual contracted salary divided by the number of pay periods per year. For all salaried workers, they have an administrative field recording their weekly, bi-weekly or monthly contracted salary rate depending on the frequency of their pay period. We refer to the contractually obligated per-period wage rate as a worker's "base wage."[11]

A separate administrative field for all workers is their "monthly gross earnings" (excluding employer-provided fringe benefits). A worker's base pay is only one part of their monthly gross earnings. During a given month, a worker may also receive tips, commissions, overtime payments, performance pay, bonuses, and cashed-out vacation days. Monthly gross earnings can also include meal and travel reimbursements that are occur through a worker's paycheck. The fact that meal and travel reimbursements can show up in workers' paychecks implies that there is not a one-to-one mapping between monthly gross earnings in our dataset and monthly W2 earnings.[12] Monthly gross earnings is literally the sum of all paychecks (before taxes) earned by the worker during the month.

To isolate the importance of base wages in worker earnings, we define the concept of a worker's "monthly base earnings" using information on their base wage. If the worker is an hourly worker, their monthly base earnings is their base wage times the total number of hours actually worked during the month. If the worker is a salaried worker, their monthly base earnings is their base wage times the number of paychecks received during the month. Any difference between a worker's monthly gross earnings and their monthly base earnings is the result of the worker earning some combination of bonuses, tips, commissions, overtime premiums, performance pay, meal and travel reimbursements or other non-standard payments during the month.

Table 2 shows the distribution of base earnings out of total gross earnings (excluding employer-provided fringe benefits) for U.S. workers during the 2008-2016 period. The table has five columns. The first column uses our total sample and computes the share of total monthly base earnings out of monthly total gross earnings. As seen from column 1, the median worker in a typical month has all of their earnings coming from their base earnings. However, 25 percent of workers have about six percent of their monthly earnings coming from sources other than their base pay while 10 percent of workers have about one-fifth of their monthly earnings coming from sources other than their base pay.

Overtime premium, commissions, performance pay, and bonuses are likely not to accrue

[11]63 percent of workers in our ADP sample report being an hourly worker. This is slightly higher than the 57 percent in the CPS for a similarly-defined sample. The reason for this is that some firms choose to report all their workers as being hourly. The actual salaried workers in these firms have a contracted hourly wage that is computed as their weekly earnings divided by 40 hours per week. These workers are then reported as always working 40 hours per week. While such reporting structure on the part of firms may alter the patterns of nominal wage adjustment when comparing hourly workers to salaried workers, it will have no effect on our results when we pool the two groups of workers together.

[12]We do not have a worker's W2 earnings in the data provided to us by ADP. We only have access to the payroll data.

every month for a given worker. To see how important these sources are for a typical worker, we aggregate our data to calendar years. For this analysis, we restrict our analysis to workers who remain continuously employed with the same firm for all twelve calendar months of a given year. We refer to this sample as our "full-year" sample. Column 2 shows that our monthly analysis does not change at all after restricting attention to the full year sample. Column 3 shows the share of *annual* gross earnings that come from *annual* base earnings. To compute annual measures of both gross earnings and base earnings, we simply sum the monthly measures over the twelve calendar month.[13] About one-quarter of all workers receive essentially all of their annual compensation from base earnings. The median worker earns only 3.8 percent of their annual earnings from sources other than their base pay. This suggests that for most workers, base pay is their primary form of compensation. However, for some workers, other forms of compensation (e.g., bonuses, commissions, tips, overtime) comprise a more substantive portion of their annual earnings. Ten percent of workers earn at least 20 percent of their annual earnings from sources other than their base pay. Columns (4) and (5) show patterns separately for workers paid hourly and salaried. Base earnings are an especially large share of gross earnings for hourly workers.

3.2 Measuring Overtime, Bonuses, and Commissions

Ideally, one would decompose workers' "residual earnings" – gross earnings less base earnings – into various sub-components. However, the ADP data is not well-suited for such disaggregation. Firms are not required to separately report the different potential subcomponents that comprise residual earnings. Despite the limitation, we can make four refinements to our residual earnings measures. First, we can impute the amount of monthly overtime premiums paid to hourly workers using an often-reported "overtime earnings" field in the data. For hourly workers, therefore, we can create a measure of monthly residual earnings net of overtime payments.[14]

Second, we define large residual earnings to be any residual earnings net of overtime that accrue to a worker in a given month that exceeds 1% of their annual earnings. For example, if a worker earned $50,000 during a given calendar year, we would classify that worker as having large residual earnings during a given month if residual earnings net of overtime

[13] Note, given that our data starts in May 2008, we cannot make an annual measure for 2008. Our full-year sample includes data from 2009-2016.

[14] We discuss this imputation procedure in greater detail in the Online Appendix. Firms are asked to report total hours worked (inclusive of overtime) and total earnings from hourly work (inclusive of overtime). Comparing these measures to our measures of base earnings allows for a crude imputation of overtime earnings. Consistent with anecdotal evidence, these overtime wage rates center on 1.5 and 2 times base wage rates.

Table 2: Share of Base Earnings out of Gross Earnings, 2008-2016

	Monthly Share (1)	Monthly Share (2)	Annual Share (3)	Annual Share (4)	Annual Share (5)
10^{th} Percentile	80.6%	80.8%	81.6%	85.7%	75.2%
25^{th} Percentile	93.9%	93.9%	90.3%	92.1%	86.9%
Median	100%	100%	96.2%	96.9%	94.7%
75^{th} Percentile	100%	100%	99.4%	99.4%	99.5%
90^{th} Percentile	100%	100%	100%	100%	100%
Full Year Restriction	No	Yes	Yes	Yes	Yes
Type of Worker	All	All	All	Hourly	Salaried
Sample Size (millions)	18.25	9.01	0.75	0.46	0.28

Note: Table shows the distribution of the share of worker base earnings out of worker gross earnings. Columns 1 and 2 report data for each worker-month pooled over our 2008-2016 sample. Columns 3, 4 and 5 report data for each worker-calendar year over our 2009-2016 sample. Given our data starts in May 2008, we cannot compute a full calendar year measure for our 2009 data. Columns 2-5 restrict our data to include only workers who remain employed continuously with the same firm over the entire 12 calendar months of a given year. Columns 1-3 pool together both workers paid hourly and workers paid salary, while columns 4 and 5 look at only hourly workers and only salaried workers, respectively. For columns 4 and 5, we drop workers who switch from hourly to salaried status, or vice versa, within the year. See text for definitions of base and gross earnings.

pay exceeded \$500 during that month. By making this restriction, we exclude any small payments made to the worker during a given month such as small meal reimbursements.

Third, we compute the frequency of months a worker receives large residual payments during a given year. We define a worker to be a "commission worker" if they receive large residual earnings net of overtime in four or more calendar months during a given year. We are interpreting "commission workers" broadly in that these workers could have residual payments in four or more months during a given year due to frequent commissions, frequent tips, frequent performance pay, frequent mis-measured overtime pay, or even frequent large meal and travel reimbursements. The key for our commission worker definition is that these workers have large residual payments in many months during a given year. We can then segment workers into non-commission workers and commission workers. According to this definition, roughly 10 percent of workers each year during our sample can be classified as commission workers.

Finally, for non-commission workers, we define a worker as having received a "bonus" if that worker received a large residual earnings payment net of overtime in at least one month but no more than three months during a given calendar year. Again, our definition of bonus is broad in that it applies to any large infrequent extra non-overtime payments received by workers during a year. These payments could be annual bonuses but could also be cashed out vacation days, large mis-measured overtime hours, infrequently dispersed performance pay, and infrequent large meal or travel reimbursements. During our sample period and given our definition, roughly 30 percent of non-commission workers receive a bonus during a given year.[15]

Table 3 shows the importance of annual base pay and bonuses as a share of annual earnings for non-commission workers. The first two columns show results pooling together hourly and salaried workers. The remaining columns show the same patterns for hourly and salaried workers separately. Removing the 10 percent of workers we define as commission workers results in much higher share of base pay in annual earnings. For the median non-commission worker, nearly 98 percent of their annual earnings is in base pay. Furthermore, nearly all remaining compensation for non-commission workers is in what we classify as bonuses. Specifically, for the median worker, over 99% of all annual gross earnings are base earnings and what we classify as bonuses. This is important in that for the rest of the paper we are going to focus on nominal wage adjustments of base pay and bonuses. Doing so, captures essentially all of the compensation for most non-commission workers. The remaining gross earnings for most non-commission workers is in overtime pay and other

[15] It should be noted that most of these extra payments occur in December, February and March suggesting that many of them are likely linked to annual bonuses.

Table 3: Share of Annual Base Earnings and Bonuses out of Annual Gross Earnings, 2009-2016, Non-Commission Workers

	All		Hourly		Salaried	
	Share Base	Share Base+ Bonus	Share Base	Share Base+ Bonus	Share Base	Share Base+ Bonus
	(1)	(2)	(3)	(4)	(5)	(6)
10^{th} percentile	89.7%	93.5%	91.6%	92.8%	86.6%	96.0%
25^{th} percentile	93.8%	96.8%	94.8%	95.7%	91.6%	99.0%
Median	97.5%	99.3%	97.8%	98.5%	96.5%	100%
75^{th} percentile	99.7%	100%	99.6%	99.8%	100%	100%
90^{th} percentile	100%	100%	100%	100%	100%	100%
Sample Size (thousands)	611	611	378	378	222	222

Note: Table shows the distribution of the share of worker annual base earnings out of annual worker gross earnings and annual worker base earnings plus annual bonuses out of annual worker gross earnings. We restrict our attention to our sample of non-commission workers who remain continuously employed with the same firm for all twelve months of a calendar year. See text for definitions of base earnings, bonuses, gross earnings and non-commission workers. The remaining columns show similar data separately for workers paid hourly (columns 3 and 4) and workers who are salaried (columns 5 and 6).

small infrequent residual earnings payments. Throughout the paper, we present results on nominal wage adjustments separately for both non-commission and commission workers.

3.3 Employer-Provided Fringe Benefits

Lastly, we create a broader measure of worker compensation that includes employer-provided fringe benefits. The data contain all forms of fringe benefit that would appear on an employee's paycheck, including employer-provided health insurance and contributions to a retirement plan or pension - such as a 401(k) or Roth IRA - made by the employer.[16] Using these data, we create a measure of "annual fringe benefits" by summing the monthly employer-provided health benefits and retirement contributions over all months of a year. The fringe benefit measures were not-consistently reported prior to 2012. Starting in 2012, as part of the Affordable Care Act, employers were required to report their contributions to employee health benefits. Given this, when analyzing measures of broader compensation, our analysis is limited to workers who remain continuously employed with the same firm

[16]We exclude all tax measures from our analysis including employer paid payroll taxes.

during the 2012-2016 period.

Using these measures, we create a measure of a worker's "total annual compensation" by summing their annual gross earnings with their annual employer-provided fringe benefits. Table 4 shows the distribution of the share of total compensation that is in fringe benefits for workers. Fringe benefits accounts for 9.4% of the median worker's total compensation, but there is large variation around this number, with 10% of workers receiving more than 26.5% of their compensation through fringe benefits, and many workers receiving no fringe benefits at all. Hourly workers tend to receive fewer fringe benefits than do salaried workers: the median hourly worker has 7.9% of their total compensation in fringe benefits, compared with 10.5% for salaried workers, However, the right tail of fringe benefits for hourly workers is thicker for hourly workers than for salaried workers, with the 90th percentile of hourly workers receiving 28.3% of their compensation from special compensation, compared with 24% for salaried workers.

The largest form of fringe benefit is the provision of health benefits. Of the 11.6% of income that the mean worker receives in fringe compensation, 7.8% is accounted for by health benefits, such as employer-provided health insurance, or contributions to a flexible spending account. The second largest fringe benefit comes from deferred compensation programs, such as pension schemes, and tax free retirement accounts. Such deferred compensation programs account for 2.8% of total compensation on average, and 4% of salaried workers' compensation.

Encouragingly, the numbers presented in this table match those found by the BLS in their Employer Cost for Employee Compensation (ECEC) reports. For example, the June 2016 report finds that 7.6% of workers' total compensation is accounted for by the cost of health insurance, and 3.9% is accounted for by retirement and savings account contributions.[17] The very small discrepancy between our numbers and those of the ECEC are in part driven by the different weighting of our samples - while we present results at the *employee* level, the ECEC measures the average share of a *firm's* total compensation bill accounted for by each category, and thus dollar-weights within a firm.

3.4 Heterogeneity in Bonuses and Fringe Benefits Across Workers

The left panel of Figure 1 shows the share of annual bonus income out of annual total earnings sorted by workers' base wage percentile.[18] As with the results above, we exclude

[17]See, for instance `https://www.bls.gov/news.release/ecec.nr0.htm`. The aggregate fringe benefit share does not match exactly, as the BLS includes paid leave, bonuses, and legally-required benefits such as social security payments, the first two of which will be included in our measure of gross earnings.

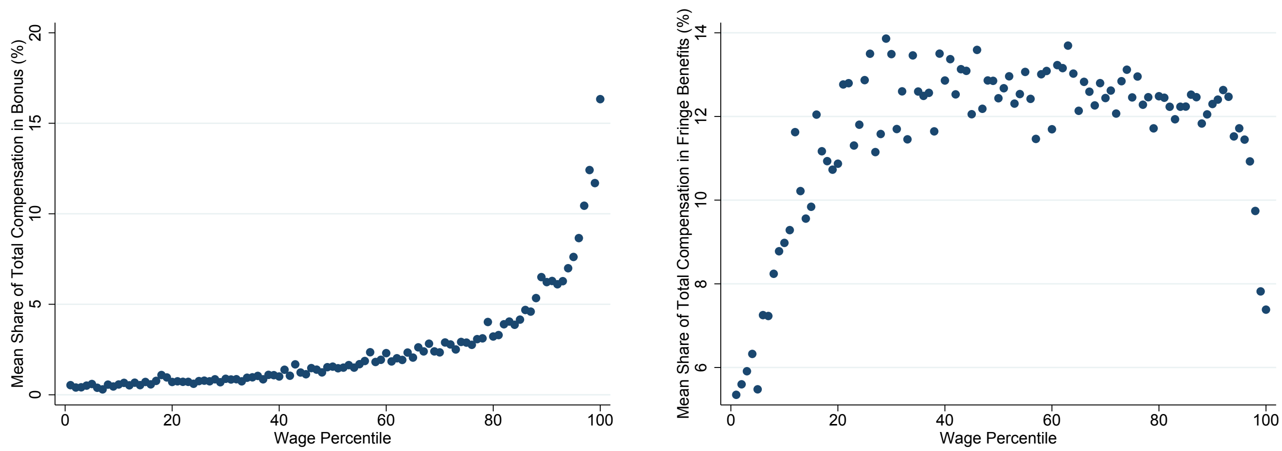
[18]To make the base wage percentile, we combine data on both hourly and salaried workers. For hourly workers, we use their base hourly wage. For salaried workers, to put things in the same hourly wage units,

Table 4: Share of Fringe Benefits out of Total Compensation, 2012-2016 Period

	All		Hourly		Salaried	
	(1)	(2)	(3)	(4)	(5)	(6)
10^{th} percentile	0.0%	0.0%	0.0%	0.0%	0.4%	0.3%
25^{th} percentile	2.2%	2.0%	0.0%	0.0%	5.0%	4.9%
Median	9.4%	9.3%	7.9%	7.8%	10.5%	10.6%
75^{th} percentile	18.4%	18.5%	19.5%	19.5%	17.2%	17.3%
90^{th} percentile	26.5%	26.7%	28.3%	28.4%	24.0%	24.1%
Mean Total Fringe Share	11.6%	11.6%	11.5%	11.5%	11.8%	11.8%
Mean Health Fringe Share	7.8%	8.0%	8.7%	8.8%	6.7%	6.7%
Mean Pension Fringe Share	2.8%	2.8%	2.0%	2.0%	4.0%	4.0%
Non-Commission Workers Only?	No	Yes	No	Yes	No	Yes
Sample Size (Thousands)	623	556	363	344	260	211

Note: Table shows the distribution of the share of worker fringe benefits out of total worker compensation during the 2012-2016 period. Columns 1 shows data for only all commission workers while column 2 shows data for all workers (including both commission and non-commission workers). The remaining four columns show the same patterns separately for workers paid hourly (columns 3 and 4) and workers who are salaried (columns 5 and 6). All data is restricted to include only workers who remain employed continuously with the same firm over the entire 12 calendar months of a given year. Total compensation is the sum of gross earnings and fringe benefits. See text for additional details.

Figure 1: Bonus and Fringe Benefit Share by Employee Base Wage Percentile, Two-Year Job-Stayers, Excluding Commission Workers



Panel A: Share in Bonus Out of Total Earnings

Panel B: Share in Fringe Benefits Out of Total Compensation

Note: Panel A shows the share of bonus earnings out of total earnings by worker percentile within the base earnings distribution. Panel B shows the share of fringe benefits out of total compensation by worker percentile within the base earnings distribution. Sample restricted to our sample of job-stayers who remain in the sample for two full calendar years. Commission workers are excluded.

commission workers. Workers at the lower end of the base wage distribution receive, on average, only less than 0.5% of their annual earnings in bonuses. The share of earnings in bonuses increases monotonically throughout the wage distribution. The median worker earns about 2% of their annual earnings in bonuses. Systematically, workers at the top of the wage distribution earn a substantial amount of their annual earnings in bonuses. Therefore, while annual bonuses are not an important form of compensation for most workers, they are substantial for high wage workers.

The right panel of the figure shows the share of annual fringe benefits provided by the employer out of a worker's annual total compensation (earnings plus fringe) as a function of the worker's base wage percentile. Fringe benefits are much less important for lower wage workers (below the 20th percentile). However, from the 20th percentile through the 95th percentile of the wage distribution, the share of total compensation in fringe is roughly constant in the 12 to 14 percent range. For really high wage earners, fringe becomes a smaller fraction of total compensation. This is likely because fringe benefits are not usually provided on bonus income and given that tax exempt employer-provided retirement contributions are capped.

we divided their base weekly earnings by 40 hours.

4 Nominal Wage Adjustments for Job-Stayers

In this section, we begin by exploring the nature of nominal wage adjustments for workers who remain continuously employed in the same job. For some macro models, this measure of nominal wage adjustment is an independent moment of interest. For example, Schoefer (2016) shows that wage rigidity among incumbent workers drives firm-level employment fluctuations when firms are financially constrained. Additionally, the extent of nominal wage rigidity can help to explain aggregate employment fluctuations in canonical models of labor market search and matching (Hall, 2005). For other macro models, how the wages of incumbent workers adjust is an input into a broader measure of aggregate wage stickiness. For example, most New Keynesian models examine a measure of individual-level nominal wage adjustments that combines data from job-stayers and job-changers.[19] While the focus of this section is on the nominal wage adjustment of job-stayers, in subsequent sections we examine separately the nominal wage adjustments of job-changers and new hires as well as combining the various measures to create measures of aggregate wage adjustments.

Empirically, we define "job-stayers" as those workers who remain continuously employed with the same firm between the two periods where the nominal wage is being measured. In terms of timing, we explore nominal wage changes at the monthly, quarterly and annual frequencies. For the monthly, quarterly and annual samples, we ensure that workers are continuously employed with the same firm for one, three and twelve consecutive months, respectively. Finally, when exploring nominal wage adjustments of individuals inclusive of bonuses and fringe benefits, we restrict our analysis to a sample of workers who are continuously employed with the same firm for two consecutive calendar years. This allows us to make measures of annual nominal wage compensation for each worker and then explore how annual nominal wage compensation evolves over time.[20]

We first showing the distribution of base wage adjustments for our sample of job-stayers. We then explore the adjustment of broader measures of worker compensation that includes both bonuses and fringe benefits. We end this section by comparing and contrasting our results with existing studies in the literature.

