# Are Entry Wages Really (Nominally) Flexible?*

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**Abstract**

No, entry wages simply appear flexible because of composition bias. Unemployed workers with flexible reservation wages are more likely to become re-employed than those with rigid reservation wages, so they are over-sampled in the observed wages of job finders. We document in the microdata that the wages of job finders appear to respond more to labor market conditions than the wages of job stayers, consistent with previous studies. In contrast, we show that the wages of both types of workers exhibit substantial downward nominal wage rigidity as measured using standard methods. We present a model in which employed and unemployed workers both face Calvo-style downward nominal wage rigidity. The estimated model produces substantially larger elasticities of the observed wages of job finders than of job stayers with respect to labor market conditions. Nonetheless, the model implies that the (unobserved) reservation wages of unemployed workers are nearly as rigid as the wages of employed workers. We therefore conclude that the labor market data are consistent with an important role for downward nominal wage rigidity among unemployed workers.



**JEL Codes**: E20, E24, J23, J30, J63, J64

# 1 Introduction

Downward nominal wage rigidity is often hypothesized to amplify unemployment fluctuations by constraining the responsiveness of wages to negative shocks. There is considerable evidence that the wages of incumbent workers are downwardly rigid, but the wages of new hires appear to be significantly more flexible. Because entry wages determine job creation over the business cycle, a substantial literature argues that downward nominal wage rigidity (hereafter, wage rigidity) is unlikely to explain unemployment dynamics.[1]

We argue that the apparent flexibility of entry wages is an artifact of selection bias. If unemployed workers are heterogeneous in their ability or willingness to reduce their reservation wages, those workers with more flexible reservation wages will be more likely to become re-employed. Because new hires will be disproportionately workers with flexible wages, the observed wages of new hires will appear flexible. The unobserved reservation wages of the workers who are not hired, however, may be quite rigid.

We estimate worker wage elasticities with respect to aggregate labor productivity and unemployment in the Panel Study of Income Dynamics and the Current Population Survey. We confirm the consensus in the literature that wages appear to be more elastic for new hires than for incumbents. We contrast this evidence with histograms of nominal wage changes from the same survey data, which exhibit substantial downward nominal wage rigidity in all years for both incumbent workers (hereafter job stayers) and for workers with recent spells of non-employment (job finders).

We construct a search and matching model of the labor market and show that hiring wages can appear flexible even if unemployed workers' reservation wages are quite rigid. We estimate the parameters of the model using indirect inference and find substantial wage rigidity for both job stayers and finders. Dynamic model simulations find that the wages of job finders are substantially more elastic than for job stayers, just as in the observed data. Further, those elasticities are not targets of the model estimation: the model's ability to generate disparate wage elasticities among job stayers and job finders stems naturally from the selection bias inherent in conditioning the sample on observed wages.

Model simulations demonstrate how aggregate observed wages can appear more responsive to labor market conditions than the underlying levels of wage rigidity would imply. Although the observed wages of job finders fall sharply in response to a negative shock, the reservation wages of unemployed workers remain rigid. This asymmetry highlights the pitfalls of selecting on successful

[1] For papers noting that wage rigidity amplifies unemployment variation, see for instance Shimer (2005) and Hall (2005). For papers documenting wage rigidity among incumbent workers, see for instance Card and Hyslop (1997), Kahn (1997), and Ehrlich and Montes (2015), who also show that wage rigidity affects employment outcomes. For the contribution of wage rigidity to unemployment fluctuations, see for instance Pissarides (2009), Haefke et al. (2013), and Kudlyak (2014).

job finding to measure wage responsiveness to aggregate economic conditions among potential new hires. Layoffs rise immediately in response to a negative shock, followed by a persistent decrease in the job finding rate, the majority of which can be attributed to the rigid reservation wages of unemployed workers. The importance of wage rigidity in our model to flows into and out of unemployment re-establishes its potential as an explanation for observed unemployment volatility.

At least since Shimer's (2005) demonstration that a canonical search and matching model of the labor market with perfectly flexible wages cannot replicate the observed volatility in unemployment, a large literature has explored whether adding some form of wage rigidity can help reconcile the model to the data.[2] Prominent examples include Hall (2005), who introduces real wage rigidity via a bargaining norm between workers and employers, Gertler and Trigari (2009), who model wage bargaining with staggered multi-period contracts, and Christiano et al. (2015), who endogenously derive wage rigidity from alternating offers in bargaining negotiations.

Several empirical studies, however, show that the wages of new hires are much more responsive to labor market conditions than the wages of longer-tenured workers. Bils (1985), Shin (1994), Solon et al. (1994), Devereux (2001), and Shin and Solon (2006) all find lower elasticities of wages with respect to the unemployment rate for tenured workers than for all workers. Bils (1985), Shin (1994), and Barlevy (2001) find specifically that the elasticity for those in new matches is much higher than the estimates for incumbent workers. Furthermore, Haefke et al. (2013) estimate much higher elasticities for the aggregate wages of new hires with respect to average labor market productivity than for the worker population generally. As Pissarides (2009) summarizes the evidence, "Time-series or panel studies on the cyclical volatility of wages show considerable stickiness, but this evidence is dominated by wages in ongoing jobs and is not relevant for job creation in the search and matching model."[3]

Notably, the time series evidence contrasts starkly with the direct survey evidence on unemployed workers' reservation wages reported by Krueger and Mueller (2014). They find that "self-reported reservation wages decline at a modest rate over the spell of unemployment." They argue that their evidence suggests that "many workers persistently misjudge their prospects or anchor their reservation wage on their previous wage." Likewise, Gertler, Huckfeldt, and Trigari (2016) present evidence that the greater wage cyclicality of non-stayers relative to stayers reflects primarily job-to-job switchers, rather than workers hired out of non-employment. They argue that the excess cyclicality of wages among job switchers reflects variation in the ease with which workers

[2] See Pissarides (2000, chapter 1) for an example of such a model and a survey of the related literature.

[3] Elsby et al. (2016) are also skeptical of the role that downward nominal wage rigidity plays in unemployment fluctuations. They find a significant number of nominal wage cuts in CPS data and point out that in the Great Recession the most notable distinction from previous contractions, which occurred in times of higher inflation, is not in separations but in the duration of unemployment. This result puts the onus on entry rigidity to explain the data, a hypothesis for which they find little theoretical and no empirical support in the existing literature.

can climb the "job ladder" over the business cycle. We show that a model with heterogeneity in the rigidity of unemployed workers' reservation wages can resolve the apparent contradiction between the aggregate and individual-level evidence.

The remainder of the paper proceeds as follows. In section 2, we establish within two different data sources the key empirical elasticities regarding entry wage rigidity. In section 3 we employ those same data sources to provide evidence in favor of wage rigidity for both job stayers and job finders. In section 4 we introduce a labor search model with explicit downward nominal wage rigidity for all workers. In section 5 we estimate the model and illustrate the results. Section 6 concludes.

# 2 Elasticities for Job Stayers, Switchers, and New Hires

Our empirical analysis utilizes longitudinal data from two sources, the Panel Study of Income Dynamics (PSID) and the Current Population Survey (CPS). We use the PSID to conduct analyses similar to those in Solon, Barsky, and Parker (1994) and Devereux (2001), in which we estimate the elasticities of the real wages of job stayers and all employed workers with respect to the unemployment rate. We use the CPS to estimate the elasticity of real wages of all workers and job finders with respect to average labor productivity, in the spirit of Haefke et al. (2013). In both cases, we confirm the qualitative patterns in the original studies: the wages of job stayers are less responsive to the unemployment rate and the wages of job finders are more responsive to labor productivity than are the wages of all workers.

## 2.1 Panel Study of Income Dynamics

The PSID contains data on employment, salary, and hourly wages for household heads and their spouses. We combine the 1980-1997 annual surveys with the 1999-2013 biannual surveys to construct an employment history for respondents that spans 1980-2013.[4] The number of respondents in these surveys averages about 12,500 per year.[5] The PSID includes occupational codes and industry codes, as well as job start and end dates, which allows us to determine worker tenure over several years.

Table 1 provides a summary description of some key variables in the analysis. The labor force participation rate is roughly 65 percent, and the unemployment rate averages 4.3 percent,

[4]We begin the analysis in 1980 because hourly wages are top-coded at very restrictive levels in the 1978 and prior surveys.

[5]We include spouses in the analysis when we consider the entire universe of working adults. The inclusion of spouses is necessary to ensure that the primary earner in a family is present in the analysis because the PSID codes household heads by gender. We have also used specifications that are restricted to male heads of household to facilitate comparisons with past studies. That restriction does not change the qualitative results.

reflecting the restriction of the sample to heads of household and spouses.[6] About 41 percent of employed workers are salaried, while about 44 percent are hourly employees; the remainder comprises workers whose primary income is significantly affected by bonuses, commissions, etc. Our analysis focuses on hourly workers and salaried workers. Most salaried workers do not provide a consistent measure of hours for their primary job, so we assume a fixed number of hours from year to year; this assumption seems reasonable for those who stay at the same job from one survey to the next (about 66 percent of salaried workers), but potentially biases the hourly wage for those who switch jobs.

We categorize the set of employed workers with valid wage observations in the current and previous surveys as job stayers, job switchers, and job finders.[7] Job stayers, who make up 61 percent of employed workers, are defined as workers who provided a start date at their current job prior to the last time they were surveyed, when available, or who provided a tenure length at their current employer exceeding the time between survey dates if the start date is unavailable. In addition, job stayers must have had continuous employment between survey dates without spells of unemployment or time out of the labor force. Job switchers are defined as workers who maintained continuous employment, defined by no months in which they were unemployed or out of the labor force, but who provided a start date between survey dates; they comprise 20 percent of employed workers. Job finders are defined as workers who were employed at the time of both the current and prior surveys, but who report having spent time between surveys as either unemployed or out of the labor force; they make up 11 percent of employed workers.[8] Job stayers, switchers, and finders are not exhaustive of the set of all employed workers because some workers do not have a valid wage in the prior survey, for instance if they were unemployed or out of the labor force.