4.1 Base Pay Adjustments

Figure 2 highlights the first key set of facts of the paper. The figure plots the distribution of 12-month nominal base wage changes for all job-stayers pooled over all years of our sample. As discussed above, base wages make up essentially all annual compensation for most workers.

[19]See, for example, Christiano et al. (2005).

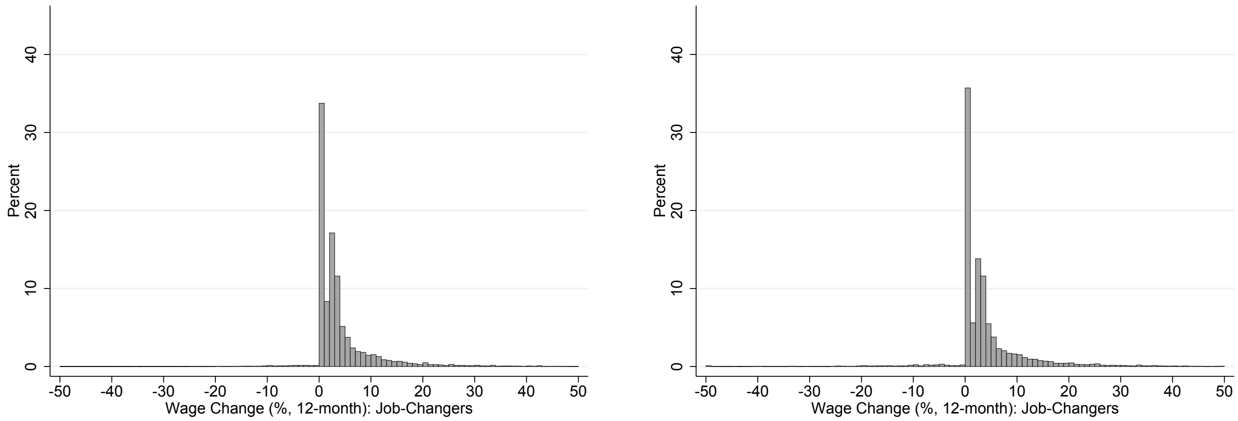
[20]Aggregating to the annual level is important for this analysis given the strong seasonality in bonuses.

Panel A plots the distribution for hourly workers, while Panel B plots the distribution for salaried workers. Four key observations are apparent from the figure. First, a large share of workers - 33% of hourly, and 35% of salaried do not receive a nominal base wage change in a given year. Second, the patterns of nominal base wage adjustments for hourly workers and salaried workers are nearly identical. Given this, we often pool the data for hourly and salaried workers together going forward when describing base wage adjustments. Third, there is a clear asymmetry in the base wage change distribution, with the overwhelming majority of changes being wage increases. Only 2.4 percent of all workers (combining hourly and salaried) in the U.S. who remained continuously employed with the same firm for 12 months received a nominal base wage decline. Of the roughly 66% of all individuals who receive a nominal base wage change over a given 12-month period, only 3.6% received a nominal base wage cut (2.4/66). Finally, there are very few small nominal base wage changes for either hourly or salaried workers. Just 8.6% of all workers received a nominal base wage change of between 0.1 and 2 percentage points, compared with 27.1% receiving between 2 and 4 percentage points. This missing mass of very small wage changes is consistent with the random menu cost models that are prevalent in the price setting literature.

While the asymmetry between nominal wage increases and nominal wage cuts is a feature of many existing empirical papers (see, e.g. Lebow et al. (2003); Kahn (1997); Card and Hyslop (1997)), the results in Figure 2 are quantitatively different from much of the existing literature. As we highlight below, measurement error in household data sets has resulted in estimates of nominal wage adjustments (both up and down) that are higher than what we find using administrative payroll data. In addition, the missing mass of small wage changes urges consideration of models of state dependent wage adjustment, which we explore in more depth in Section 7. Again, because of measurement error, this missing mass has been difficult to detect in prior work.

The patterns of nominal wage adjustments for job-stayers are fairly robust across workers who are compensated in different ways. The top panel of Figure 3 shows the patterns of nominal base wage adjustments separately for non-commission workers (left) and commission workers (right). The bottom panel shows similar patterns for non-commission workers who do not receive a bonus (left) and non-commission workers who do receive a bonus (right). All of those panels pool together hourly and salaried workers. The patterns are strikingly similar across the four groups. Notice that essentially none of the groups receive a nominal cut to their base wage. All groups have between 30 and 40 percent of workers receiving no nominal base wage adjustments during the 12 month period. Non-commission workers who receive an annual bonus are the *most* likely to get a nominal base wage increase during the year. These workers both receive a bonus and are more likely to receive a wage increase. As

Figure 2: 12-Month Nominal Base Wage Change Distribution, Job-Stayers



Panel A: Hourly Workers Panel B: Salaried Workers

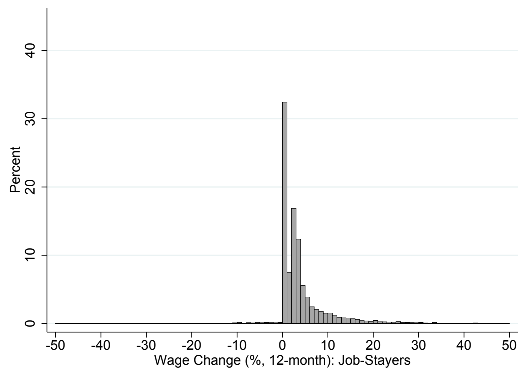
Note: Figure shows the annual change in nominal base wages for workers in our employee sample who remain employed on the same job. We use our employee sample for this analysis (including commission workers).

seen above, these workers are more likely to be high earning workers. Conversely, roughly 40 percent of commission workers receive no nominal base wage change during the year. Finally, the patterns of nominal base wage adjustment for workers who receive essentially all of their earnings from base pay are nearly identical to the patterns for all workers highlighted in Figure 2. Non-commission workers who do not receive a bonus have annual earnings that is comprised essentially of only base pay. For this group, only about 2 percent of workers receive a nominal base wage cut and about 62 percent receive a nominal base wage increase during a 12 month period.

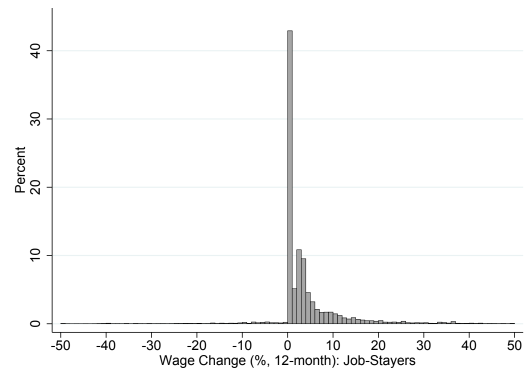
Figure 4 explores the extent to which nominal base wages are allocative. Specifically, we focus on our sample of hourly workers whose monthly hours worked fluctuates over the year. The number of pay weeks in the month varies over time, so we adjust our monthly hours for the number of pay periods making a measure of hours worked per week. This procedure is discussed in detail in the appendix. We restrict the sample to only include those households whose hours worked per week varies substantively over the year.

The left hand panel of Figure 4 shows that wages are potentially allocative for these workers. Exploiting the panel nature of the data, we show that one-year base wage changes are associated with one-year hours worked changes, with an elasticity of 0.23. The right hand panel of the figure shows the one-year distribution of nominal base wage changes. It is nearly identical to the results shown in Figures 2 and 3. Even for workers whose hours fluctuate, there are essentially no nominal base wage cuts and roughly one-third of workers

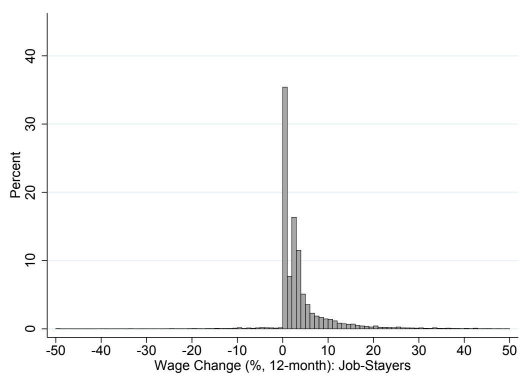
Figure 3: 12-month Changes in December Base Wages, 24-month Job-Stayers



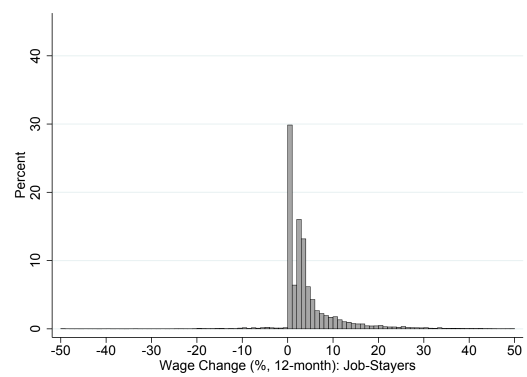
Panel A: Non-Commission in Year $t-1$



Panel B: With Commission in Year $t-1$



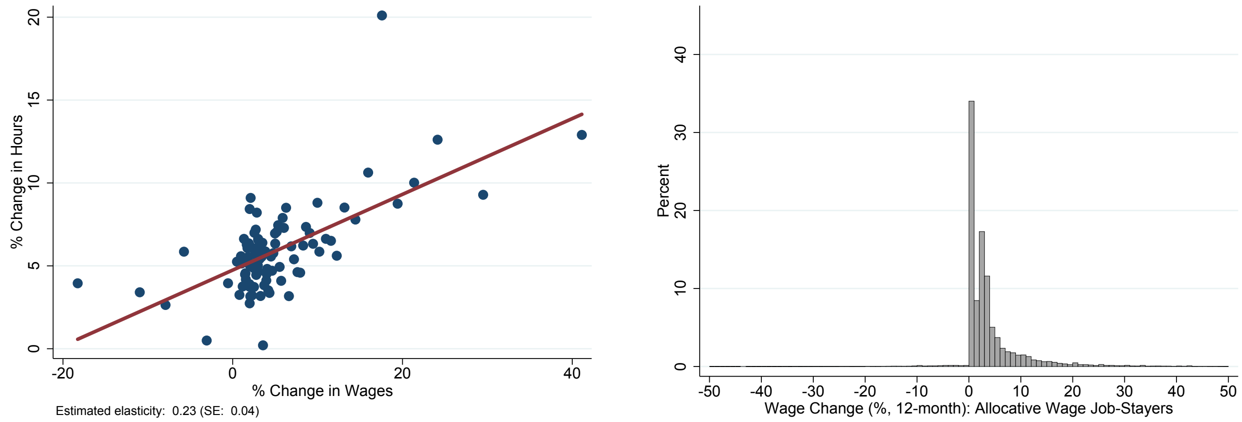
Panel C: No Bonus in Year $t-1$



Panel D: With Bonus in Year $t-1$

Notes: Figure plots the 12-month change in December contract wages between year $t-1$ and t for workers who remain on a job for at least 24 months. Panel A plots the distribution of changes for workers who do not work commission in year $t-1$, while Panel B plots the distribution for commission workers in $t-1$. Panels C and D plot the distribution for workers who did and did not receive a bonus in year $t-1$, respectively, excluding workers who work for commission.

Figure 4: 12-month Base Wage Changes, Job-Stayers, Hourly Workers w/ Variable Hours



Panel A: Changes in Hours vs Changes in Wages

Panel B: Base Wage Change Distribution

Notes: Figure shows results from a sub-sample of hourly workers whose weekly hours varies over the year and who remained continuously employed with the same firm during the 12 month period. We pool results over the entire 2008-2016 period. The left hand picture shows the relationship between the percent change in nominal base wages over the 12 months and the percent changes in hours worked. Each dot is a percentile of the wage change distribution. The right panel shows the distribution of the 12-month nominal base wage change.

do not receive a year-over-year nominal base wage increase.

Table 5 provides a set of summary moments on the probability of base wage increases and base wage declines for three frequencies: monthly, quarterly and annual. The annual frequencies correspond to the underlying data shown in Figure 2. The first column pools together hourly and salaried workers while the second and third columns, respectively, show the frequency of base wage changes for hourly and salaried workers separately. A few things are of note from the table. First, the frequency of base wage changes is roughly similar between salaried and hourly workers at all horizons. Roughly two-thirds of both receive annual base wage changes over the entire sample period (summing over wage increases and wage declines). Second, while the average probability of a base wage change is similar between the two groups in our sample of job-stayers, salaried workers are slightly more likely to receive a nominal base wage cut. Over the entire sample, only 1.8% of hourly workers receive a nominal base wage cut over a 12 month period while 3.6 percent of salaried workers receive a nominal base wage cut. Third, one cannot simply extrapolate monthly nominal base wage changes to quarterly or quarterly base wage changes to annual. The probability of a quarterly nominal base wage change is less than three times the monthly base wage change and the probability of an annual nominal base wage change is less than four times the quarterly change. This is likely due in part to well-known time aggregation issues arising

Table 5: Probability of Base Wage Change, Pooled 2008-2016 Sample of Job-Stayers

	All Workers	Hourly	Salaried
Annual			
Probability of Positive Base Wage Change (%)	63.9	65.3	61.6
Probability of Negative Base Wage Change (%)	2.4	1.8	3.6
Quarterly			
Probability of Positive Base Wage Change (%)	18.5	19.5	16.7
Probability of Negative Base Wage Change (%)	0.9	0.7	1.3
Monthly			
Probability of Positive Base Wage Change (%)	6.3	6.6	5.8
Probability of Negative Base Wage Change (%)	0.6	0.3	0.6

Note: Table shows the frequency of base wage increases and base wage decreases at different horizons for our sample of job-stayers during the 2008-2016 period. The first column pools together hourly and salaried workers while the second and third columns, respectively, show the frequency of changes for hourly and salaried workers separately. The top panel shows results at the annual horizon while the middle and bottom panels show results at the quarterly and monthly horizons. We use our full employee sample for this analysis (including commission workers).

from workers who receive multiple wage changes during the year, as well as to the fact that the samples differ between the three horizons: for monthly base wage changes, workers need to only remain with their employer for one month, while for annual base wage changes workers need to remain with their employer for the full year.

Table 6 shows additional moments of the base wage change distribution. For this table, we only report results pooling together both hourly and salaried workers given the frequency of adjustment distributions were similar between the two groups.[21] During this period, mean and median nominal base wage growth for workers who remain on the same job equaled 3.9 percent and 2.4 percent, respectively.[22] Conditional on a base wage change occurring, annual mean and median base nominal wage growth was 5.6 and 3.2 percent. A key statistic we will focus on throughout the paper is the standard deviation of nominal wage growth. Unconditionally and conditional on a base wage change occurring, the standard deviation of

[21] To limit the effect of extreme outliers when computing mean wage changes, we winsorize both the top and bottom 1% of nominal wages and the top and bottom 1% of wage changes. We only do this when computing the size of wage changes conditional on a wage change occurring. This does not affect our frequency of wage change results in any way.

[22] It should be noted that our wage growth for job-stayers includes a combination of cohort, time and age effects. The presence of age effects implies that wage growth for job-stayers are higher than the wage growth for the economy as a whole. See Beraja et al. (2016) who make a similar point when comparing time series and panel data wage growth patterns in the CPS during the Great Recession.

annual nominal base wage growth during the full 2008-2016 period was 6.5 percent and 6.9 percent, respectively. Consistent with the patterns in Figure 2, annual base wage changes display very large amounts of both skewness and kurtosis. Additionally, conditional on a positive base wage change occurring during a 12 month period, the mean and median size of the increase was 6.3 and 3.5 percent. The fact that the mean is much higher than the median reinforces the fact that some workers receive very large nominal base wage changes on the job, perhaps due to promotions. The mean and median size of a base wage cut, conditional on the worker experiencing a nominal base wage reduction were both around 7 percent. While the frequency of base wage increases is much higher than wage cuts, the mean size of a base wage increase is very similar to the mean size of a base wage cut.

In the Online Appendix, we show a set of additional results surrounding time dependence in base wage adjustments. Conditional on a job-stayer receiving a base wage change during a year, most only receive one change. Most firms change the base wages of their employees in the same month. Most job-stayers receive a base wage change one-year from their last wage change. Workers who receive a wage change off-cycle (in a different month from most workers within the firm) tend to get higher wage increases than those who receive a wage change on-cycle. At the firm-worker level, there is strong evidence of staggered contracts (see (Taylor, 1979)). However, different firms adjust the base wages of most of their workers in different months. There is a fair bit of monthly seasonality in the probability of a worker receiving a wage change with January, April, July and October being the months with most frequent adjustments. However, when aggregating the data to quarterly levels, there is little quarterly seasonality. Given these facts, we compute a measure of the average duration of a base wage increase for a worker assuming Calvo adjustment. This is a crude measure given the evidence of state dependence presented in 7. But, given that the literature focuses on a measure of average duration in Calvo models of wage adjustments, we feel it is a useful statistic to use when comparing the nature of nominal wage adjustment across our different wage concepts. The results in Table 5 suggest an average duration of a nominal base wage for job-stayers is about 5.5 to 6.0 quarters depending on whether the quarterly or annual frequencies of adjustment are used.

4.2 Bonus Payments and Nominal Wage Adjustments

In this sub-section, we gauge the importance of bonuses in providing an additional margin of flexibility for job-stayers. Bonuses have long been considered a potential source of additional wage cyclicality and earnings flexibility (Shin and Solon, 2007). For this analysis, we restrict our sample to non-commission workers and to workers who remain continuously employed

Table 6: Base Wage Change Statistics, Pooled 2008-2016 Sample of Job-Stayers

	Monthly	Quarterly	Annual
Unconditional			
Mean Base Wage Change (%)	0.3	1.0	3.9
Median Base Wage Change (%)	0.0	0.0	2.4
Standard Deviation of Base Wage Change (%)	2.6	3.7	6.5
Skewness of Base Wage Changes (%)	9.7	5.3	2.8
Kurtosis of Base Wage Changes (%)	175.4	49.5	14.4
Conditional on Any Wage Change			
Mean Base Wage Change (%)	5.0	4.9	5.6
Median Base Wage Change (%)	3.0	3.0	3.2
Standard Deviation of Base Wage Change (%)	8.1	6.5	6.9
Skewness of Base Wage Changes (%)	2.1	2.1	2.4
Kurtosis of Base Wage Changes (%)	15.9	13.6	12.1
Conditional on Positive Wage Change			
Mean Base Wage Change (%)	6.2	5.7	6.3
Median Base Wage Change (%)	3.3	3.3	3.5
Standard Deviation of Base Wage Change (%)	7.7	6.4	7.0
Conditional on Negative Wage Change			
Mean Base Wage Change (%)	-10.7	-8.7	-7.3
Median Base Wage Change (%)	-8.3	-7.7	-6.6
Standard Deviation of Base Wage Change (%)	8.1	5.8	4.6

Note: Table shows moments of the wage change distribution for different horizons for a sample of job-stayers in the ADP data between 2008 and 2016. For this table, we use our employee sample and pool together hourly and salaried workers. All data are weighted to be nationally representative of sample of workers working in firms with more than 50 employees.

with the same firm for 24 consecutive calendar months. The reason for the former restriction is that it is hard to isolate bonuses separately from other frequent irregular payments in our sample of commission workers. The latter restriction is necessitated by the fact that bonuses accrue annually. Given that our data starts mid-year through 2008, our bonus sample pools together workers for all two year periods between 2009 and 2016.

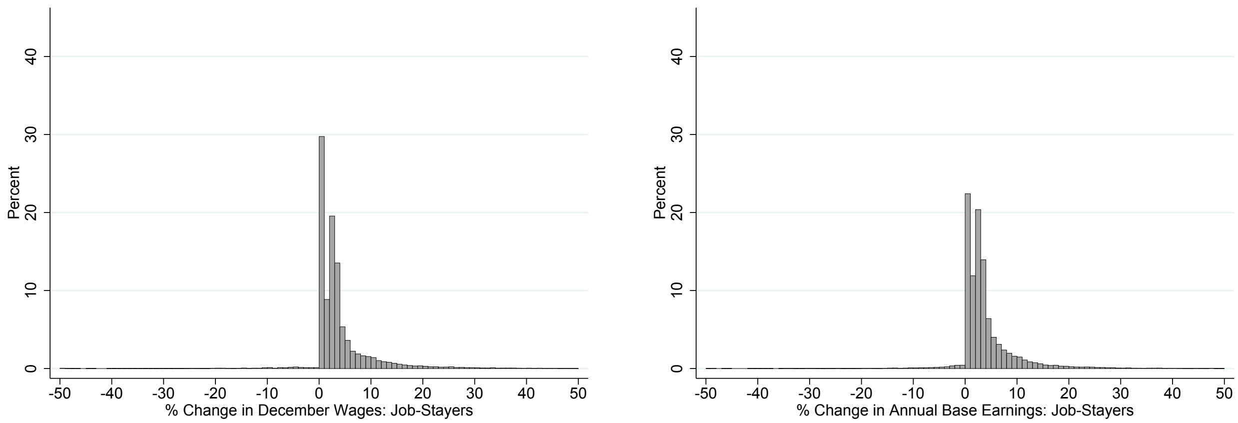
During our sample period, 44.5 percent of non-commission job-stayers received no bonus both in year t and year $t + 1$ while 32.4 percent of non-commission job-stayers received a bonus in both year t and $t + 1$. The remaining 23.1 percent of workers received a bonus in only one of the two years. Bonus receipt is fairly persistent.

To assess how bonus flexibility affects the frequency of nominal wage adjustment, our bonus and our base wage measures must be in the same units. We therefore define a measure of "modified monthly base earnings," which will allow us to isolate fluctuations in a worker's base pay which arise from changes in wages rather than hours. Modified monthly base earnings for salaried workers is simply their monthly base earnings (their base wage times the number of pay periods per month). However, modified monthly base earnings for hourly workers is their monthly base wage times the *average* monthly hours worked over the relevant two year period. Specifically, when we explore changes in nominal wage adjustments inclusive of bonuses between year t and $t+1$, average monthly hours worked is simply the total annual hours worked in both years t and $t+1$ divided by 24. We normalize the modified base monthly earnings for hourly workers by the average number of hours worked over the two year period so that all the movements in modified monthly earnings is coming from changes in the base wage; it is in this sense that the earnings are "modified". Given that bonuses are measured annually, we then make a measure of "modified annual *base earnings*" by summing the monthly modified earnings for each worker over a 12 calendar month period.

Our key variable of interest is "modified annual *total earnings*" which is computed as the sum of modified annual base earnings plus annual bonuses. It is worth stressing that our *modified* annual total earnings variable differs from annualized total earnings in two ways. First, the measure includes only earnings from base wages and bonuses. It excludes any earnings from overtime premiums and other small infrequent payments. Second, it normalizes the hours for hourly worker to be the average annual hours worked over a given two year period. The benefit of this is that any movement in this earnings measure across the two years is attributed to a change in base wages or a change in bonuses.

As a way of comparison, Figure 5 shows annual changes in nominal base wages for non-commission workers (left panel) and the changes in annual base modified earnings as defined above (right panel). The left panel is similar to the results shown in Panel A of Figure 3 in that it shows the 12 month percent change in December wages for a sample of non-

Figure 5: Annual Changes in Base Pay and Modified Base Earnings: 24-month Job-Stayers, Excluding Commission Workers



Panel A: Base Wage

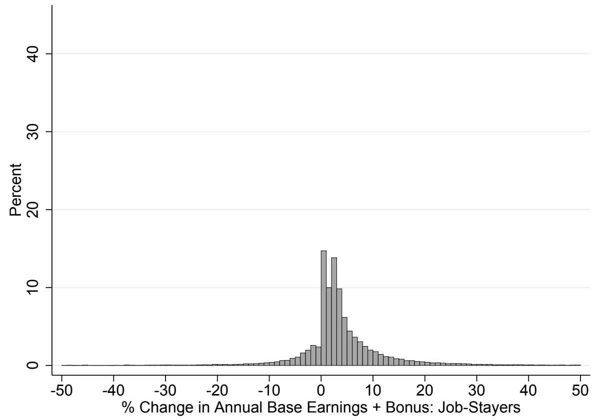
Panel B: Modified Base Earnings

Notes: Figure plots the distribution of year-over-year changes in base wage (Panel A) and modified base earnings (Panel B). Panel A considers changes in December base wages, while Panel B shows changes in annual modified base earnings.

commission workers who remain on the job for two consecutive calendar years. The only slight difference between this figure and the one in Figure 3 is that in this figure we further restrict the sample to include workers who are non-commission workers in both years. The right hand panel of Figure 5 shows the change in annual base earnings for a sample of non-commission workers who remain continuously employed on the same job for two calendar years. Not surprisingly, the left and right panels of this figure are nearly identical. Both are measuring only variation in base wages over time. The only difference between the two figures results from time aggregation. Given that the left hand picture is measuring nominal wage adjustments between December of $t-1$ and December of t and the right hand panel is measuring nominal wage adjustments between all of $t-1$ and all of t, wage changes that occur prior to December of $t-1$ will show up as an additional amount of nominal wage adjustment in the right hand figure. As a result, the variance of changes is slightly higher for annual modified base earnings relative to 12-month changes in base wages. However, even despite the time aggregation issues, there distribution of changes in modified base earnings include essentially no nominal wage cuts.

Figure 6 present another of our key results. It shows the annual change in annual modified earnings (inclusive of bonuses) for all the non-commission workers in our sample. Notice relative to Panel B of Figure 5, the change in annual modified earnings (inclusive of bonuses) is more dispersed. While only 2.9 percent of workers received a modified base earnings decline over a 12 month period, 15.7 percent of workers saw reduced nominal wages inclusive

Figure 6: Annual Changes in Modified Base Earnings Plus Bonus: 24-month Job-Stayers, Excluding Commission Workers



Notes: Figure plots the distribution of year-over-year annual base earnings plus bonus changes for a sample of 24-month job-stayers excluding commission workers.

of bonuses. Accounting for bonuses provides much more downward wage flexibility for workers. Additionally, accounting for bonuses also increases the standard-deviation of nominal wage changes from 4.6 percent to 7.7 percent. The addition of bonuses reduces the average duration for a given wage from about 6 quarter to just over 4 quarters. Accounting for bonuses provides workers and firms with an additional level of wage adjustment. The first three columns of Table 7 summarizes these results for our sample of 2-year job-stayers.

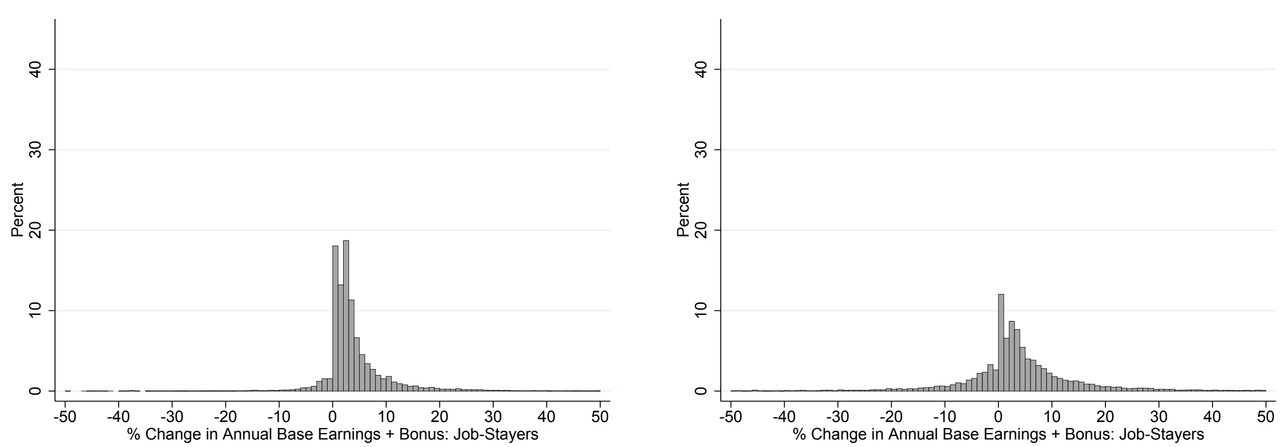
The extent to which bonuses provide flexibility differs across workers. Figure 7 segments in annual change in modified base earnings plus bonuses for workers in the bottom quartile of the base wage distribution (left panel) and the top quartile of the base wage distribution (right panel). For low wage workers, bonuses are not important. As a result, accounting for bonuses has little effect on a worker's nominal wage adjustment. In particular, low wage workers hardly ever receive a nominal wage cuts. However, for high wage workers, bonuses provide a large amount of additional flexibility. Incorporating bonus adjustments results in 23.6 percent of workers in the top wage quartile experiencing a nominal wage cut during a year. This result is interesting given the fact that much of the displacement of workers at business cycle frequencies comes from the bottom of the wage distribution. The results in Figure 7 suggest there are potential gains from modeling heterogeneity across workers in the extent to which bonuses are part of their compensation. For workers that do not receive bonuses, there appears to be less of an ability to downwardly adjust wages.

Table 7: Moments of the Annual Change Distribution Across Wage Notions, 2-year Job-Stayers, 2012-2016

	2009-2016			2012-2016	
	Base Wage	Modified Base Earnings	Modified Base + Bonus	Modified Base + Bonus	Modified Base + Bonus + Benefits
<u>Extensive Margin</u>					
Prob of Positive Change (%)	69.8	80.4	75.0	76.6	77.8
Prob of Negative Change (%)	2.1	2.9	15.7	15.4	18.9
<u>Unconditional Moments</u>					
Mean Change (%)	3.7	3.7	4.0	4.2	6.1
Median Change (%)	2.5	2.7	2.7	2.8	3.8
SD of Change (%)	5.4	4.6	7.7	7.7	10.9
<u>Conditional on Any Change</u>					
Mean Change (%)	5.4	4.5	4.4	4.6	6.4
Median Change (%)	3.0	3.0	3.0	3.0	4.0
SD of Change (%)	5.7	4.7	7.9	7.9	11.0

Notes: Table plots key moments of the wage change distribution for the sample of two-year job-stayers. We restrict attention to the period 2012-2016 where we have high quality benefits information. Each column presents the moments of the distribution of a separate notion of wage.

Figure 7: Modified Annual Earnings Fluctuations by Base Wage Quartile, 2-Year Sample of Job-Stayers Excluding Commission Workers, 2008-2016



Panel A: Base + Bonus Changes: Bottom Quartile Wages

Panel B: Base + Bonus Changes: Top Quartile Wages

4.3 Incorporating Fringe Benefits

We conclude this section by discussing how accounting for fringe benefits affect the frequency of nominal wage adjustments. As noted above, our data on fringe benefits was not measured consistently within the ADP data set prior to 2012. As a result, when examining fringe benefits, we restrict our sample to the 2012-2016 period. Within this time period, we continue to restrict our analysis to job-stayers who remain continuously employed with the same firm for all months in two consecutive calendar years. Our measure of a worker's wage is modified annual earnings (inclusive of bonuses) plus the annual value of employer-provided health insurance and contributions to deferred compensation plans.

The results of incorporating fringe benefits into our analysis are shown in the last two columns of Table 7. Adding in benefits does not substantively alter the frequency of annual changes either up or down. Comparing columns (4) and (5), the probability of an increase in base earnings plus bonuses and fringe was about 78 percent. The comparable probability for the increase in base earnings plus bonuses is 77 percent. Both the size of the increase and the variance of the change are larger after including fringe benefits. These patterns are consistent with benefits being either relatively constant fraction of a worker's earnings. As a worker's base earnings change, so does their fringe benefits but the change moves with their earnings. Under this scenario, accounting for fringe would not alter the propensity for a worker to receive a wage change. However, accounting for fringe would scale the changes implying both the mean change and the standard deviation of changes would be larger.

4.4 Summary of Nominal Wage Adjustments for Job-Stayers

Collectively, the results in Tables and 5 and 6 provide a set of high quality statistics on the wage change distribution for job-stayers that can be used to calibrate many different types of macroeconomic models. There is an existing literature trying to measure nominal wage rigidity. However, the moments we document above differ markedly from many of the existing findings in the literature. Across most papers, a consensus has emerged that most job-stayers experience a nominal wage change during a given year and that wages are more downwardly rigid than upwardly rigid for job-stayers, yet the literature has yet to come to a consensus regarding the magnitudes of this difference.[23] These differences stem from the fact that measuring nominal wage changes in household and administrative

[23] There is a long literature, surveyed by Bewley (2004) and Howitt (2002), examining the root causes of nominal wage rigidity. In a series of interviews with business managers responsible for compensation policy, studies have documented that the primary resistance to wage cuts arises from concerns over damaging worker morale. See, for instance, Kaufman (1984), Blinder and Choi (1990), Agell and Lundborg (1995, 1999), Campbell III and Kamlani (1997), and Bewley (1999).

datasets is notoriously difficult given the presence of measurement error (household surveys) or missing hours (administrative datasets).[24] Additionally, different types of compensation have different adjustment patterns. None of the existing studies either using household or administrative datasets are able to highlight this distinction; indeed respondents in different datasets may report different concepts of the wage – some may include bonuses, while others may not.

While often not explicitly discussed, most papers in the literature imply that they are measuring the frequency of adjustment for base wages - the per hour or per period wage. For example, using the panel component of the CPS, Daly and Hobijn (2014) report that roughly 85 percent of wages of job-stayers change annually during a sample period that overlaps with ours.[25] As noted above, we find that only about two-thirds of job-stayers receive an annual nominal wage change during the 2008-2016 period. Using the methodology of Daly and Hobijn (2014), the Federal Reserve Bank of San Francisco has created a "Wage Rigidity Meter." They report higher wage flexibility for salaried workers relative to hourly workers. Again, this finding is inconsistent with the findings in our paper. But, the fact that measurement error in earnings and hours is high in household surveys can explain the higher variance of wage changes in the CPS. Additionally, the fact that hours are likely measured with more error for salaried workers would generate more measured wage volatility for salaried workers relative to hourly workers in household surveys.

Using data from the Survey of Income and Program Participation, Barattieri et al. (2014) try to account for the measurement error in wages and hours in household data by looking for structural breaks in their individual hourly wage series. Their primary focus is on workers who are paid hourly. Given that they focus on an individual's self-reported hourly wage (reported in dollars per hour), their measure is similar in concept to our measure of a base wage for hourly workers. When they make their correction for measurement error, they find that the frequency of quarterly wage changes for job-stayers falls from over 50 percent to between 15 and 20 percent - depending on their adjustment procedure - during their period of study. Our quarterly frequency of base wage changes for job-stayers who are paid hourly is 20 percent which is at the upper range of their estimates. More importantly, however,

[24]There is a literature documenting sizable amounts of measurement error in both income and hours in household surveys using audit studies. See, for example, Bound et al. (1989) and Bound and Krueger (1991). Bound and Krueger (1991) finds that just about forty percent of cross-sectional variance of the change in income for men in household surveys can be explained by measurement error. Bound et al. (1989) documents that the measurement error in reported hours in household surveys is even larger than the measurement error in income.

[25]One of the earliest papers to estimate the extent of nominal wage rigidity using household level data was Kahn (1997), who used data from the Panel Study of Income Dynamics (PSID) to find that about 92% of workers receive a nominal wage change during a given year.

they estimate a much larger fraction of downward wage adjustments. Specifically, they find that 12 percent of all quarterly wage changes for job-stayers are downward changes. That is three and half times larger than our administrative data reports. As discussed in Section 4, we estimate only 3.5 percent of all quarterly base wage changes for job-stayers who are paid hourly are downward changes (1.7/19.5).[26] As Barattieri et al. (2014) highlight, there is substantial measurement error in household surveys with respect to measuring how nominal wages adjust. The fact that their patterns still differ relative to the ADP results is consistent with some residual measurement error remaining even after implementing their structural break procedure.

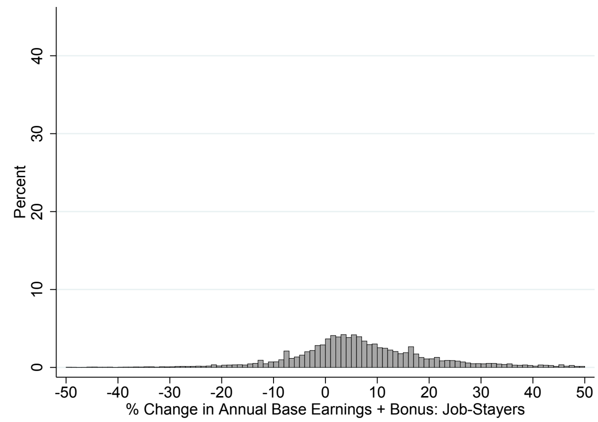
A more recent literature has emerged using firm-level data to measure wage stickiness. Both Lebow et al. (2003) and Fallick et al. (2016) use data from the BLS's Employment Cost Index (ECI) to measure nominal wage rigidity. Unlike the household surveys or other administrative payroll data, the unit of analysis in the ECI is a job not a worker. To the extent that workers who populate a specific job are heterogeneous with respect to underlying skills, nominal wage variation could occur due to shifting sampling of different quality workers over time. Consistent with this fact, the nominal wage variation in the ECI for a given job is much larger than what we document in the payroll data for job-stayers.

Kurmann and McEntarfer (2017) use data from the US Longitudinal Employer Household Dynamics (LEHD) to examine nominal earnings-per-hour adjustments for a sample of job-stayers who reside in Washington state over a two year period.[27] They focus their sample on residents of Washington state because Washington requires employers to report the hours worked of their employees as part of their Unemployment Insurance program. The hours measures are reported at a quarterly frequency by the firm administrator filling in the unemployment insurance records. For salaried workers, the reported hours are often but not always set to 40 hours per week. Using their measure of earnings per hour, Kurmann and McEntarfer (2017) shows much more downward nominal adjustment relative to the results we emphasize above. Part of this is simply due to the inclusion of commission workers in their analysis. To illustrate this, we show the change in modified annual earnings (modified base earnings plus bonuses and commissions) for commission workers. These results are shown in Figure 8. Commission workers have much larger modified annual earnings fluctuations than non-commission workers. Additionally, many more commission workers receive

[26] Additionally, our results differ from those in Barattieri et al. (2014) in other ways. In particular, they find no differences in wage change probabilities across occupations and industries. As we highlight in the Online Appendix, we document that some substantive variation across industries in their propensity for nominal wage adjustments. Also, as we highlight later, our results for job-changers are also substantively different than those in Barattieri et al. (2014).

[27] Le Bihan et al. (2012) and Sigurdsson and Sigurdardottir (2016) also use administrative establishment level data from France and Iceland, respectively, to measure nominal wage rigidities.