We estimate regressions of the form:

$$\Delta \ln w_{it} = \beta_0 + \beta_1 t + \beta_2 \Delta U_t + \beta_3 X_{it} + \varepsilon_{it}, \tag{1}$$

in which $w_{it}$ is the nominal hourly wage, $U_t$ is the national unemployment rate, and $X_{it}$ is a polynomial measure of work experience and job tenure for worker $i$ at year $t$. These regressions follow Devereux (2001), who in turn builds on Solon et al. (1994). We use both the dependent variable in Devereux (2001), which is limited to earnings in the worker's primary job, as well as

[6] All statistics and figures using PSID wage information are weighted by individual longitudinal weights except for information pertaining to survey counts.

[7] Although our categorization involves some subjective judgment, which may induce misclassification, we classify workers using identical definitions in our estimation of the theoretical model. This method of indirect inference allows us to correct for possible misspecification in these definitions. See section 5.1 for more details. Our categorization is a partition of all workers who have valid wages in consecutive surveys.

[8] Note that this definition excludes first-time entrants and re-entrants who spent multiple years unemployed or out of the labor force. According to our CPS dataset, over the past 20 years, new entrants constitute between 6-12 percent of the unemployed looking for work and average only 8.6 percent of the total unemployed during that time.

that in Solon et al. (1994), who use all earnings in the surveyed year. In addition, although Solon et al. (1994) and Devereux (2001) include only men, we include both men and women in our sample.[9]

Table 2 presents the results of our regressions. Although our sample periods differ, and our inclusion of women alters our sample slightly compared to Solon et al.'s, our analysis recovers the same basic fact pattern as the earlier studies. When we confine our sample to the years in which we have annual surveys (1980 to 1997), we estimate that the elasticity of all wages with respect to the annual unemployment rate is -0.83, versus -0.56 for job stayers. When we extend the analysis to include job switchers and job finders, we estimate an elasticities of -1.80 and -1.82, respectively, far larger (in absolute value) than for all workers or job stayers. Modifying our approach to analyze two-year wage changes allows us to extend our sample to 1981 to 2013. This approach yields uniformly smaller elasticities, but the relative magnitudes among all workers, job stayers, and job finders are unaffected.

Our specifications using the average annual wage give similar qualitative results. Using annual wage changes through 1997, we estimate that the elasticity of real wages with respect to unemployment is -0.7 for all workers and -0.49 for job stayers. When we analyze job finders separately, we estimate an elasticity of -1.65, consistent with the notion that job finders' wages are more responsive to labor market conditions than the wages of other workers. We see somewhat higher elasticities in our analysis of biannual wage changes through 2013, but the relative magnitudes among all workers, job stayers, and job finders are unaffected.

## 2.2 Current Population Survey

We use the CPS's basic monthly microdata files from 1984 through 2013, which include the employment history of each member of a surveyed household. Additionally, the CPS's outgoing rotation groups include data on wages and weekly hours worked for all members of a household, job codes, and demographic information. To track individuals longitudinally across outgoing rotation groups, we use the merged datasets of Drew et al. (2014), who build on the methodology of Madrian and Lefgren (2000). That dataset, which tracks individuals up to 16 months, is available beginning in 1989. The structure of the CPS is such that individuals are surveyed for four consecutive months, are out of the survey for eight months, and then are surveyed again for four more months. This design allows us to construct a year-over-year measure of wage changes for individuals in the outgoing rotation groups. Finally, we merge the monthly surveys with aggregate labor market data such as the unemployment rate, labor productivity, and the personal consumption expenditures implicit price deflator.

[9] Both papers use a two-step process to address potential bias in their standard errors due to common time effects across workers. We address this issue by clustering standard errors by year and estimate the regression in equation 1 directly.

Table 1 presents summary statistics for the CPS in the second column. The labor force participation rate averages 66 percent during the sample period, while the unemployment rate averages 6.2 percent. 60 percent of employed workers are salaried, and 40 percent are hourly. We use typical hours worked per week as our divisor in the determination of the hourly wage for salaried workers.[10] We construct a variable for years of school and a standard measure of potential experience (age minus years of school minus 6). Following the procedure of Haefke et al. (2013), we restrict the dataset to nonfarm, nonsupervisory, private-sector workers, trim outliers in hours worked and in implied hourly earnings, impute top-coded earnings according to the procedure in Schmitt (2003).

Haefke et al. (2013) investigate the effect of changes in productivity on aggregate real wages of both job finders and all workers. To account for composition bias in each group, they remove demographically explainable wage determinants for all workers via a Mincer regression, and then analyze the effects of labor market indicators on the respective residualized aggregate wages. They define a job finder, or new hire, as any worker who had a nonemployment spell in the prior 3 months. We adopt that definition of a job finder in the CPS, as we do not have employment information for the 8 months prior to those 3. Therefore, our definition of job finder is more restrictive in the CPS than in the PSID, which allows for the measurement of nonemployment spells further from the survey date. The structure of the CPS does not allow us to identify job stayers or switchers. Therefore, our analysis of the CPS parses workers into job finders, who make up 12.6 percent of workers, and non-finders, who make up 87.4 percent.