Figure 8: Year over Year changes in Modified Base Earnings, Commission Workers



Notes: Figure plots the year-over-year changes in annual modified earnings (i.e. base earnings plus bonuses) for the sample of commission workers only.

modified earnings declines year over year. The existence of commission workers makes annual earnings divided by annual hours more volatile than what we document in Figure 6. Another difference between our results and the results in Kurmann and McEntarfer (2017) stems from excluding overtime premiums from our measures of wages and earnings. Commission compensation and overtime premiums are certainly important for earnings fluctuations. However, given that such compensation components are partially linked to worker effort, they may not be moments that are appropriate to discipline models of wage rigidities.[28]

Our paper is closest in spirit to the results in Altonji and Devereux (2000) and Fehr and Goette (2005). Altonji and Devereux (2000) uses administrative payroll data similar to ours for one large financial service company during 1996 and 1997 while Fehr and Goette (2005) uses administrative payroll data from two Swiss firms in the early 1990s. The patterns of base (administrative) wage adjustment for job-stayers these authors document within their selected companies closely match the patterns we document for the whole U.S. economy during the 2008-2016 period. In particular, Altonji and Devereux (2000) documents that only 0.5% of workers receive a nominal base wage cut during a given year. The fact that firm-level payroll data from an earlier period within the U.S. and Switzerland broadly matches the job-stayer results from the recent ADP data highlights the importance of using administrative payroll data to measure base wage stickiness. The results on nominal wage adjustments with payroll data are consistent with each other but are very different than the results on

[28]Some of the remaining difference between our results and those in Kurmann and McEntarfer (2017) stem from the fact that they create measures of earnings per hour. Given that hours are likely measured with error for salaried workers, this adds an additional potential reason their measure of earnings per hour displays higher variance than our measure of modified annual earnings. We discuss this point in further detail in the appendix.

nominal wage adjustments using household survey data and administrative earnings records. The strength of the ADP data is that it can examine the payroll patterns for a nationally representative sample of firms over a long timer period, as well as break down compensation adjustment into its components.

5 Nominal Wage Adjustments for Job-Changers

The prior section focuses on nominal wage adjustments for individual job-stayers. However, models in which most wage adjustment originates from movements across firms or due to the arrival of outside offers, such as many labor search models (Menzio and Shi (2011); Cahuc et al. (2006)), may be better calibrated to moments measuring nominal wage adjustments for job-changers. In this section, we use the ADP data to provide such moments for the literature.

There is a large literature documenting that wages of job-changers are more pro-cyclical than those of job-stayers (see, for instance, Bils (1985); Haefke et al. (2013); Pissarides (2009); Martins et al. (2012) and Gertler et al. (2016)). These studies show that the wages of employees entering new jobs tend to move almost one-for-one with labor productivity, and that this high degree of pro-cyclicality persists even after controlling for detailed job characteristics; it does not appear to be completely due to pro-cyclical "job upgrading". Our paper directly contributes to this literature by bringing to bear high quality administrative data on wages to measure not only the *mean* wage adjustment of job-changers, but also provides a number of moments of the distribution of wage changes for job-changers as a whole.

The analysis in this section uses our job-changer sample. When measuring wage adjustment for job-changers, three issues are worth noting. First, we stress that we are measuring wage changes for workers who move from one ADP firm to another ADP firm. An implicit assumption we make throughout the paper is that the patterns of nominal base wage adjustments for workers who migrate across ADP firms are similar to the patterns of nominal base wage adjustment for workers who migrate to and from non-ADP firms.

Second, the notion of a "firm" within the ADP dataset is a unit that contracts with ADP. Sometimes, multiple establishments within a firm contract separately with ADP or firms will spin off into multiple units each contracting separately with ADP. In this case, a movement from one establishment within a firm to another establishment within the same firm will look like a job-change. To account for such flows, we measure the percent of job-changers leaving a given firm in month t and showing up at another ADP firm in month $t+1$ or month $t+2$. If more than twenty percent of job-changers leaving firm i and subsequently show up in firm j with no intervening employment spell elsewhere between t and $t+2$, we treat those as within firm movements and do not include them in our job-changer sample. In addition, if a worker's reported tenure does not reset after switching firms, we exclude that worker from the job-changer sample.

Finally, the choice of timing is more nuanced given the nature of our data. As with job-stayers, we can measure base wage changes for job-changers at one-month, one-quarter, and one-year frequencies. However, when we see a worker at firm i in month t and then see a worker at firm j in month $t+12$, the worker may have multiple other jobs in the interim. Because we only measure labor market outcomes for ADP firms, if a worker disappears from our dataset for a short time but reappears later, we are not able to distinguish if the worker was not employed or whether the worker was employed but at a non-ADP firm. For many applications, such distinctions are not important. However, it is important to keep such timing issues in mind when interpreting our wage adjustment measures for job-changers.[29]

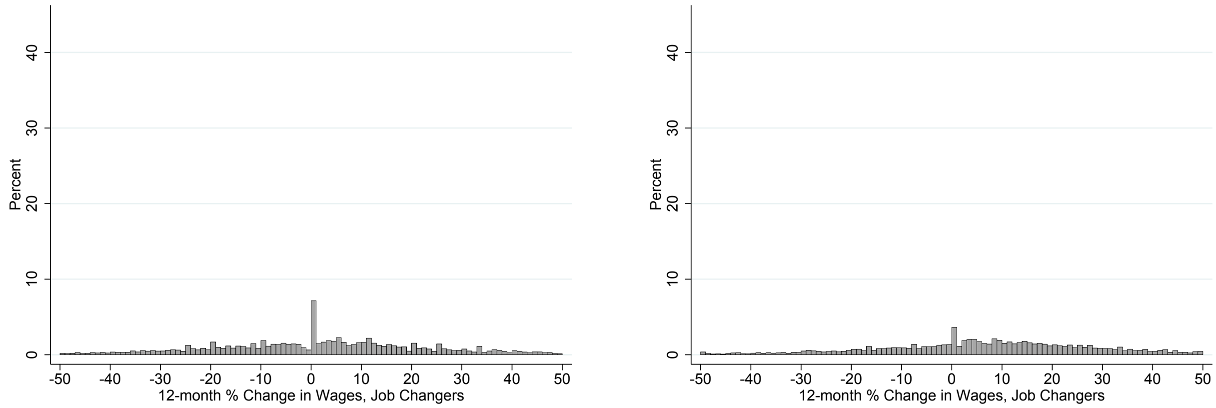
Figure 9 plots the distribution of 12-month nominal base wage changes for a sample of job-changers. The patterns are strikingly different from the patterns in Figure 2. First, essentially all workers receive a base wage change over a given year if they change jobs. Only about 6.5 percent of hourly job-changers and 3.3 percent of salaried job-changers do not receive a year-over-year base wage change. Second, the propensity for a base wage cut is very high for job-changers. Specifically, 39.2% of workers paid hourly and 31.2% of workers who are salaried receive a base wage decline during a job-change. Finally, the distribution of base wage changes is much more symmetric around zero. As seen from the figure, there are roughly as many small base wage increases (0-2 percent) as there are slightly larger base wage increases (2-4 percent). There is much more base wage adjustment for job-changers than there is for job-stayers.

Table 8 shows key statistics on the distribution of base wage changes for job-changers. Conditional on a job change and a base wage change, mean and median annual base wage growth was 9.0 and 4.6 percent accordingly. Base wage growth is much larger for job-changers than it is for job-stayers.[30] As seen from Figure 9, there is a tremendous amount of heterogeneity in base wage changes for job-changers. Job-changers whose nominal base wage

[29] When measuring "quarterly" nominal wage changes for job-changers, we include workers who show up in another ADP firm between 1 and 5 months after leaving their original ADP firm. When measuring "annual" nominal wage changes for job-changers, we include workers who show up in another ADP firm between 10 and 14 months after leaving their original ADP firm. We create wider bins to include more job-changers in our analysis. When we examine patterns by year, having larger overall samples is helpful for power reasons. Additionally, we restrict our analysis to include only those workers who switch between either hourly jobs or who switch between salaried jobs. We exclude those who switch between the two types of jobs. These switches across payment types are relatively rare, but generate large swings in base wages in almost all cases.

[30] Faberman and Justiniano (2015) documents a tight correlation between aggregate nominal wage growth and aggregate job-switching rates.

Figure 9: 12-Month Base Wage Change Distribution for Job-Changers



Panel A: Hourly-to-Hourly Changers Panel B: Salaried Changers

Note: Figure shows the 12 month change in nominal base wages for workers in our employee sample who switched jobs. We include all data from 2008-2016. See text for additional details.

increased over the year experienced, on average, about a 26.1 percent increase. Job-changers whose nominal base wage fell over the year experienced, on average, a 18.5 percent wage cut. Moreover, the standard deviation of annual nominal base wage changes for job-changers is 29.3 percent - almost five times larger than the standard deviation of annual nominal base wage changes for job-stayers.

The patterns of nominal base wage changes for job-changers in our ADP sample differ from the reported findings in Barattieri et al. (2014). Using their structural break procedure to adjust for measurement error in reported hourly wage changes for hourly workers in the SIPP, Barattieri et al. (2014) find that only between 69 and 77 percent of hourly job-changers receive a nominal wage change. In the ADP data, 90 percent of hourly workers receive an hourly wage change during a quarter. Conversely, the patterns of nominal wage changes of job-changers that we document are similar to the patterns using French data in the 1990s as documented in Postel-Vinay and Robin (2002), who document that about one-third of French workers experience a real wage decline as the move from job-to-job with no intervening unemployment spell. Overall, this section highlights that the possibility that a worker will change jobs is a major contributor to aggregate wage adjustment, in a manner consistent with administrative datasets in other countries.

Table 8: Nominal Base Wage Change Statistics, Pooled 2008-2016 Sample of Job-Changers

	Quarterly	Annual
Extensive Margin		
Prob of Positive Change (%)	52.7	56.8
Prob of Negative Change (%)	37.4	38.0
Unconditional Moments		
Mean Wage Change (%)	6.3	8.0
Median Wage Change (%)	2.3	4.6
Standard Deviation of Wage Change (%)	25.9	29.3
Skewness of Wage Changes (%)	1.0	0.9
Kurtosis of Wage Changes (%)	5.6	5.0
Conditional Moments, Any Wage Change		
Mean Wage Change (%)	7.8	9.0
Median Wage Change (%)	5.6	6.3
Standard Deviation of Wage Change (%)	27.6	29.9
Conditional on Positive Wage Change		
Mean Wage Change (%)	23.5	26.1
Median Wage Change (%)	16.7	18.5
Standard Deviation of Wage Change (%)	22.3	24.4
Conditional on Negative Wage Change		
Mean Wage Change (%)	-16.5	-18.5
Median Wage Change (%)	-13.6	-15.8
Standard Deviation of Wage Change (%)	12.2	13.5

Note: Table shows moments of the wage change distribution for job-changers for different horizons. For this table, we use our employee sample and pool together hourly and salaried workers.

6 Aggregate Nominal Wage Adjustments

We now combine our measures of wage adjustments for job-stayers and job-changers into an aggregate measure of nominal wage adjustments.[31] This measure is appropriate for the study of movements of macro variables in models with no defined notion of a job-stayer of job-switcher, as is the case in canonical models such as Christiano et al. (2015), Christiano et al. (2005) and Schmitt-Grohé and Uribe (2012). The large sample of both job-stayers and job-changers at a high frequency is a unique feature of the ADP data which allows us to construct such a measure for the first time. The inclusion of job-switchers vastly reduces the degree of realized nominal wage rigidity in the economy, particular on the downside, relative to the job-stayer benchmark which has been measured in the literature to-date.

To construct an aggregate measure of nominal wage flexibility, one must combine the patterns of wage adjustment for job-stayers with the patterns for job-changers. Were the universe of workers available, this would be a relatively easy task. However, as noted above, we can only measure job-changers who migrate between one ADP firm and another ADP firm. Given that ADP only has information on a subset of US workers, most job-to-job flows involve a non-ADP firm.

To circumvent this problem, we use aggregate data on job-to-job flows published by the US Census Bureau using data from the Longitudinal Employer Household Dynamics (LEHD) database.[32] Using matched employee-employer records, Census creates measures of quarterly job flows. In particular, we use the Census's Job-to-Job Flows Data (J2J) focusing on transitions between workers' main jobs. For any given worker in quarter t whose main job is at firm i, the J2J data measures whether the worker's main job in quarter $t+1$ remained at firm i (job-stayers), whether the worker's main job in quarter $t+1$ was at a different firm j (job-changers), and whether the worker was not employed in quarter $t+1$ (become non-employed). The sum of these three measures sum to 1 within each quarter. Using data from 2008 through 2016, the quarterly job staying rate averaged 88.7 percent, the quarterly job switching rate averaged 4.6 percent, and the quarterly transition rate to non-employment was 6.9 percent. At the time of writing, the Census has not yet released annual job-to-job flows. As a rough approximation, we construct annual job changing rates by multiplying the quarterly rates by 4. Doing so implies that 18.5 percent of workers switch job annually.[33] In order to aggregate our job-staying and job-changing results, we weight our

[31] New entrants to the labor market also provide another margin of potential nominal wage adjustment. We are unable to measure job entrants within the ADP data so we abstract from them in our analysis.

[32] See https://lehd.ces.census.gov/data/j2j_beta.html, accessed June 30, 2018. We focus on the job-to-job flows at the quarterly frequency allowing for at most short unemployment spells between the job transitions.

[33] This approximation is consistent with aggregate data on job tenure. Hyatt and Spletzer (2016) use

job-changing data by the fraction of job-changers in the LEHD data relative to one minus the fraction of job-changers. For quarterly data, we ensure that job-changers are weighted so that they represent 4.8 percent of workers (0.046/(1-0.046)). For annual data, we ensure that job-changers are weighted so that they represent 22.7 percent of workers (0.185/(1-0.185)).

Table 9 shows statistics for the aggregate nominal base wage change distribution combining data from both job-stayers and job-changers. Column 1 of the table shows quarterly statistics on aggregate base wage changes while column 2 shows similar annual statistics. The table shows that there is much more aggregate nominal base wage flexibility than one would conclude from looking at job-stayers alone. Over the entire sample period, roughly 71.3 percent of workers receive a nominal wage change. Of those, nearly 9 percent received nominal base wage declines, compared with 2 percent of job-stayers. While nominal base wage declines are still rare in the aggregate relative to nominal wage increases, including data on job-changers quadruples the amount of nominal base wage cuts relative to looking at only job-stayers. Moreover, the standard deviation of base wage growth – both unconditionally and conditional on a wage change – is over twice as large in the aggregate compared as amongst job-stayers. For example, unconditionally, the standard deviation of nominal base wage growth in the aggregate is 12 percent while the standard deviation of base wage growth for job-stayers is about 6 percent.

Column 3 of Table 9 show a measure of aggregate nominal wage adjustments inclusive of bonus income for job-stayers. Specifically, we focus on annual modified earnings for job-stayers and combine that with annual base wage changes for job-changers with the job-changers weighted accordingly using the aggregate J2J weights.[34] In aggregate data, wages are more flexible both because of job-changers and because bonuses are moving around at annual frequencies. As seen from Column 3, in aggregate data, 21.4 percent of all workers receive a nominal wage decline during a given year when accounting for job-changers and bonuses received by job-stayers.

Overall, the inclusion of job-changers in our measures of wage rigidity greatly increases realized flexibility in the economy. This has important consequences for the quantitative predictions of existing macro models. The excessive price rigidity inferred by simply considering base wage adjustment for job-stayers will lead New Keynesians to overstate the pass-through of monetary policy to real quantities. Similarly, those studying the extent to which downward nominal rigidities could contribute to sluggish wage growth should be aware that roughly 9% of workers received an annual base wage cut and 21% received an annual

tenure supplements to the CPS and matched employer-employee data from the LEHD to document that roughly 20-25 percent of workers have tenure less than a year during the 2008-2014 period.

[34]We cannot include bonuses for job-changers, as we do not observe a full year of data for job-changers that join their jobs in months other than January.

Table 9: Moments of Aggregate Wage Change Distribution Combining Job-Stayers and Job-Changers, Pooled 2008-2016

	Quarterly Base Wage	Annual Base Wage	Annual Base Wage + Bonus
Probability of Wage Change			
Probability of Positive Wage Change (%)	20.6	62.8	68.7
Probability of Negative Wage Change (%)	3.2	8.5	21.4
Unconditional			
Mean Wage Change (%)	1.2	4.4	5.2
Median Wage Change (%)	0.0	2.5	2.8
Standard Deviation of Wage Change (%)	6.7	12.0	16.7
Skewness of Wage Changes (%)	3.6	1.7	1.4
Kurtosis of Wage Changes (%)	38.6	12.3	9.0
Conditional on Any Wage Change			
Mean Wage Change (%)	5.3	6.2	5.8
Median Wage Change (%)	3.1	3.5	3.3
Standard Deviation of Wage Change (%)	13.1	13.9	18.6
Skewness of Wage Changes (%)	1.1	1.2	1.2
Kurtosis of Wage Changes (%)	9.5	9.1	8.1

Note: Table shows aggregate moments of wage adjustment combining data on both job-stayers and job-changers during the 2008-2016 period. For this table, we pool together both hourly and salaried workers. The first column shows results at the quarterly horizon while the second column shows the results at the annual horizons. We use our employee sample for this analysis. See text for additional discussion of our job-changer sample. We use data from the LBD to compute the weights for job-changers and job-stayers. See the text for additional details.

modified earnings cut from the period 2008-2016. Even if base wages for job-stayers appear exceptionally downwardly rigid, aggregate wage levels have not been as inflexible over the past ten years, owing to the high churn of employment in the US economy and adjustments to other forms of compensation. We now turn to a discussion of wage rigidity over the cycle, and the extent to which wages may respond to real economic shocks.

7 State Dependence in Aggregate Nominal Wage Adjustment

In this section, we examine the extent to which aggregate wage adjustments move with aggregate and firm specific conditions. Many macro models of wage adjustments assume a constant parameter for the probability that a worker receives a wage adjustment. Using a variety of methodologies, we highlight that the probability of a wage adjustment varies substantively with business cycle conditions.

7.1 Time Series Variation in the Nominal Wage Adjustments, Job-Stayers

There are two principal reasons why one might observe state dependence in realized nominal wage changes for job-stayers. The first is if there is some explicit cost for firms to adjusting wages of existing workers. Non-convex adjustment costs, or "menu costs," are commonly employed in New Keynesian models of price setting in order to match moments of the price data. The presence of fixed adjustment costs generates an inaction region whereby firms that are close to their optimal price in a frictionless economy do not adjust their prices until they move sufficiently far away from their optimal price. Thus, with a menu cost of adjusting prices, the state of the firm - its distance from the optimal pricing rule - is crucial in determining price adjustment decisions. As a result, price changes are infrequent, and relatively large when they occur. Although menu cost models of wage adjustments are rare, principally due to challenges arising from wage bargaining, the intuition gained from the output pricing literature helps guide analysis of state dependence in wage setting.

A second reason for state dependence in nominal wage adjustments for job-stayers might arise in a framework with asymmetric rigidity. For instance, suppose that it is harder for firms to cut wages than to raise them, possibly due to concerns over morale or because of union pressure. Under this scenario, firms receiving a negative productivity shock would have a lower probability of being able to adjust wages to the desired level than firms receiving a positive productivity shock. This would imply that wages would then appear less flexible in downturns than in booms.

Figure 10 plots the time series of base wage adjustments for job-stayers pooling together both hourly and salaried workers. The top panel plots the extensive margin of base wage changes: the percent of all employees in month t who have a different base wage from month $t-12$. As a reminder, our data starts in May 2008. That means the first observation in each of the panels in Figure 10 is for May 2009 and measures the fraction of job-stayers who received a base wage change between May 2008 and May 2009. The fact that our data spans the Great Recession allows us to explore business cycle variation in the extent of base wage adjustments.

As seen from the top left panel of Figure 10A, wage adjustments of job-stayers exhibits striking pro-cyclicality. Only about 55 percent of continuing wage workers received a year-over-year wage change during the depths of the recession. However, after the recession ended during the 2012 to 2014 period, between 65 and 70 percent of workers received a wage change. As of the end of 2016, nearly 75 percent of all workers received a nominal base wage change. While most of the time series variation was between the recession and non-recessionary periods, there is still a trend upwards in the share of workers receiving an annual base wage change between 2012 and 2016.

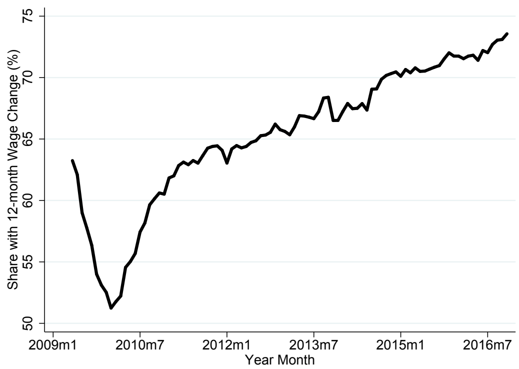
The top right panel of Figure 10 separates the probability of a base wage change of job-stayers into the probability of a base wage increase (solid line - measured on the left axis) and the probability of a wage declines (dashed line - measured on the right axis). During the Great Recession, the propensity of base wage increases for job-stayers fall sharply and the propensity of base wage declines increases sharply. Another one of the key findings of the paper is that while nominal base wage cuts are exceedingly rare for job-stayers during non-recessionary periods, nearly 6 percent of all continuing workers received a nominal base wage cut during late 2009 and early 2010.

The bottom panels of Figure 10 plots the mean size of base wage changes, restricting attention to those who have indeed received a base wage change in the prior 12 months. The bottom left panel pools together all wage base changes while the bottom right panel separately looks at base wage increases and wage declines. The overall mean base wage change size is highly pro-cyclical.

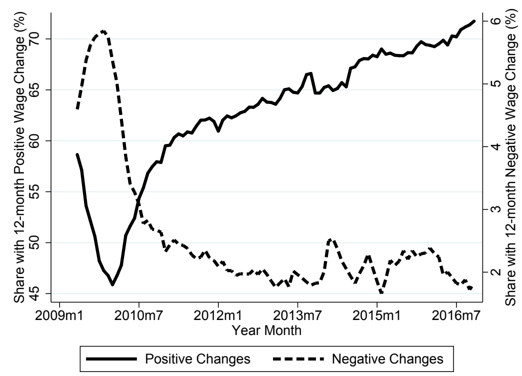
Putting the above results together, within-firm nominal base wage growth for job-stayers is highly pro-cyclical. For employees who remain with the firm, both the probability and size of nominal base wage raises are increasing in business cycle conditions. There is a large literature on the cyclicality of aggregate wages.[35] Our results show that for a given worker

[35]See, for example, Solon et al. (1994), Gertler et al. (2016) and the recent survey by Basu and House

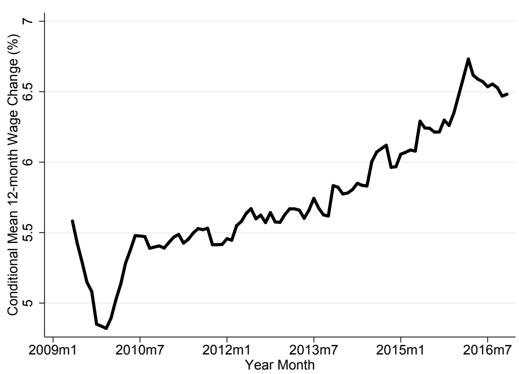
Figure 10: Time Series of Nominal Base Wage Adjustments, Job-Stayers



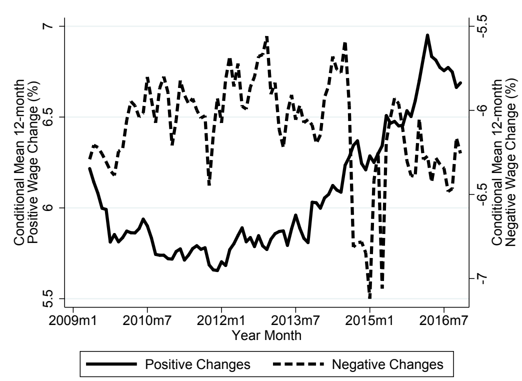
Panel A: Has Wage Change



Panel B: Has Wage Change: Pos. vs Neg.



Panel C: Mean Wage Change Size



Panel D: Mean Wage Change Size - Pos. vs Neg.

Note: Figure plots the propensity to receive a 12-month base wage change (Panels A and B) and the mean size of base wage changes (Panels C and D) over time for our employee sample of job-stayers between May 2009 and December 2016. The data are weighted to match the firm size × industry mix found in the BDS. Since the first month of our ADP data is May 2008, we may only observe 12-month base wage changes beginning in May of 2009.

on the job, nominal base wage *changes* are also strongly pro-cyclical.

The first two columns of Table 10 summarizes the business cycle differences in nominal base wage adjustments for job-stayers. We separate the sample into two periods: a period representing the depths of the Great Recession (May 2009-December 2010) and a period well into the recovery (January 2012 - December 2016). The top panel table pools together both salaried and hourly workers while the bottom two panels look at hourly and salaried workers separately. Consistent with the results in Figure 10, nominal wage cuts were more prevalent during the recession than during the recovery period. A few things are of note from the table. First, 6 percent of salaried workers who remained on their job received a nominal base wage cut during the Great Recession. During the post-recession period, only 2.8 percent of salaried workers received a nominal base wage cut. Again, for salaried workers, base wages are much less downwardly rigid during the Great Recession. While base wages were more downwardly flexible during the Great Recession for job-stayers, the fraction of workers receiving a zero nominal base wage change also increased for both salaried and hourly workers. Interestingly, the unconditional standard deviation of base wage changes fell slightly during the recession for all workers from 7.0 percent to 6.3 percent. In summary, overall nominal base wage adjustments fell during the Great Recession but downward adjustments increased.

Figure 11 shows time series trends in the probability of a nominal base wage increase (left panel) and a nominal base wage cut (right panel) for job-stayers by industry. During the Great Recession, manufacturing and construction were two of the hardest hit industries. Roughly 10 percent of construction workers and 8 percent of manufacturing workers who remained on their job received a year-over-year nominal base wage cut during 2009. The comparable numbers for retail and finance, insurance, and real estate (FIRE) were 6 and 3 percent, respectively. By 2012, continuing workers in all industries had a roughly 2 percent probability of receiving a nominal base wage cut. Note, the probability of a nominal base wage increase did not differ markedly across industries during the Great Recession. There are persistent level differences in the propensity of a nominal base wage increase across industries for job-stayers in all years. However, these differences remained relatively constant during the 2008-2016 period. These cross-industry patterns reinforce the time series patterns with respect to the state dependence of nominal base wage cuts of continuing workers. Not only were nominal base wage cuts more likely for job-stayers during the Great Recession, the propensity of nominal base wage cuts was highest in the industries hit hardest during the Great Recession. Firms in manufacturing and construction both were more likely to shed workers during the Great Recession and also were more likely to cut the base wages of the workers who remained with their firm.

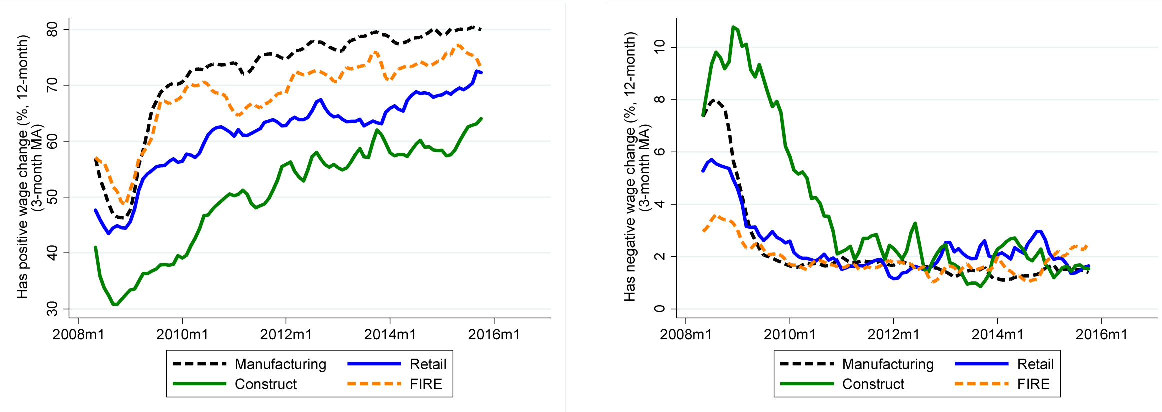
(2016).

Table 10: Summary of 12-Month Wage Change Distribution During and After the Great Recession, Job-Stayers and Job-Changers

	Job-Stayers		Job-Changers	
	2009-2010	2012-2016	2009-2010	2012-2016
All				
Prob of Negative Wage Change(%)	4.2	2.0	44.0	36.4
Prob of No Wage Change (%)	43.3	30.6	5.5	5.5
Prob of Positive Wage Change (%)	52.5	67.4	50.5	58.1
S.D. of Wage Change (%)	6.3	7.0	31.4	28.9
Hourly				
Prob of Negative Wage Change(%)	2.8	1.5	46.3	38.1
Prob of No Wage Change (%)	42.1	29.8	6.4	6.2
Prob of Positive Wage Change (%)	55.1	68.7	47.3	55.7
S.D. of Wage Change (%)	6.1	6.8	28.4	28.3
Salaried				
Prob of Negative Wage Change(%)	6.6	2.8	37.6	29.7
Prob of No Wage Change (%)	45.2	31.9	3.1	3.4
Prob of Positive Wage Change (%)	48.2	66.3	59.3	66.9
S.D. of Wage Change (%)	7.4	7.2	35.9	31.1

Note: Table shows the distribution of 12-month wage adjustment for job-stayers (columns 1 and 2) and job-changers (columns 3 and 4) over the cycle. The top panel shows results for a sample including both hourly and salaried workers while the bottom two panels show the results for hourly and salaried workers separately. For both job-changers and job-stayers, we show statistics for the period between May 2009 and December 2010 and the period between January 2012 through December 2016. The first two columns use our employee sample focusing on workers who remain continuously employed on their job for the entire twelve months between when the wage changes are measured. The last two columns use our job-changer sample and explore the 12 month change for workers who were employed at firm i in t and another firm j in $t+12$. All data are weighted to match the firm size $\times$ industry mix found in the BDS.

Figure 11: Time Series of Wage Changes by Industry, Job-Stayers



Panel A: Positive Change | Panel B: Negative Change

Note: Table shows the propensity to receive a 12-month wage increase (Panel A) and decrease (Panel B) for job-stayers over the cycle, broken out for select broad industry groups. This figure makes use of our employee sample, weighted to match the firm size distribution found in the BDS within each industry. Since the first month of our ADP data is May 2008, we may only observe 12-month wage changes beginning in May of 2009. "FIRE" refers to Finance, Insurance, and Real Estate.

The results in this subsection show that the composition of nominal base wage adjustment for job-stayers varies over the business cycle. Any model that assumes a constant hazard of base wage adjustments for job-stayers over the business cycle is at odds with the underlying wage setting data, and may lead to incorrect conclusions regarding the responsiveness of the economy to countercyclical monetary expansions.

7.2 Time Series Variation in Aggregate Nominal Wage Adjustments

As highlighted above, much of the flexibility in nominal base wage adjustments results from job-changers. The last two columns of Table 10 shows that the distribution of base wage adjustments for job-changers also varies over the business cycle. For the table, we report statistics of 12 month base wage changes for workers employed at firm i in t and then are subsequently employed at firm j in $t+12$.[36] During the Great Recession, 44 percent of workers who changed jobs received a nominal base wage decline. The comparable number during the recovery period was 36.4 percent. Like job-stayers, there was more downward nominal adjustment during the Great Recession. Some of the increased downward adjustment may

[36] In the Online Appendix, we also show quarterly changes in the base wages of job-changers. The quarterly base wage changes display very similar cyclical patterns. In the work below, we compute aggregate base wage adjustments - combining job-stayers and job-changers - at both the quarterly and aggregate frequencies.

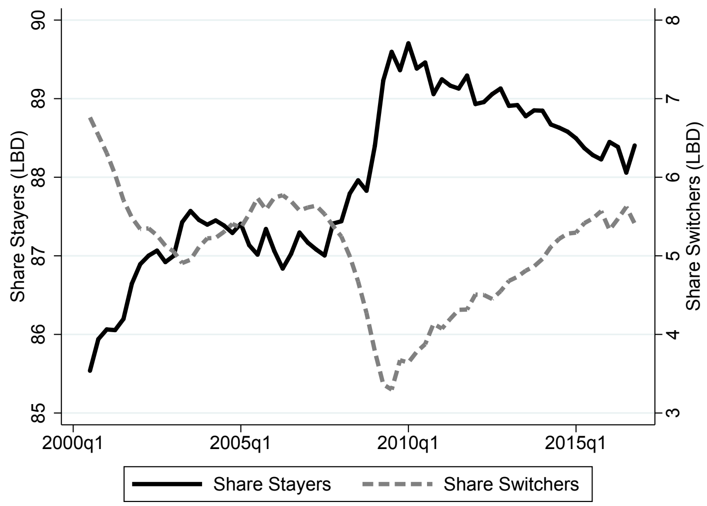
be the result of selection. Workers who transition jobs during the Great Recession may be systematically different than the workers who transition during non-recessionary times. Below, when we explicitly look at new hire wages, we discuss such selection issues in greater depth. Putting the potential issue of selection aside, it is interesting that the differential patterns of adjustment over the business cycle are roughly similar for both job-changers and job-stayers.

Aggregate nominal base wage flexibility is a function of both the base wage adjustments for job-stayers and job-changers. However, in order to measure the cyclical nature of aggregate wage adjustments, we also need to know how the composition of job-stayers relative to job-switchers evolves at business cycle frequencies. We again use data from the Census's Job-to-Job Flow Data (J2J) made from the underlying data of the LEHD. Figure 12 shows the quarterly share of job-stayers and job-switchers in the J2J data between 2000 and 2015. The difference between the sum of the two lines and one is the fraction of workers who left employment for longer non-employment spells during the quarter. During the Great Recession, the quarterly job-switching rate fell to 4 percent while during the 2012-2016 period the quarterly job-switching rate returned to a pre-recession level of about 5.1 percent. Job-staying rates were roughly the mirror image of job-changing rates. As above, we construct annual job changing rates by multiplying the quarterly rates by 4. Doing so implies that during the Great Recession 16 percent of workers switched jobs compared to roughly 20 percent during the recovery. When weighting the job-stayer and job-changer data, we ensure that 16 percent of workers were job-changers during the Great Recession and roughly 20 percent were job-changers during the recovery. Since job-changers receive nominal wage changes and cuts at a substantially higher rate than job-stayers, this composition effect therefore pushes towards lower aggregate flexibility during the recession, even if both changers and stayers observe less downward rigidity in recession periods.

The first two columns of Table 11 shows the cyclical patterns of aggregate nominal base wage adjustments combining data on both job-stayers and job-changers. As with Table 10, we break our sample into two periods: May 2009-December 2010 and January 2012-December 2016. Focusing on the annual aggregate nominal base wage adjustments, 10.4 percent of workers in the aggregate economy received a nominal base wage decline during the Great Recession. The comparable number during non-recession times was 8.5 percent. While downward adjustments were more common, upward adjustments were less common with only 52 percent of workers receiving a base wage increase during the 2009-2010 period. This is likely due to the composition effect noted above. The unconditional standard deviation of base wage changes was slightly lower during the Great Recession.

Downward nominal wage rigidity has received a substantial attention as an explanation

Figure 12: Time Series of the Share of Workers who are Stayers versus Switchers, LBD Job-to-Job Flows data



Note: Figure plots the quarterly share of workers who are job-stayers (left axis, solid black line) and job switchers (right axis, dashed gray line) in the LBD's Job-to-Job (J2J) flows data over the period 2000Q1 through 2016Q4.

Table 11: Key Moments of Aggregate Wage Change Distribution by Recession Period

	12-Month Base Wage		Modified Annual Earnings	
	2008-2010	2012-2016	2008-2010	2012-2016
Prob of Increase (%)	52.0	66.1	64.4	70.5
Prob of Cut (%)	10.4	8.1	24.0	20.3
Unconditional Mean Change (%)	3.0	5.0	4.08	5.61
Unconditional Median Change (%)	1.3	2.6	2.32	2.99
Unconditional Std Dev of Change (%)	11.7	12.2	17.2	16.4

Notes: Table reports key moments of the distribution of year-over-year changes in bas wages (columns 1 and 2) modified annual earnings - base pay plus bonuses - (columns 3 and 4) for the aggregate economy including the increased adjustment of job-changers. The samples differ slightly between the two different notions of wages. For the base wage results, we restrict the job-stayer part of the sample to include those who remain continuously employed with the same firm for 12 consecutive months. For the modified annual earnings results, we restrict the job-stayer part of the sample to include those who remain with the same firm for two consecutive calendar years. In both cases, we use our results from the 12-month changes in base wages for job-changers. We then aggregate job-changers and job-stayers by upweighting job-changers in order to match the ratio of job-changers to job-stayers observed in the LBD. See text for additional details.

for why aggregate wages did not fall more during the Great Recession. The results above show that 10.4 percent of workers did receive nominal wage cuts and another 37.6 percent received no nominal wage increase. Much of the downward adjustments occur through job-changers. Moreover, both job-stayers and job-changers experienced more nominal base wage declines during the Great Recession than during the 2012-2016 recovery. However, the job-changing propensity also fell during the Great Recession reducing some of the aggregate flexibility in nominal base wage adjustments. The results in Table 11 provide a set of moments for researchers to calibrate models to assess whether the moments of the base wage adjustment distribution can lead to sufficient rigidities to explain why aggregate wage growth did not fall more during the 2008-2012 period. Again, we stress the importance of considering measures of *aggregate* base wage flexibility when assessing such claims: both the level and trend of rigidity implied by the job-stayer sample is substantially different than those found in the aggregate economy.

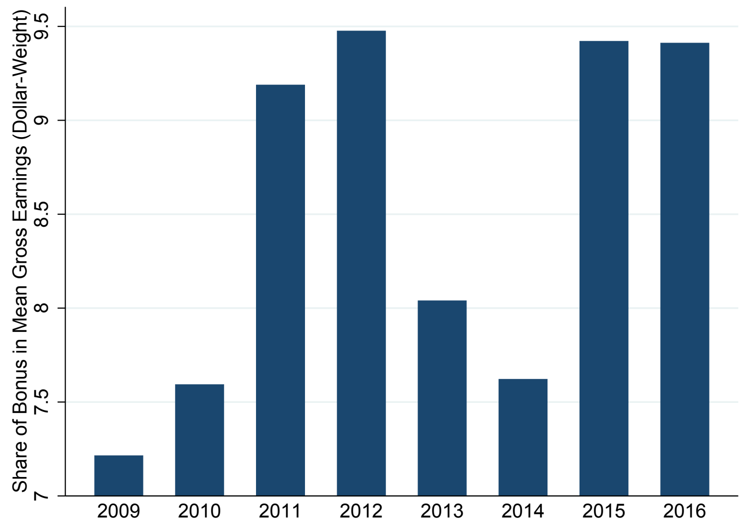
These results have been mirrored in a related literature measuring the cyclicality of the wages in order to study the potential influence of downward nominal wage rigidity on hiring contractions. Elsby et al. (2013) find a sluggish response of aggregate wages for men in the CPS around the Great Recession. This is *prima facie* consistent with the hypothesis that downward nominal wage rigidity constrains wage increases and hiring. However, they find little evidence for this elsewhere in the data. Like us, they find a substantial number of wage cuts, both in the CPS and in Great Britain's New Earnings Survey (NES), which is based on administrative payroll records. In addition, they find large wage cyclicality amongst women in the US, and in Great Britain, and conclude that downward wage rigidity is unlikely to be a major driver of quantity adjustments during the Great Recession.