Haefke et al. (2013) estimate the following specification by quarter for each subgroup $j$ of workers (i.e., job finders and all workers) from 1984 to 2006q1:[11]

$$\Delta \ln w_{jt} = \beta_{0,j} + \beta_{1,j} \Delta \ln y_t + \varepsilon_{jt}, \tag{2}$$

where $w_{jt}$ is their residualized real wage series for group $j$ and $y_t$ is a measure of labor productivity. Haefke et al.'s preferred specification deflates wages by the BLS private nonfarm business sector implicit deflator and uses aggregate labor productivity as their aggregate labor market indicator of interest.[12]

Table 3 presents estimates of equation 2 for the periods 1984-2006q1 and 1984-2013 in the first two columns. The first period corresponds to Haefke et al.'s analysis and produces similar results. A slight difference between our results and theirs arises from our use of current data for

[10] In contrast, Card and Hyslop (1997) and Elsby et al. (2016) use usual weekly earnings for salaried workers.

[11] They exclude 1995q3 and 1995q4 from analysis because of a change in sample design that makes it difficult to match workers, add quarter dummies to account for residual seasonality, and add a dummy for 2003q1 to reflect the change in occupation classification in 2003 that increases the fraction of supervisory workers.

[12] The aggregate labor productivity series published by the Bureau of Labor Statistics has been revised subsequent to the publication of their paper, which complicates the comparison of our results to theirs.

labor productivity; when we use the same vintage data as Haefke et al. (not reported), we obtain the same estimates reported in their paper.[13] The second period extends the analysis through 2013 to be consistent with the end date of our PSID data. Including the later period reduces the estimated elasticities slightly, but does not change the qualitative pattern that job finders exhibit more elastic wages than non-finders.

The second set of columns of table 3 uses the longitudinal aspect of the CPS to calculate the year-over-year changes in wages for individual workers; those changes serve as the outcome of interest. This approach corrects for both observable and unobservable compositional changes among worker groups, which as Solon et al. (1994) show, can attenuate estimated wage elasticities. Requiring a year-over-year wage change restricts the sample of workers who could potentially be considered new hires and also necessitates year-over-year, as opposed to quarter-over-quarter, comparisons. Additionally, the results extend back only to 1989, consistent with the longitudinally matched dataset of Drew et al. (2014). We run the following regressions for job finders, non-finders, and all workers:

$$\Delta \ln w_{ijt} = \beta_{0,j} + \beta_{1,j} \Delta \ln y_t + \beta_{2,j} X_{it} + \varepsilon_{it}, \tag{3}$$

where an observation is a worker $i$ in worker group $j$ and calendar quarter $t$, and the first difference terms represent year-on-year changes. $X_{it}$ is a cubic polynomial in experience, consistent with our analysis using the PSID data.

The estimated elasticities using individual wage changes indicate that job finders have more elastic wages than other workers, as in the previous estimates. The large standard errors on the estimates, however, mean that the differences among worker types are not statistically significant for either individual or group wage changes.[14] Consistent with the results of Solon et al. (1994), the estimated elasticities using individual wage changes are larger than using group wage changes. More broadly, the estimates in this section confirm the key patterns in the literature: the observed real wages of job finders are roughly twice as responsive to changes in labor market conditions as the real wages of other workers.

# 3 Estimating Downward Nominal Wage Rigidity

In this section, we employ a complementary approach to those in section 2 to measuring wage rigidity. We focus particularly here on downward nominal wage rigidity by attempting to measure

[13] Specifically, Haefke et al. (2013) used data from the May, 2006 Productivity and Costs release, while we use data from the June, 2016 release; the Bureau of Labor Statistics periodically revises the historical data in that release.

[14] The standard errors for the individual wage change estimates are clustered at the year level, consistent with our analysis of the PSID data.

the proportion of wage cuts that would have occurred in a counterfactual environment with perfectly flexible wages that are "missing" from the observed data. We estimate this proportion using the method in Ehrlich and Montes (2015), which builds on the method of Card and Hyslop (1997). The essence of the method is to extrapolate from the upper half of the observed wage change distribution to what the nominally negative portion of the distribution would look like in the absence of rigidity, and calculate the proportion of counterfactual mass that is missing in the observed distribution.[15] Although such analyses have typically focused on the wages of job stayers, the same method can be extended to job switchers and job finders, as shown in the subsections below.

The key results that emerge from performing this analysis in the PSID and CPS are that the observed wages of job finders exhibit less downward nominal wage rigidity than the wages of job stayers, but the degree of rigidity in job finders' wages is nonetheless substantial. We begin this section by describing the visual evidence for wage rigidity in the PSID and CPS, before providing formal estimates of the degrees of nominal rigidity.

## 3.1 PSID

Figure 1 displays histograms of one-year nominal wage changes for job stayers, job switchers, and job finders for survey years 1980-1997, and two-year changes for survey years 1981-2013.[16] The histograms are truncated at -35 and 35 percent, with a dotted vertical line to indicate a zero percent nominal wage change.[17]

The first row of histograms in figure 1 contains a spike in the proportion of reported wage changes at nominal zero, which we interpret as one of the hallmarks of downward nominal wage rigidity. There is a also a visually-evident asymmetry between the nominally positive and nominally negative portions of the distribution, as the proportions of nominally negative wage changes are smaller than a simple extrapolation from the nominally positive portion of the distribution would indicate. This asymmetry is especially visible in the 2-year changes in the histogram for job stayers, which contain sample years with lower inflation, among other factors, leading to smaller nominal wage increases. Negative wage changes have nevertheless remained relatively uncommon; thus, the distribution of wages has "piled up" against the barrier at nominal zero.

The second and third rows of figure 1 show similar histograms for job switchers and job finders, respectively. The dispersion of wage changes is higher for both job switchers and job finders than for job stayers. Furthermore, the median wage change for job finders in the second column, at 3.1 percent, is lower than for job stayers, which is 4.3 percent. Nevertheless, the histograms share

[15] The appendix describes the method in detail.

[16] The two-year wage changes use non-overlapping samples for the period in which annual surveys were available, e.g. 1981-1983, 1983-1985, etc.

[17] Individual-year histograms of wage changes for stayers, switchers, and finders are also shown in the appendix. Each year exhibits the same basic pattern, with a spike at nominal 0 wage change.

significant similarities with those for stayers: 1) a spike at nominal zero, and 2) asymmetry between the nominally positive and nominally negative portions of the wage change distribution. There is less mass in the nominally negative portion than would be implied by a symmetrical wage change histogram, consistent with the idea that the wages of job switchers and job finders exhibit some degree of downward nominal rigidity.

## 3.2 CPS

Figure 2 provides wage change histograms for all workers, all workers excluding job finders, and job finders only in the CPS outgoing rotation groups for the years 1989 to 2013. We again censor the histograms at -35 percent and 35 percent.[18] The sample is limited to those workers who can be matched between their 4th and 16th months in the survey. We divide these workers into job finders and non-job finders as described in section 2.2. There are 25,317 total wage changes on average per surveyed year, of which approximately 1,077 per year come from workers we classify as job finders.

The histograms in figure 2 are qualitatively similar to those in figure 1. There are large spikes at nominal zero and an asymmetry between the nominally positive and negative portions of the distributions, with the latter displaying "missing" mass. Again, the wage change distributions of job finders display weaker, but still suggestive, evidence of downward nominal rigidities than the distributions for other workers.

## 3.3 Systematic Measurement of Wage Rigidity

In this section we provide formal estimates of the proportion of nominal wage cuts that would have occurred in an environment with perfectly flexible wages that are instead prevented by downward nominal wage rigidity. The basic approach, described in detail in the appendix, is to construct an empirical distribution of log nominal wage changes and reflect the 50-100th percentile of changes back on the 0-50th percentiles. The implied share of nominal wage cuts that would be expected based on the upper half of the wage change distribution is compared to the actual share of nominal wage cuts. The statistic

$$\widehat{wr} = 1 - \frac{\hat{F}^{obs}(0^{-})}{\hat{F}^{cf}(0^{-})}. \tag{4}$$

represents the fraction of wage changes that are "missing", where $\hat{F}^{cf}(0^{-})$ is the estimated counterfactual distribution of log wage changes and $\hat{F}^{obs}(0^{-})$ is the empirical distribution of log wage

[18] Year-by-year histograms for each category of worker are found in the appendix. The histograms for 1995 are omitted because a change in sampling design does not permit matches of worker wages to their employment history.

changes.

This statistic reflects the combination of two phenomena associated with downward nominal wage rigidity. First, it captures the extent to which slightly negative nominal wage changes are "swept up" to nominal 0. Second, it may also capture the share of workers who would have received a wage cut in an environment with flexible wages but who instead separated from their employer either through a layoff or a quit.

Table 4 displays our estimates of the proportion of nominal wage cuts prevented by wage rigidity both in the PSID and in the CPS. The table presents estimates for the PSID for job stayers and job finders for one-year wage changes from 1980 to 1997 and for two-year wage changes from 1981 to 2013. The table also shows estimates for one-year wage changes in the CPS for job finders and non-finders for the years 1989 to 2013. Separate estimates are provided for salaried and hourly workers.

Among job stayers in the PSID, we estimate that 53.3 percent of counterfactual nominal two-year wage cuts and 53.5 percent of one-year wage cuts are missing. Among job finders, those estimates are 20.1 and 48.9 percent, respectively. These estimates imply that even over a period of two years, a substantial proportion of counterfactual nominal wage cuts are prevented by downward nominal wage rigidity. The estimated proportion of missing wage cuts among stayers does not change meaningfully from one-year to two-year intervals, perhaps reflecting a high degree of persistence of working conditions for job stayers, who have an average job tenure of 9.6 years. The estimates for salaried and hourly workers do not differ systematically by worker type or one-year versus two-year wage changes.

The estimates using the CPS data are qualitatively similar, especially to the one-year wage changes in the PSID. We estimate that among non-finders, 46.9 percent of counterfactual nominal wage cuts were prevented by wage rigidity, versus 40.3 percent for job finders. Again, the estimates for salaried and hourly workers do not vary in a consistent fashion.