7.3 Time Series Variation in Bonuses

Bonuses also vary with business cycle conditions. Figure 13 shows the share of aggregate bonuses over average aggregate gross earnings for non-commission workers over the 2009 to 2016 period. Specifically, we compute the bonus share of earnings in year t by computing average bonus income across all non-commission workers in year t and then dividing it by the average yearly gross earnings for all non-commission workers over the 2009-2016 period. The denominator of the ratio is fixed over time implying that all the variation in the ratio is due to variation in annual bonuses. The denominator just scales the per-worker annual bonus income in year t by the average annual earnings over the entire sample period.

A few things are of note from the figure. First, the share of bonus income out of total income was between 7 and 7.5 percent during 2009 and 2010 while it was between 9 and

Figure 13: Share of Gross Earnings in Bonus by Year, 12-month Job-Stayers, 2008-2016



9.5 percent during most other years of the recovery. Second, there was a dip in bonus income during 2013. This decline resulted from the acceleration of bonuses 2012 given an expectation in that Bush tax cuts would expire in 2013. As widely reported in the popular press, bonuses that were normally paid in early 2013 were shifted to late 2012 to minimize the tax burden.[37] Overall, the figures suggests that bonus income also declines when aggregate economic conditions deteriorate.

The final two columns of Table 11 highlight the cyclicality of Modified Annual Earnings (base earnings plus bonuses). Again, nominal wage declines are more common during recessions. During the recession years, 24 percent of workers saw reductions in their modified annual earnings, compared with 20.3 percent during the recovery period.

7.4 Within Firm Variation in Nominal Wage Adjustments

To further shed light on the extent to which nominal wage adjustments respond to firm-level shocks, we explore patterns in nominal wage adjustments by growing and contracting firms. To do so, we consider state dependence at the firm level by comparing moments of the wage change distributions for firms with differing levels of employment growth. We view this analysis as being reduced form and combining two potential effects. First, firms who experience negative employment growth should have been more likely to receive a negative

[37] We are also explored the low bonus share in 2014. The decline in the 2014 bonus share may be the result of IRS rulings in late 2013 affecting when bonuses can be deducted relative to when the bonuses are actually paid. While we have found many articles discussing the IRS rulings, we have not found popular press articles discussing firms shifting the timing of their bonuses around in response to the ruling.

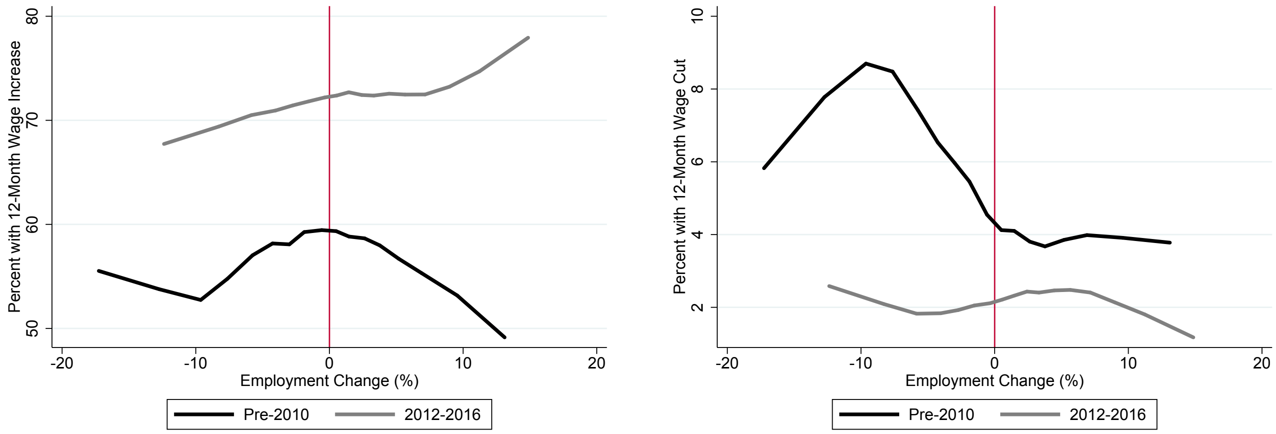
firm-level shock. Firms receiving negative shocks are likely to adjust their labor inputs on multiple margins. As a result, firms experiencing negative employment growth may also be more likely to cut the wages of their existing workers and be less likely to give their existing workers a wage increase. Second, there is some trade-off between wage adjustments and employment adjustments within a firm conditional receiving a shock of a given size. For example, a firm who receives a given size shock may choose to cut more of the wages of their workers thereby reducing the number of workers they have to layoff. Such differences in the extent to which firms are willing to cut the wages of their workers conditional on a given shock could result in a negative relationship between firm employment growth and firm propensity to cut nominal wages.

Figure 14 plots the propensity for a firm to increase their workers nominal base wages (left panel) and the propensity for a firm to cut their workers' nominal base wages (right panel) as a function of observed firm size growth. To make this figure, we use our firm-level sample. All firm-level changes are at the annual level. As a result, the x-axis is the observed change in firm employment between months $t-12$ and t, while the y-axis is the share of the firm's workers which had their wages adjusted (up or down) between months t and $t+12$. Each panel has two lines, reflecting LOWESS smoothed regression lines. The LOWESS estimator provides a non-parametric estimate of the conditional expectation function of the propensity to receive a wage change conditional on the firm's growth rate. The darker line restricts our firm samples only to firm behavior during the Great Recession (2009-2010) while the lighter line restricts the sample to firm behavior during the recovery (2012-2016).

While not overly surprising, firms that grew were slightly more likely than firms that shrank to increase their workers wages during the 2012-2016. Specifically, firms that grew by 10 percent between 2012 and 2016 increased about 73 percent of their workers wages while firms that contracted by 10 percent during that period increased only about 68 percent of their workers wages. What is more surprising, however, is that during the Great Recession there was no systematic relationship between firm size growth and the propensity to rise workers wages. Across all firms, the propensity to raise wages was systematically lower during the Great Recession regardless of firm size growth. Additionally, contracting firms were again slightly less likely to raise their workers wages relatively to firms whose size remained constant. However, growing firms not that different in their propensity relative to contracting firms.

During the Great Recession, however, contracting firms were much more likely to cut the nominal wages of their workers compared to firms that were stagnant or growing. Firms whose employment fell by 10 percent over the year during the Great Recession cut roughly 8 percent of their worker's wages. However, growing firms cut only 4 percent of their worker's

Figure 14: Probability of Wage Changes by Firm Growth Status



Panel A: Pr{Wage Increase} Panel A: Pr{Wage Decrease}

Note: Figure Locally-Weighted Scatterplot Smoothing (LOWESS) estimates of the relationship between the probability that a worker receives a wage increase (Panel A) or decrease (Panel B) and the firm's backward-looking year-over-year growth rate. The black line plots the patterns for the recession period of May 2009 through December 2010, while the gray line shows the conditional expectation function for the recover period, defined as January 2012 through December 2016. Our firm sample is used to construct this figure, and weighted to match the BDS' firm size $\times$ industry mix. Firm size is calculated *after* firm growth is taken into account.

wages. The propensity to cut wages again appears highly state dependent. The right panel of Figure 14 also shows another interesting fact. During non-recession times, there is no systematic relationship between firm size growth and the propensity to cut a worker's wage. Contracting firms in 2012-2016 were no more likely to cut nominal wages than growing firms. Moreover, growing firms during the Great Recession were much more likely to cut the nominal wages of their workers than growing firms during the recovery. This pattern would be consistent with aggregate conditions during the Great Recession being such that it is easier for any firm to cut the nominal wage of their workers when many other firms are also doing so.

The evidence presented in this section shows an important interaction between idiosyncratic and aggregate conditions for determining on-the-job wage adjustment patterns. This suggests that the value of workers' outside options are important for realized wage rigidity, a point which has been raised in, for instance, Christiano et al. (2015). The evidence here supports the hypothesis of state dependence in wage setting, which yields procyclical downward rigidity, and countercyclical upward rigidity. Further research is required to assess the impact of idiosyncratic firm shocks on aggregate wage movements over the cycle.

8 The Cyclicality of New Hire Wages

We end the paper by discussing the cyclicality of new hire wages. In many macro models, it is the flexibility of new hire wages that is important for thinking about aggregate employment fluctuations.[38] Measuring the cyclicality of new hire wages is complicated by two empirical challenges. First, the selection of workers who find new jobs may change over the business cycle. If lower quality workers are more likely to be displaced during a recession, wages of new hires may look lower in recessions than in booms but this would not speak to the flexibility of new hires. Second, if looking from firm side data, firms may change the type of workers they hire in a recession. If firms hire higher quality workers in a recession, this could potentially mask the cyclicality of the wages of new hires.

We exploit the detailed nature of our data to potentially circumvent these issues. Throughout this analysis, we focus on our job-changer sample. Define $w^i_{j,t-1}$ as the base wage (measured in dollars per hour) of worker i who works at firm j in year $t-1$. As above, for salaried workers, we assume that they work 40 hours per week when making this measure. We treat this as a measure of a worker's quality in $t-1$. Define $p^i_{j',t}$ as the new within firm base wage percentile of worker i when they migrate to firm j' in year $t+1$. A value of $p^i_{j',t} = 30$ means that worker i enters firm j' at the 30th percentile of firm j''s wage distribution. Given that we are looking at yearly transitions, the wage measurements are 12 months apart.

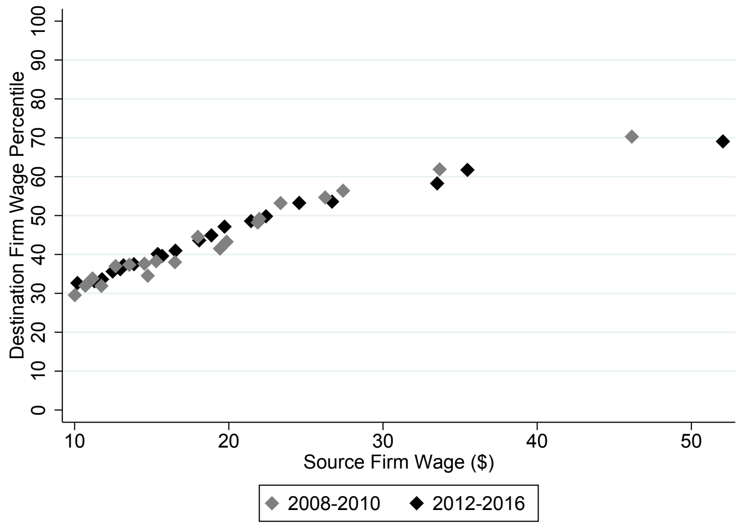
The dark diamonds in Figure 15 plot the relationship between $w^i_{j,t-1}$ and $p^i_{j',t}$ during the 2012-2016 recovery period. Instead of plotting each observation separately, we bin the data into 20 bins of the $w_{j,t-1}$ distribution where each bin contains 5 percent of the job-changer distribution during the recovery period. For example, the figure shows that during the 2012-2016 period, job-changers who made about \$15 per hour entered their new firm at roughly the 30th percentile of the new firm's base wage distribution on average. Not surprisingly, this line is upward sloping. As a worker earns more, they are more likely to systematically to enter firms at higher percentiles within the new firm's base wage distribution.

To explore the cyclicality of new hire wages partially controlling for selection, we see how the relationship between $w^i_{j,t-1}$ and $p^i_{j',t}$ changes over the business cycle. If the wages of new hires are more flexible, we should observe new hires entering their new firms at lower points in their firm wage distribution during recessions. Conditioning on the worker's prior wage controls - at least partially - for the worker's quality. If firms are more able to adjust the wages of their new hires relative to their incumbent workers during the recession, we should see the relationship between $w^i_{j,t-1}$ and $p^i_{j',t}$ shift down during the recession.

The light diamonds in Figure 15 plot the relationship between $w^i_{j,t-1}$ and $p^i_{j',t}$ during

[38] See, for example, Gertler et al. (2016) and the cites within.

Figure 15: Source Firm Wage vs Destination Firm Wage Percentile, Job-Changers, By Recession Period



the 2009-2010 recession period. Notice, the relationship between initial worker wage and their subsequent entry point into their new firm distribution is nearly identical during the recession and non-recession years. Indeed there is no statistically significant difference in the behavior of new hires in the recession conditional on observables. This suggests that the wages of new hires are roughly as equally flexible as the wages of incumbent workers at business cycle frequencies. This is consistent with the patterns shown in Table 10 showing increased downward flexibility of both job-stayers and job-changers during the Great Recession. The patterns are also consistent with the recent findings in Hazell and Taska (2018) showing that posted wages for new hires seem as equally downward rigid as the actual base wages of incumbent workers. These results do not imply that new hire base wages are not flexible; rather, they suggest that the new hire wages are equally flexible as the base wages of incumbent workers.

While the results in Figure 15 are illustrative, there may be additional selection that occurs at business cycle frequencies that are contaminating our conclusions. First, it is possible that the distribution of base wages of incumbent workers is shifting over the business cycle. If firms are more likely to shed lower wage workers during recessions, this would bias us towards finding that the relationship between $w^i_{j,t-1}$ and $p^i_{j',t}$ shift down during the recession. Given we are finding no such shift, this mitigates the concern that such selection is biasing our results. However, if firms systematically shed higher wage workers during the recession, we cannot rule out that the wages of new hires are systematically more flexible than incumbent workers. Second, it is possible that job-changers alter the type of firms they migrate to during recessions. If workers move to worse firms, they could enter at a higher point in the wage distribution. This type of selection could counteract that their wages are really more flexible. We find no evidence of such selection. In the Online Appendix, we plot the relationship between $w^i_{j,t-1}$ and $\bar{P}^i_{j',t}$ where $\bar{P}^i_{j',t}$ is the average percentile of firm j' in the average wage distribution *across* all firms in period t. Specifically, $\bar{P}_{j',t} = 50$ means that firm j' is at the median of all firms in period t with respect to the average wage of its work force. As seen in the appendix, we find no systematic shift in the average quality of firms that a worker of a given wage migrates to at business cycle frequencies.

9 Conclusion

This paper measures nominal wage adjustments for millions of US workers during the 2008 to 2016 period using administrative payroll records. Measurement error in household surveys and missing hours in administrative earnings data have prevented the development of a reliably measured set of moments of the distribution of worker compensation adjustment. Exploiting payroll data from the largest payroll processing company in the US gives measures of workers per-period contract rate as well as other forms of worker compensation without error. We define a worker's base wage as either being their per period contracted salary (for salaried workers) or their hourly contracted wage (for hourly workers). For the median worker, about 97 percent of their annual gross earnings (excluding fringe benefits) accrues from their base wages suggesting that base wages are by far the most important component of compensation for most workers. However, there exists a subset of workers who only receive about 80 percent of their compensation from base wages. For these workers other forms of compensation, like bonuses, are also important.

Some of our key findings are qualitatively similar to the existing literature. However, the magnitudes are often quantitatively quite different. Given our extensive dataset, we also provide a set of additional results that are new to the literature. In particular, we estimate that over our entire sample period, roughly one-third of workers receive no nominal base wage change over a 12 month period and only about 2 percent of workers receive a nominal base wage cut. The extreme apparent downward nominal wage rigidity for base wages is the first main take-away of the paper. The patterns of nominal base wage adjustment are strikingly similar for workers who are paid commissions, for workers who receive bonuses, for hourly and salaried workers, for hourly workers whose hours worked varies from week to week, and for workers at various points of the base wage distribution.

However, despite the fact that base contract wages are essentially never cut, there is a lot of downward flexibility for worker wages in the aggregate. Bonus payments to workers vary greatly from year to year. Specifically, we document that roughly 16 percent of workers receive an annual decline in wages on-the-job, inclusive of bonus payments. Bonus payments are far more important for individuals at the top of the wage distribution. For workers at the bottom of the wage distribution, bonuses provide little flexibility because such workers infrequently receive bonuses. Collectively, the evidence is that compensation is relatively more flexible when the use of bonuses are considered. Highlighting these additional margins of flexibility is an additional contribution of the paper. The differential adjustment patterns of various compensation forms urges careful theoretical consideration over the correct notion of "wage rigidity." The evidence presented in this paper suggests that workers *contracts*, which specify base wages and a bonus schedule, may be quite rigid, particularly on the downside. However, workers' *realized compensation*, which includes both base pay and bonuses, may be quite flexible, as stipulated by the (explicit or implicit) contract governing their employment relationship.

Another key result of our paper is that job-changers provide an additional form of wage flexibility for the aggregate economy. Approximately 40 percent of job-changers receive a nominal base wage decline within a year. This margin is key to determining the role that nominal wage rigidity plays in explaining aggregate wage dynamics. Wages in the aggregate are a combination of the wage movements of both job-stayers and job-changers. The fact that job-changers have downwardly flexible wages provides an additional margin of adjustment when interpreting aggregate wage dynamics. In summary, the combination of bonus adjustments and job-changers imply that aggregate wages are more flexible than one would infer by looking only at base contract wages.

Finally, we show that worker wage adjustments are state dependent. During the Great Recession, 6 percent of job-stayers on average received a base wage cut. In some industries, upwards of 10 percent of job-stayers received a base wage cut. Worker wage growth is procyclical for job-stayers. The state dependence is also shown using firm-level employment growth variation with shrinking firms being much more likely to cut nominal wages relative to growing firms, particularly during the Great Recession. Moreover, during the Great Recession, growing firms were much more likely to cut the wages of their workers than similarly growing firms during the 2012-2016 recovery. We also documented that new hire wages seem to adjust similarly as incumbent worker wages at business cycle frequencies.

The goal of the paper is to provide a set of moments that can be used to both guide and discipline models of nominal wage adjustments. The nominal wage flexibility we estimate using detailed micro data is broadly consistent with the flexibility of wages estimated in Beraja et al. (2016) using cross-region variation. Beraja et al. (2016) show that wage adjustments of the sort we identified cannot explain why aggregate wage growth remained robust during the Great Recession. However, one drawback of the model put forth by Beraja et al. (2016) is that it has no role for the type of asymmetry in nominal wage adjustments that this paper highlights. Going forward, research should explore whether the asymmetry in nominal wage adjustments substantially alters the conclusions of models with wage rigidity. Our state dependence results also suggest reason to move away from Calvo models of wage adjustment, which are prevalent in many modern New Keynesian models, and instead develop menu cost models of wage adjustment. Finally, our results highlight that different types of compensation have different degrees of flexibility and the compensation composition differs markedly across workers. Understanding what drives such differences and whether or not such differences have macro implications is a potentially fruitful area for future work.

Most of our results are useful for disciplining static models of wage adjustments. However, workers and firms may make dynamic contracts. In such models, a firm may hire a worker based on the present value of payments made to the worker over the expected duration of the employment relationship. Both Kudlyak (2014) and Basu and House (2016) highlight the importance of the flexibility of the user cost of hiring a worker. For space reasons, we did not include measures of user cost adjustments in our paper. However, we believe that going forward the ADP data could be useful in measuring such concepts, especially as the length of the panel grows.

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Online Appendix: "Aggregate Nominal Wage Adjustments: New Evidence from Administrative Payroll Data" (Not for Publication - In Progress)

Appendix A Benchmarking ADP Data

Table A1 shows some additional summary statistics for our employee sample pooling across all years (column 1) and for selected individual years (columns 2-4). In particular, we show statistics for 2008 (our first year of data), 2012 (a middle year of data), and 2016 (our last year of data). As discussed in the Online Appendix, the age, sex, and tenure distributions in our ADP sample matches well the age, sex, and tenure distributions of workers in nationally representative surveys such as the Current Population Survey (CPS). About one-fifth of our sample is paid weekly while three-quarters is paid bi-weekly. Less than five percent are paid monthly.