One potential limitation of using reported survey data on nominal wages over time to estimate wage changes is that respondents may round their hourly wage to the nearest dollar or half dollar, or their salary to the nearest 1000 dollar value.[19] This rounding could lead to an overstatement of the number of unchanged nominal wages from survey to survey. An inflated number of unchanged wages could bias our measure of rigidity if small wage cuts disappear due to rounding. To examine the potential effect such rounding has on our results, we re-estimate wage rigidity for hourly workers after excluding all round-dollar results (about one third of the sample for incumbents and finders, slightly less for switchers). The qualitative results do not change.

We interpret these estimates as indicating a substantial amount of downward nominal wage rigidity. Although the wages of job finders exhibit somewhat less rigidity than the wages of other

[19]See, for instance, Altonji and Williams (1997).

workers, they are by no means perfectly flexible. Therefore, these results stand in no small contrast to the results in section 2, which indicate that the wages of job finders are much more responsive to labor market conditions than the wages of job stayers. In the next section, we build a a search and matching model of the labor market that attempts to reconcile these results. The model implies that the apparent flexibility of the wages of job finders stems from composition bias in the pool of newly hired workers.

# 4 Model

We consider a general equilibrium model with search and matching in the labor market that is closely related to the canonical model of Mortensen and Pissarides (1994). However, we model wage setting differently than those authors do. We assume, as in Barattieri et al. (2010) and Daly and Hobijn (2014), that workers set nominal wage demands unilaterally, which firms either accept or reject. We further follow Daly and Hobijn (2014) by adopting a Calvo-style (1983) process: we assume that in any given period, a fraction of workers are constrained from reducing their nominal wage demands. The model allows the fractions of employed and unemployed workers who are prevented from reducing their wage demands to differ.

## 4.1 Model Environment

We consider the stationary equilibrium of a discrete time model with no aggregate shocks but with shocks to a worker's idiosyncratic productivity and their ability to reduce their nominal wage demands each period. Each firm has one job, which can either be vacant or filled and producing output. There is a unit mass of workers who can be either employed in a job or unemployed and searching for a job.

Firms and workers are infinitely lived with a common discount rate $\beta$ and have linear preferences over profits and consumption, respectively. Workers and firms cannot store goods, so workers consume their entire incomes each period. There is also no intensive margin of labor supply: workers in a filled job supply exactly one unit of labor, $L$, each period. Unemployed workers receive an unemployment benefit $b$ each period.

Firms in a match with a worker can decide whether to continue to employ the worker at the worker's demanded wage or to terminate the job. Labor is the only input into production, and the output of a filled job is given by:

$$Y = pL = p \tag{5}$$

where productivity $p$ is stochastic. The per-period profits $\pi$ of a firm employing a worker with productivity $p$ and paying wage $w$ are then:

$$\pi(p, w) = p - w. \tag{6}$$

Firms that are not in a match and that wish to meet with a worker must post a vacancy at per-period cost $c$, expressed in units of output. There is free entry in vacancy posting.

Unemployed workers and firms with vacant jobs form matches according to a matching function $m(v, u)$, where $v$ is the number of vacancies and $u$ is the number of workers who are unemployed.[20] We assume that the matching function has the Cobb-Douglas form:

$$m(v, u) = Av^{\phi}u^{1-\phi} \tag{7}$$

where $A$ is a parameter that governs matching efficiency and $\phi$ is the elasticity of the matching function with respect to the number of vacancies. Denoting 'labor market tightness' $v/u$ as $\theta$, the probability $f$ that a worker meets a vacancy is $f(\theta) = m(v, u)/u = A\theta^{\phi}$. The probability $q$ that a firm with a vacant job meets an unemployed worker is $q(\theta) = m(v, u)/v = A\theta^{\phi-1}$.[21]

There is no on-the-job search, and matches end with exogenous probability $s_x$ each period. Endogenous separations occur in two ways. First, matches end when the productivity level of the match falls to a low enough level that the match surplus between the worker and firm is exhausted. Those separations are bilaterally efficient. Second, bilaterally-inefficient separations occur when the worker is unable to cut his or her nominal wage demand below the maximum level that the firm is willing to pay, but would have been willing to do so in an environment with flexible wages.

We model wage rigidity according to the process in Calvo (1983). Employed workers set their wage demands and unemployed workers set their reservation wages unilaterally. We assume employed and unemployed workers are unable to reduce their nominal wage demands in any given period with probabilities $\lambda_E$ and $\lambda_U$, respectively. Firms then decide whether to continue or to terminate matches given workers' wage demands.

The timing of each period is as follows:

1. The period begins and employed and unemployed workers draw realizations of whether they can reduce their reservation wages in the period.

2. Workers draw their idiosyncratic productivity levels, and firms and workers observe workers'

[20] Because we have normalized the number of workers to 1, the number of unemployed is synonymous with the unemployment rate, and we will use the two interchangeably.

[21] The probabilities $f$ and $q$ do not represent the likelihood of finding or filling a job. Rather, they represent the likelihood of meeting a vacancy or an unemployed worker, respectively, and entering an interview, as will be described below. We denote the probability of finding a job as $\tilde{f}$ and the probability of filling a vacancy as $\tilde{q}$.

productivity levels.

3. Firms post vacancies, and matching between vacancies and unemployed workers occurs.

   Not every match between an unemployed worker and a vacancy will result in the formation of a new job both because of exogenous separations and because the worker's wage demand may be higher than the firm will accept. To distinguish between a match and a new employment relationship that enters production, we will call a match between an unemployed worker and a vacant job an *interview*. The probabilities $f$ and $q$ are the likelihoods of an unemployed worker receiving an interview in a period and of a firm that has posted a vacancy interviewing a worker, respectively.

4. Exogenous separations occur.

   Note that exogenous separations can occur even in new interviews, such that the worker is never employed by the firm regardless of productivity levels or wage demands.

5. Workers in a negotiation set their wage demands, while unemployed workers set their reservation wages.

6. Firms decide whether to accept matched workers' wage demands and proceed to production, or to terminate the relationship.

   We will refer to the process of workers setting their wage demands and firms deciding whether to accept them as a *negotiation*, although there is no actual bargaining involved. Note that from the firm's perspective, there is no difference between a negotiation with a previously unemployed worker and a worker in an ongoing employment relationship. Therefore, we will not usually distinguish between the two.[22]

7. Production occurs, wages and unemployment benefits are paid, profits are earned, and consumption occurs.

8. The period ends.

Firms can therefore be in two different states, with an unfilled vacancy or in a match with a worker. We will denote the values to the firm of being in these states as $V$ and $J$, respectively. Workers can find themselves in four possible states: unemployed with a flexible wage, unemployed with a rigid wage, employed with a flexible wage, and employed with a rigid wage. We will denote the values of the worker to being in these states as $U^F$, $U^R$, $W^R$, and $W^F$, respectively. We define the value functions for these states in sections 4.2 and 4.3.

We assume that a worker's log productivity follows the $AR(1)$ process:

$$\ln p = (1 - \psi_p) \ln \bar{p} + \psi_p \ln p_{-1} + \varepsilon_p,\ \varepsilon_p \sim N\left(0, \sigma_p^2\right). \tag{8}$$

Productivity is a time-varying, mean-reverting characteristic of the individual worker. Further, a worker's productivity process persists in unemployment. The productivity distribution of employed

[22] The distinction does matter for calculating employment flows such as job creation and job destruction.

workers will differ from the distribution for all workers because firms will lay off workers when their reservation wages exceed the cutoff value associated with the worker's productivity.[23]

## 4.2 Firm's Problem

The value to the firm of posting a vacancy, denoted $V$, is defined in step 3 in the timeline and given as:

$$V = -c + q(\theta)(1 - s_x) \iint J(p, w)\, \mathrm{d}G(p, w) + (1 - q(\theta)(1 - s_x))\beta\mathbb{E}[V'], \tag{9}$$

where $G(p, w)$ is the stationary joint cumulative distribution of productivity levels and wage demands from unemployed workers. The firm incurs the flow cost $c$ of posting a vacancy and gains the expected value of a negotiation with probability $q(\theta)(1 - s_x)$, which accounts for both the likelihood of a match and its survival to become a negotiation, as well as the continuation value of the vacancy conditional on not matching.

The value to the firm of being in a negotiation with a match of productivity $p$ and worker reservation wage $w$, denoted by $J$ and defined in step 6 in the timeline, is given by:

$$\begin{aligned} J(p, w) = \max_{\text{discontinue,continue}} \Big\{ &\beta\mathbb{E}[V'], \\ &p - w + \beta(1 - s_x) \iint J(p', w')\, \mathrm{d}F(p'|p)\mathrm{d}H(w'|p', w) \Big\}. \end{aligned} \tag{10}$$

The firm decides between terminating the match or entering into production with the matched worker. In production the firm receives the flow surplus $p - w$ and the expected continuation value of a filled job conditional on the current period's wage and productivity (inclusive of the risk of an exogenous separation during negotiation next period). $F(p'|p)$ is the cumulative distribution function of next period's productivity level given this period's productivity, and $H(w'|p', w)$ is the cumulative distribution function of next period's wage demands for a worker in a filled job given current wage $w$ and next-period's productivity level $p'$.[24]

Given equation 10, we can define the wage at which the firm is indifferent between continuing and terminating the employment relationship for every productivity level. That cutoff wage

[23] It is unnecessary that a worker's productivity level be higher than the worker's wage in every period due to the associated option value of a match.