For our sample, roughly 64 percent are paid hourly with the remaining 36 percent being classified as salaried workers. According to data from the CPS monthly supplements, only 57 percent of employed workers in the U.S. between the ages of 21 and 60 report being paid hourly during this time period. The difference between the CPS and ADP data may arise as the distinction between hourly and salaried workers is sometimes unclear within the ADP dataset. Some hourly workers in the ADP data are automatically entered as having worked 40 hours each week at a given hourly wage. These workers are therefore classified as hourly wage workers. However, on many levels, these workers operate as if they were salaried: their actual hours are never recorded and their hourly contract wage is just their weekly salary divided by 40. Furthermore, these workers may report being salaried in survey data such as the CPS. For our purposes, however, we consider these workers as hourly, matching the ADP-provided definition. Additionally, with respect to wage changes, all changes in per-period earnings will be associated with a change in the hourly wage given that from the payroll system's perspective hours are fixed at 40 hours per week. Despite these differences in classification, the fraction reporting being paid hourly in the ADP data is similar to the CPS averages.

Given that ADP is growing over time, so too is our sample. Of our 1 million workers, only 202,000 are in our sample in 2008 while 343,000 are in our sample in 2016. Despite the growing sample size over time as ADP expands its business, the demographic composition

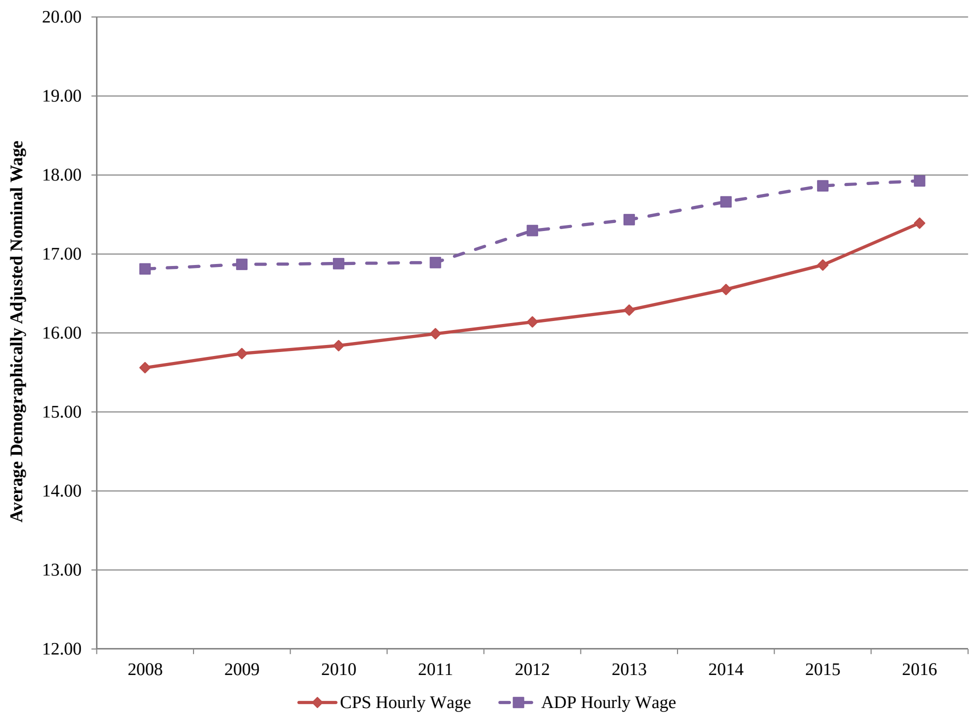
Table A1: Statistics for Employee Sample, Selected Years

	All	2008	2012	2016
Number of Workers	1,000,000	202,329	341,726	342,991
Number of Firms	89,350	89,350	89,350	89,350
Number of Observations	22,642,878	1,319,797	2,744,414	2,778,947
Age 21-30 (%)	24.9	25.2	23.9	26.4
Age 31-40 (%)	23.6	24.5	23.4	24.1
Age 41-50 (%)	23.3	24.4	23.7	21.7
Age 51-60 (%)	20.8	18.6	21.5	20.7
% Male	54.1	54.3	54.0	55.0
Average Tenure	66.8	73.2	67.8	61.4
% Paid Weekly	20.5	21.3	21.2	20.6
% Paid Bi-Weekly/Semi-Monthly	76.3	75.5	75.5	75.5
% Paid Monthly	3.3	3.1	3.3	3.8
% Hourly	65.2	64.2	65.4	65.0

of workers is essentially constant over time. One distinction is that average tenure is falling over time. Given that the Great Recession occurred early in our sample, it is not surprising that average tenure fell as many workers became displaced during the recession.

Figure A1 compares the average hourly wages for hourly workers in our ADP sample to average hourly wages in a similarly defined sample of 21-60 year olds in the CPS. To get the hourly wage in the CPS, we use data from the outgoing rotation of respondents from the CPS monthly surveys. In the outgoing rotation, workers are asked if they are paid hourly and if so their hourly wage. For hourly workers, hourly wages are slightly higher in the ADP sample than in the CPS. This may be the result of the fact that, as discussed above, some salaried workers are classified as being hourly within the ADP data. Additionally, the ADP dataset does not include workers at small firms who are, on average, paid slightly less than workers at larger firms. The differences, however, between the ADP sample and the CPS sample are small and the trends are very similar suggesting that the ADP data is roughly representative of the entire U.S. population.

Figure A1: Hourly Wage Comparison ADP vs. CPS, 2008-2016



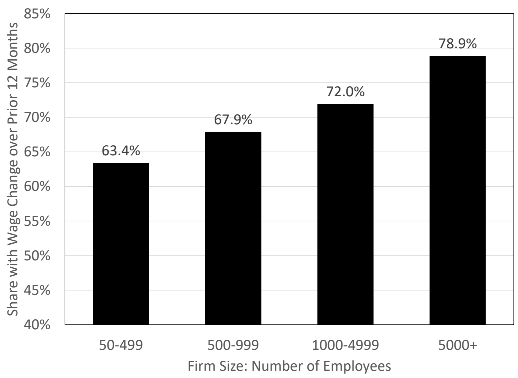
Note: Figure shows the average hourly wage for hourly workers in our ADP sample and in a similarly defined sample of CPS respondents. Specifically, the CPS sample is restricted to workers between the ages of 21 and 60 who are paid hourly. For the average hourly wage for workers paid hourly in the CPS, we use data from the monthly outgoing rotation files from the CPS. In the outgoing rotation files, workers paid hourly are asked to report their hourly wage. The ADP data is weighted so it is representative of the aggregate industry $\times$ size distribution. The CPS data is weighted by the corresponding survey weights for the respective samples.

Appendix B Nominal Wage Adjustments for Job-Stayers by Firm Size and Industry

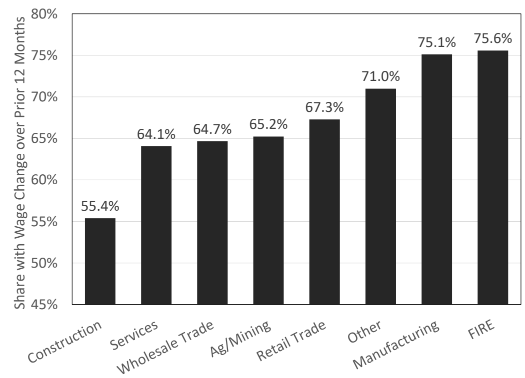
Figure A2 shows the distribution of annual wage changes over the 2008-2016 period by firm size and industry. The top panel shows patterns for hourly workers while the bottom patterns for salaried workers. The figure shows that wage changes are monotonically increasing in firm size for both hourly and salaried workers. In a given 12-month period, 63.4% of hourly workers and 66.5% of salaried workers in firms with under 500 employees receive a wage change. The comparable numbers for firms with 5000+ employees are 78.9% and 76.8%, respectively. These results complement the finding in the literature documenting that workers receive higher wages in larger firms (Brown and Medoff, 1989). Not only are workers in large firms receiving higher wages they also have a higher frequency of nominal wage adjustments. All of the variation across firm size groups is in the propensity to receive a nominal wage increase. While nominal wage cuts are rare for all workers, there is no systematic variation in the propensity of a nominal wage cut with firm size. Figure A2 also shows that there is a fair degree of heterogeneity across industries with respect to wage changes. For example, both hourly and salaried workers in the manufacturing industry are much more likely to receive a wage change than workers in construction during our sample period.

Given that firms within different industries also differ by size, a natural question is how much of the variation across industries is due to differences is firm size. To assess this, we regressed the probability of a nominal wage change during a given year on a vector of firm size dummies and a vector of industry dummies. We also included a vector of additional controls including a quadratic in worker age, a quadratic in worker tenure, an indicator of whether the worker is paid hourly, and a vector of state of residence $\times$ month-year fixed effects. We also ran a version of the regression replacing the dependent variable with either the probability of a nominal wage increase during the year or the probability of a nominal wage cut during the year. The full results of these regressions are shown in the Online Appendix accompanying the paper. The results of the regression still show that there is a large and statistically significant gradient between firm size and the propensity of a nominal wage change. Workers in firms with over 5,000 employees are 10 percentage points more likely to experience a nominal wage change than workers in firms with 50-499 employees. Likewise, workers in the manufacturing sector were 7 percentage points more likely to receive a nominal wage change relative to workers in the construction or retail trade industries, conditional on observables.

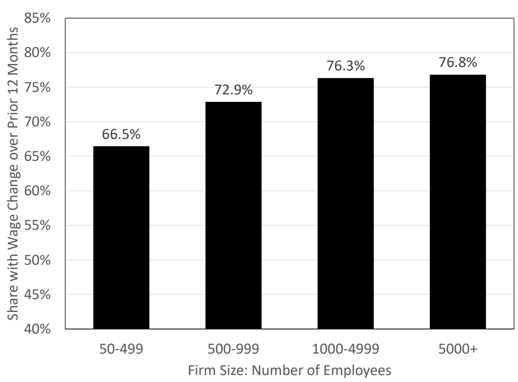
Figure A2: Share with Wage Change by Firm Size and Industry, All Years



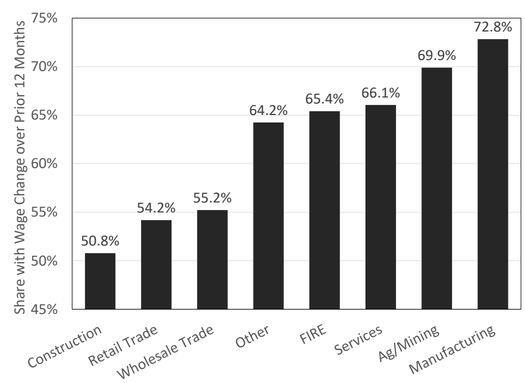
Panel A: Hourly Workers by Size



Panel B: Hourly Workers by Industry



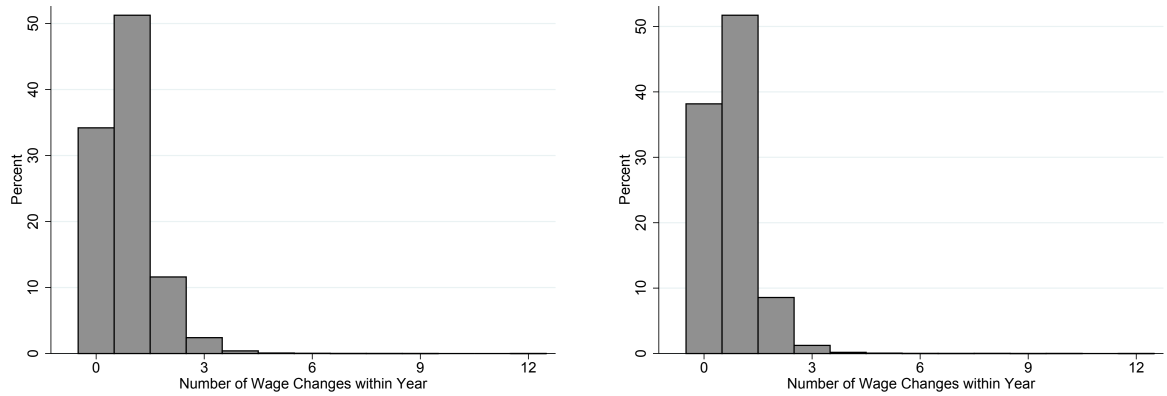
Panel C: Salaried Workers by Size



Panel D: Salaried Workers by Industry

Note: Figure shows the probability of receiving a wage change by firm size and industry for a sample of job-stayers in the ADP data between 2008 and 2016. For this figure, we use our employee sample, and separately plot the patterns for hourly workers (Panels A and B) and salaried workers (Panels C and D). All data are weighted to be nationally representative of sample of workers working in firms with more than 50 employees.

Figure A3: Number of Nominal Wage Changes over 12 month period, Job-Stayer Sample



Panel A: Hourly Workers Panel B: Salaried Workers

Note: Table shows the average number of nominal wage changes for hourly workers (left panel) and salaried workers (right panel). We use our employee sample for this analysis and restrict our sample to those workers who remain continuously employed with the same firm during a 12 month calendar year. We use all data between 2008 and 2012 and average over the calendar years.

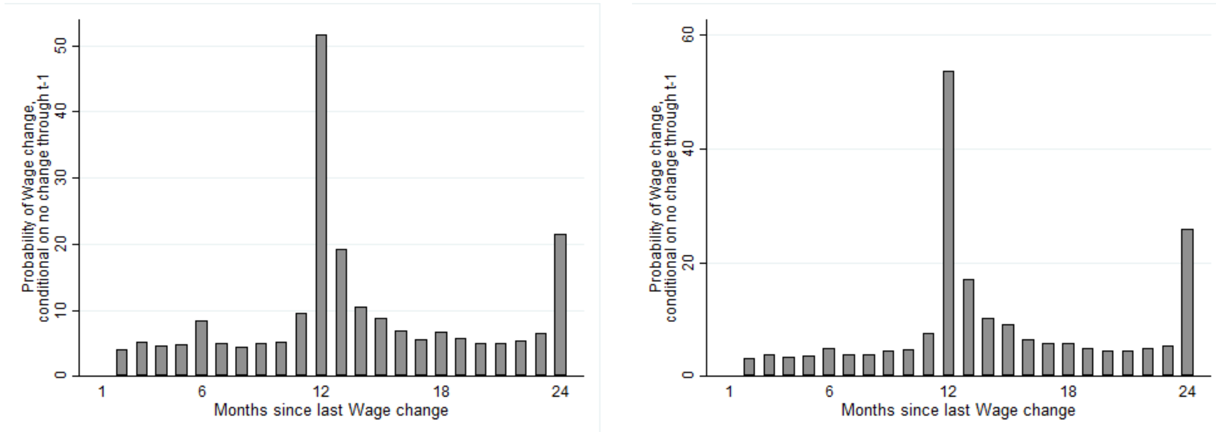
Appendix C Time Dependence in Nominal Wage Adjustments, Job-Stayers

Many modern macro models assume some time dependence in wage setting. For example, Taylor (1979, 1980) emphasizes that staggered wage contracts can amplify business cycle persistence in response to aggregate shocks. New Keynesian macro models in the spirit of Christiano et al. (2005) use aCalvo (1983) model of wage setting. In this sub-section, we use our detailed micro data to explore evidence of time dependence in wage adjustment for our sample of job-stayers. The purpose of doing so is two-fold. First, this section provides some background summary statistics on the frequency and nature of wage adjustment for job-stayers. Second, the presence of time dependence in wage setting informs the models of wage setting that should be considered in labor and macroeconomics going forwards.

Figure A3 plots the average number of wage changes during a given year for workers in our employee sample. As seen from Table 5, roughly 35 percent of job-stayers receive no wage change during a 12 month period. Over 50 percent of both hourly and salaried workers receive exactly one wage change during a 12 month period where they remained continuously on the job. Between 10 and 15 percent of job-stayers receive multiple wage changes during a given year. The take away from Figure A3 is that roughly 90 percent of job-stayers receive either zero or one nominal wage change during a given year. Multiple nominal wage changes within a year are rare for continuing employees who remain on the same job.

To begin formally studying time dependence in wage setting, we exploit the individual

Figure A4: Hazard Function of Wage Change, Job-Stayers



Panel A: Hourly Workers Panel B: Salaried Workers

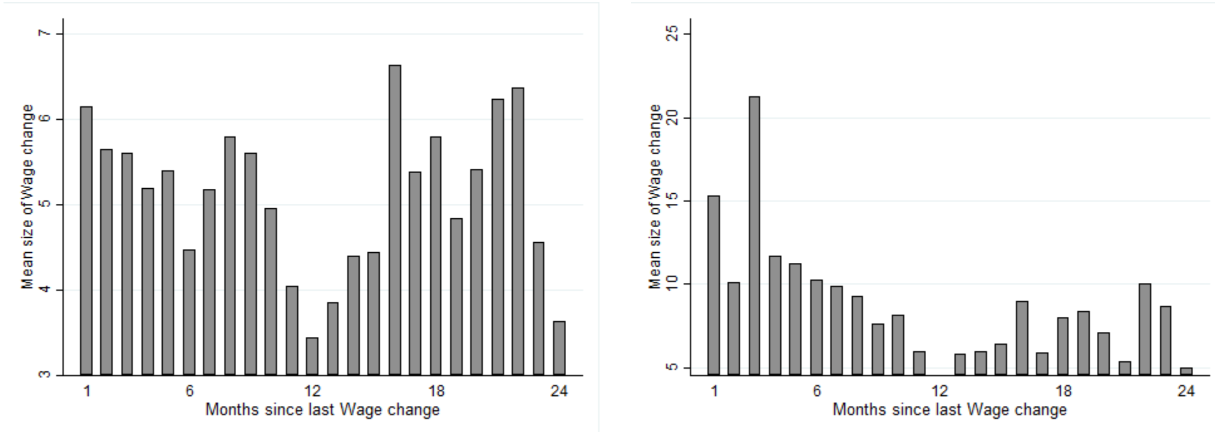
Note: Figure shows the hazard rate of a wage change between $t-1$ and t conditional on surviving to t without a wage change at the same firm. Sample only includes individuals with at least two wage changes. We use all data between 2008 and 2016 for this analysis, and weight the data to be representative of the firm size × industry mix in the BDS.

level micro data and estimate an individual duration model of wage changes. Figure A4 plots the resulting hazard functions of wage adjustment for the subset of job-staying employees who experience at least two wage changes over our sample period. Specifically, the figure shows the probability of a one month wage change between $t-1$ and t conditional on the worker surviving to month t without a wage change at the same firm.

The figure rejects the Calvo prediction that the probability of wage change is constant over time at the individual level for job-stayers. In most months, the probability of a wage change is roughly constant at about 3-4%. However, roughly 12 months after the last wage increase, individuals are much more likely to get another wage increase. Conditional on making it to month 11 with no wage change, there is over a 50% probability than an individual gets a wage increase in month 12. Note, given a little bit of calendar variation, there are small spikes at 11 and 13 months as well. We also see another spike in the hazard at 24 months and a more modest spike at 36 months. Moving away from a hazard analysis, we can define a sample of individuals who remained on their job for the next 18 months after a prior wage change. We can then ask how many of these workers got their next wage change 11-13 months later. Of consistently employed workers, 30% receive their next wage change exactly one year after their prior wage change.

Figure A4 provides some evidence of time dependence in wage adjustment. The majority of wage changes occur annually. However, basic models of purely time dependent wage setting have predictions regarding the average size of wage changes. Under standard productivity

Figure A5: Mean Size of Wage Changes by Time Since Last Change, Job-Stayers



Panel A: Hourly Workers Panel B: Salaried Workers

Note: Figure shows the mean size of wage increases for workers receiving a wage increase t months after their last wage change. Sample only includes individuals with at least two wage changes. Additionally, we restrict our analysis to the job-stayer sample.

processes with positive drift, individuals who are able to renegotiate their wage every month would negotiate smaller increases in their wages than those who renegotiate only once per year, on average. As a result, those who wait longer between wage changes should observe larger average changes in absolute value. We explore this prediction next.

Figure A5 shows the average size of the wage change for job-stayers by the time since last wage change. Since the vast majority of wage changes for job-stayers are positive, this figure only includes workers who received a positive wage change. While most wage changes occur at 12 month frequencies, Figure A5 shows that the size of the wage changes at these annual frequencies are much smaller than wage changes that occur at other times of the year. These predictions are not consistent with a standard Calvo (or Taylor) model at the individual level. However, the patterns could be consistent with a broader model of selection. If the workers who get these wage changes that occur off-cycle are positively selected in some way, this could explain why they receive higher wage increases. For example, if the worker receives an outside offer, the firm may have to raise the worker's wage earlier than their annual cycle in order to retain the worker. Or, if a worker is promoted internally and the promotions are distributed throughout the year, it is not surprising that workers who receive a wage change off cycle also get larger wage changes.

Figure A6 shows the time dependence in wage setting at the firm level. For this analysis, we use our sample of 3,000 unique firms. We restrict the firm-level sample to only include firms who remain in the sample of all 12 months during a given calendar year. Then, for each firm-year pair, we compute the fraction of workers who received a nominal wage change during each calendar month. We then rank the months within a given firm-year pair from the month with the highest fraction of nominal wage changes to the month with the lowest fraction of nominal wage changes. For example, for some firms the highest month may be September while for other firms the highest month may be January. We then take the simple average probability of a worker receiving a wage change across firm-year pairs for each ranked month. [39]

The figure shows that when a firm tends to adjust wages, it makes all their wage adjustments during one particular month of a given year. For example, a typical firm adjusts 50 percent of their workers wages in the month where they make the most wage changes. Given that only about 65 percent of workers get a wage change (in the population as a whole) and the fact that we are averaging over firms and not workers, the figure suggest that firms do most of their wage changes in one month out of the year.[40] As a point of contrast, firms only adjust roughly 10 percent of their workers wages in the second highest ranked month. The fact that the share of wages adjusted are roughly flat between the second highest ranked month and the 12 highest ranked month is consistent with the worker data where some adjustments are occurring off-cycle at a roughly constant hazard. These changes are likely due to promotions and/or the response to outside offers.

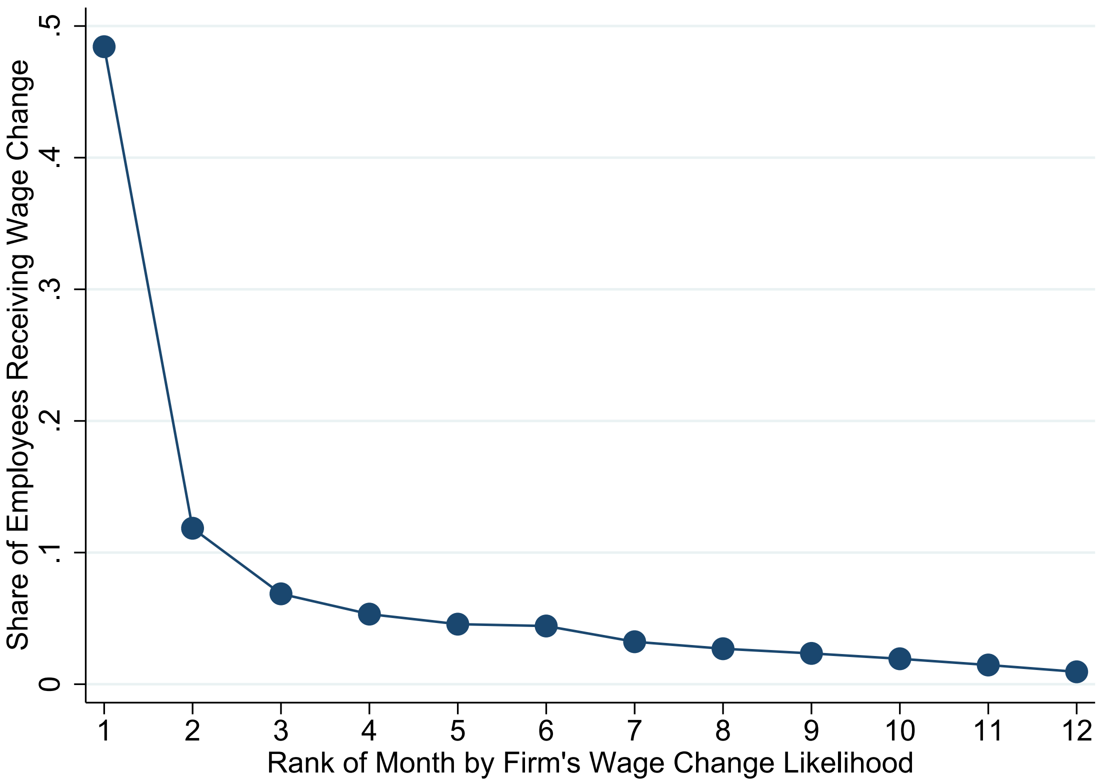
While the Calvo predictions may be rejected at the individual and firm level, Calvo may still be a good approximation for the aggregate macro economy if firms stagger the months in which they adjust wages. Indeed, this is the underlying intuition behind the staggered wage contract model. Instead of each individual probabilistically getting a wage change each period, individuals deterministically get a wage changed at a fixed frequency but a constant fraction of the wage contracts adjust each period. To see whether Calvo is a good approximation for job-stayers in the aggregate economy, we explore the extent to which wage changes are coordinated within a given calendar month.

Figure A7 shows the probability of wage changes by calendar month pooling together hourly and salaried workers. For this analysis, we return to our employee sample and focus only job-stayers. The figure shows some slight seasonality in the data. The probability that a worker receives a wage change is highest in January. The next highest months are the beginning months of each calendar quarter (April, July and October). However, these

[39]We also restrict our sample to only firm-year pairs where the firm adjusted at least 25 percent of their workers wages at some point during the calendar year. We do this to focus on firms who are adjusting wages to avoid a problem with firms no wages during the year. This restriction is not too binding as 91% of firm-year pairs in our sample adjusted at least 25 percent of their workers wages during the year.

[40]This observation represents the labor market analogy to the price-setting rule employed in Midrigan (2011) in which multi-product firms enjoy economies of scale in coordinated output price adjustment.

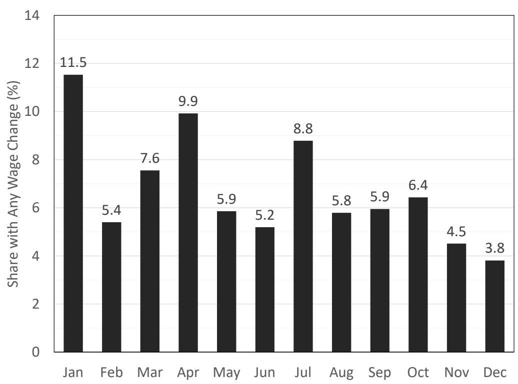
Figure A6: Share Receiving Wage Change in Firm's Months with Most Wage Changes, Firm-Level Data



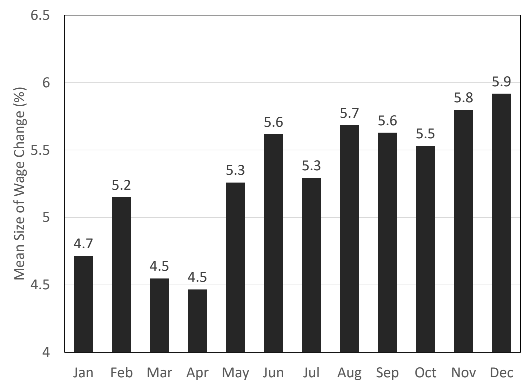
Note: Figure uses data from our firm sample. We restrict the sample to include only firms who remain consistently in the sample during a given calendar year. We then compute for each calendar month within a firm-year pair, the fraction of workers who received a nominal wage change during that month. We then rank the months within a given firm-year pair from highest month of wage changes to lowest month of wage changes. We then take the simple average across all firm-year pairs for each month rank. When making the figure, we restrict our analysis to only those firms who adjusted at least 25 percent of their workers wages at some point during the calendar year.

differences mostly wash out at the quarterly frequency. 23.4 percent of workers receive a wage change in the first quarter of the year while 21.1 and 21.5 percent of workers receive a wage change in the second and third quarters. Only 16.6 percent of workers receive a wage change in the last quarter of the year.

Figure A7: Seasonality in Wage Changes, Job-Stayers, All Years



Panel A: Pr{Change}



Panel B: Mean Change Size

Note: Figure plots moments of the wage change distribution in each calendar month, averaged over our full sample of job-stayers pooled between 2008 and 2016. Panel A plots the probability of adjustment, while Panel B plots the mean size of a wage change, conditional on the change occurring. This figure combines hourly and salaried workers.

Overall, the evidence presented in this section shows strong evidence of time dependence in wage adjustment. The majority of wage changes occur annually, usually at the beginning of a firm's fiscal year - either in January, April, or July. However, there is a roughly constant probability of wage adjustment across the four quarters of the year, suggesting that models of Calvo adjustment may be a reasonable approximation of the wage adjustment process. However, as we will document in Section 7, wage adjustment appears to be state dependent. Modelers seeking to use a Calvo wage adjustment process should consider simple extensions, such as incorporating an asymmetric probability of wage cuts and increases (see, e.g. Schmitt-Grohé and Uribe (2012)).

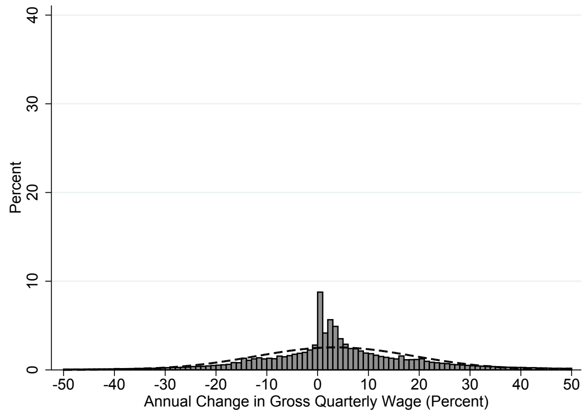
Appendix D Variation in Annual Earnings and Annual Earnings Per Hour

To illustrate the point that measurement error in hours worked can significantly alter patterns of wage flexibility in administrative datasets, we treat our data similarly to that of other administrative data sources. In particularly, we forgo the pay-rate level variation in our data and aggregate total earnings of a worker to the quarterly level for our sample of job-stayers. Panel A of Figure A8 plots the distribution of wage changes that would be inferred if we used our administrative payroll data to carry out a similar procedure to that done in administrative records that track worker quarterly earnings without adjusting for hours. For our quarterly earnings measures, we compare changes for a worker who work at firm i in a given quarter in year t to the same worker who continues to work at firm i during the same quarter in year $t+1$. So, these are annual changes in quarterly earnings measures for a sample of job-stayers. Panel A plots the distribution of quarterly earnings changes, not correcting for variation in hours. Unsurprisingly, failing to account for variation in hours leads to a far more dispersed earnings change distribution than is shown by the wage change distribution in Figure 2 in the main text. Using this measure, 32.2 percent of job-stayers receive a nominal wage cut during a given period. Moreover, the unconditional standard deviation of nominal earning adjustments is 20.0 percent.

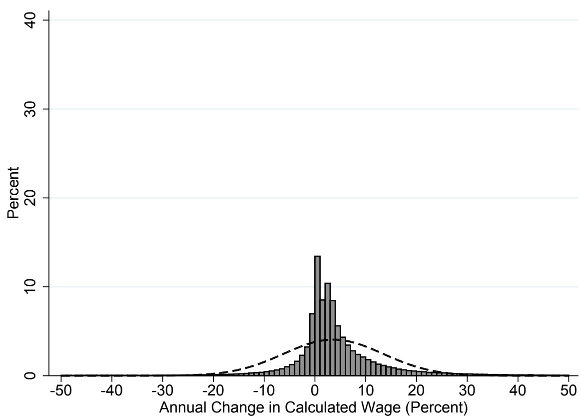
To partially address the problem of not accounting for hours, Panels B and C plots the distribution of changes in a worker's imputed quarterly earnings per hour separately for hourly workers and salaried workers, which are calculated by dividing a worker's quarterly earnings by the hours worked as reported in their payroll records. For hourly workers, this is the actual hours they worked. For salaried workers, this is often set at 40 hours. Even with an hours measure which is as high quality as can be reasonably expected - the number of hours reported on a worker's paycheck - the figure shows a substantially more dispersed distribution of annual wage changes than we document in the paper. Although we observe that 10-15% of workers receive no imputed earnings per hour change over a given year, this is much smaller than the 35% of workers who receive no actual base wage change during a quarter as discussed in Table 5. Moreover, with this earnings per hour measure, 21.2 percent of wage workers and 25.3 percent of salaried workers receive a nominal wage cut during the year over our sample period. Recall, the comparable number using our detailed nominal base wage measures is about 2.5 percent per year. However, we wish to stress that controlling for hours reduces the unconditional standard deviation of nominal wage adjustments to 19.2 percent, and 15.9 percent for hourly workers.

Why do nominal earnings-per-hour vary so much relative to what we document using our more accurate nominal wage measures described above? There are three reasons for the difference. First, similar to the household data sets, hours are not measured accurately for salaried workers in administrative data sets. The noise in the hours measures for salaried workers results in spurious variation in measures of earnings per hour. This is the benefit of using nominal earnings per pay period - which does not rely on hours - to measure nominal

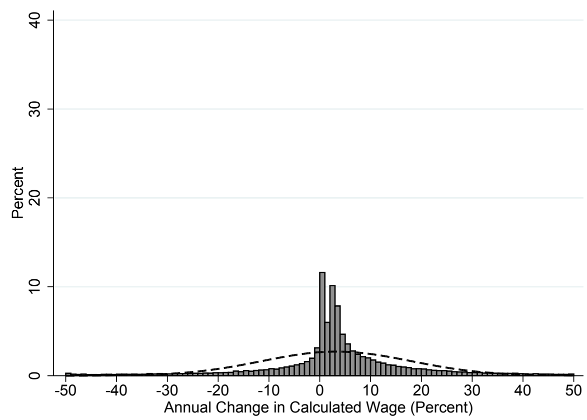
Figure A8: Imputed Quarterly Earnings Per Hour Changes



Panel A: Quarterly Gross Earnings



Panel B: Imputed Earnings Per Hour
Hourly Workers



Panel C: Imputed Earnings Per Hour
Salaried Workers

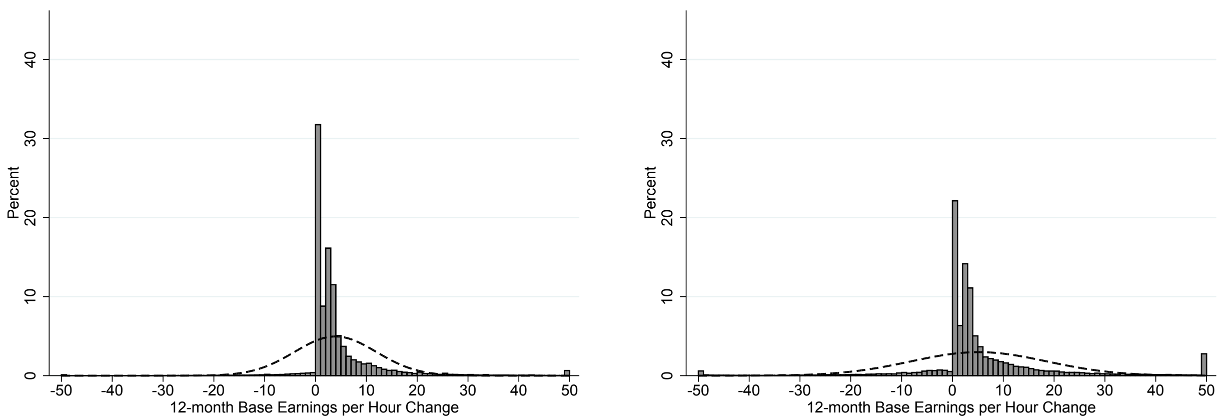
Note: Panel A plots the distribution of four-quarter earnings changes for our sample of job-stayers pooled between 2008 and 2016. Panels B and C report the distribution of quarterly earnings per hour changes, where earnings per hour are imputed by dividing total quarterly earnings by total hours worked in a quarter, for hourly and salaried workers, respectively. Data are weighted to match the firm size $\times$ industry mix found in the BDS.

wage stickiness. We illustrate this point more forcefully below. Second, as highlighted in the text, about 10 percent of workers are commission workers. Lastly, as we also highlight in the text, individual earnings accrued during a quarter includes many forms of compensation such as bonuses and overtime premiums.

To help shed light on the potential measurement error in hours worked for salaried workers, we perform a few additional analyses. Specifically, we exploit our detailed data on base pay compensation. For each individual, we derive total quarterly base pay compensation divided by total hours worked during the quarter. We further exclude commission workers. This measure should exactly match the patterns in Figure 2 for hourly workers. For hourly workers quarterly base pay divided by quarterly hours should match the quarterly per-period contract wage. However, this measure could differ substantially for salaried workers if hours of salaried workers are measured with noise.

Figure A9 shows quarterly base-pay per hour changes over a 12 month period for both hourly workers (panel A) and salaried workers (panel B) during our sample period restriction our sample to include only those workers who receive standard base pay compensation during the month. Notice for hourly workers, the patterns of quarterly earnings per hour changes using this measure of earnings is essentially identical to the quarterly nominal wage change described above. Again, this has to be the case given our measurement. The only differences that accrue are due to time aggregation given that some of the wage change will occur in the middle of the quarter. However, for salaried workers, base earnings per hour is far more volatile than our per-pay period nominal wage measures. This is not the results of bonuses, commissions, tips, or any other residual earnings given we are only looking at base pay compensation. The only reason for the difference in patterns for salaried workers between Figures 2 and A9 is the adjustment for hours worked. As seen from the figure, there are lots of really large differences in base wage per hours for salaried workers. The unconditional standard deviation of nominal wage changes in this figure is 19.7 percent (compared with 8.5 percent for hourly workers). Part of the reason for this is that hours for salaried workers do not have much meaning. Because the number of hours worked has no bearing on take-home pay for these workers, neither the worker, nor the firm has strong incentives to accurately report true hours worked. This manifests in large swings in hours worked for these workers, which drastically changes the imputed wage. Although the studies which use administrative earnings data to measure earnings rigidity are very useful contributions, one should therefore be cautious about using their estimates to discipline traditional models with wage stickiness, in which the nominal rigidity is on the *per hour* payment rate for a worker's time.

Figure A9: 12-month Changes in Base Earnings per Hour, Job-Stayers



Panel A: Hourly Workers Panel B: Salaried Workers

Note: Figure plots the distribution of four-quarter base earnings per hour changes for our sample of job-stayers pooled between 2008 and 2016. Panels A reports the patterns for hourly workers, while Panel B plots the distribution for salaried workers. Base earnings defined to be the product of contract wage rate and total hours worked for hourly workers, and weekly pair multiplied by four or five for salaried workers. Data are weighted to match the firm size × industry mix found in the BDS.