[24] The expected value of a match next period can be further decomposed based on the probability of wage adjustment next period, but we omit that characterization here.

schedule, denoted as $\tilde{w}(p)$, solves the equation:

$$\beta\mathbb{E}[V'] = p - w + \beta(1 - s_x) \iint J(p', w')\,\mathrm{d}F(p'|p)\mathrm{d}H(w'|p', w). \tag{11}$$

## 4.3 Worker's Problem

We define the worker's value functions at step 5 in the model, after matching and exogenous separations have occurred, when the worker must decide his or her reservation wage. The value of being in a negotiation with a flexible wage is a function of this period's productivity level, and we denote it $W^F(p)$. The value of being in a negotiation with a rigid wage depends on both this period's productivity and last period's wage demand, and we denote it $W^R(p, w_{-1})$. It is sometimes convenient to represent expectations of next period's value of being employed, without knowing whether the worker's wages will be flexible or rigid. We denote this expectation as $\mathbb{E}[W(p', w)] = \mathbb{E}[(1 - \lambda_E)W^F(p') + \lambda_E W^R(p', w)]$.

Likewise, the value of being unemployed at step 5 with a flexible reservation wage is a function of this period's productivity only, so we denote it $U^F(p)$. The value of being unemployed with a rigid reservation wage is a function of this period's productivity and last period's wage demand, so we denote it $U^R(p, w_{-1})$. When we wish to denote the expected value of being unemployed next period, we use the notation $\mathbb{E}[U(p', w)] = \mathbb{E}[(1 - \lambda_U)U^F(p') + \lambda_U U^R(p', w)]$.

The value to the worker of being in a negotiation with a flexible wage and productivity $p$ is given by:[25]

$$\begin{aligned} W^F(p) = &\max_w \Bigg\{ \mathbb{1}\Big(w \leq \tilde{w}(p)\Big)\Big(w + \beta \int \big\{(1 - s_x)\mathbb{E}[W(p', w)] + s_x\mathbb{E}[U(p', w)]\big\}\,\mathrm{d}F(p'|p)\Big) \\ &+ \mathbb{1}\Big(w > \tilde{w}(p)\Big)\Bigg(b + \beta \int \Big(f(\theta)(1 - s_x)\mathbb{E}[W(p', w)] \\ &+ (1 - f(\theta)(1 - s_x))\mathbb{E}[U(p', w)]\Big)\,\mathrm{d}F(p'|p)\Bigg)\Bigg\}. \end{aligned} \tag{12}$$

The worker chooses his or her wage demand $w$ knowing the firm's cutoff wage given the current productivity level, $\tilde{w}(p)$. Choosing a wage demand lower than that cutoff, as in the first term of the value function, yields the demanded wage this period and a continuation value associated with starting the next period in an ongoing match with the firm. Choosing a higher wage leads to a termination of the match, yielding the worker flow payoff $b$ this period and a continuation value associated with starting the next period unmatched with a firm. We denote the wage schedule that

[25] We distinguish between being employed and being in a negotiation because an unemployed worker could receive a job match in a period but have a reservation wage higher than the firm will accept. In that case, the worker will not actually be employed in the period.

solves this maximization problem as $w^\star_{EF}(p)$.

The value to the worker of being in a negotiation with productivity $p$ and downwardly rigid wage $w_{-1}$ is given by:

$$
\begin{aligned}
W^R(p, w_{-1}) &= \mathbb{1}\Big(\frac{w_{-1}}{1+\pi} \leq w^\star_{EF}(p)\Big) W^F(p) + \mathbb{1}\Big(\frac{w_{-1}}{1+\pi} > w^\star_{EF}(p)\Big) \times \cdots \\
&\Big\{ \mathbb{1}\Big(\frac{w_{-1}}{1+\pi} \leq \tilde{w}(p)\Big)\Big(\frac{w_{-1}}{1+\pi} + \beta \int \Big[(1-s_x)\mathbb{E}[W(p', \frac{w_{-1}}{1+\pi})] + s_x \mathbb{E}[U(p', \frac{w_{-1}}{1+\pi})]\Big)\Big] \,\mathrm{d}F(p'|p)\Big) \\
&+ \mathbb{1}\Big(\frac{w_{-1}}{1+\pi} > \tilde{w}(p)\Big) U^R(p, w_{-1}) \Big\}. \qquad (13)
\end{aligned}
$$

The previous period's real wage, $w_{-1}$, divided by $1+\pi$, where $\pi$ is the rate of inflation, represents the new real wage that corresponds with a downwardly rigid nominal wage.[26] The first term in the value function represents the state in which the optimal wage demand is below last period's wage, in which case the problem reduces to the problem of the worker with a flexible wage. In the case that the previous period's wage demand is binding, it may or may not be acceptable to the firm. If the wage demand is acceptable to the firm, the worker receives that wage plus next period's continuation value. If it is not acceptable, the worker receives the payoffs associated with unemployment, defined below. Implicit in $W^R(p, w_{-1})$ is an optimization problem, because workers have freedom to raise their reservation wages. As written, this choice is subsumed in $W^F(p)$. The wage schedule associated with this value function is $w^\star_{ER}(p)$. Note that $w^\star_{ER}(p, w_{-1})$ is the minimum of $w_{-1}$ and $w^\star_{EF}(p)$.

The value to the worker of being unemployed with productivity $p$ and a flexible reservation wage is given by:

$$
\begin{aligned}
U^F(p) = \max_w \Big\{ & b + \mathbb{E}[f(\theta')](1-s_x)\beta \int \mathbb{E}[W(p', w)] \,\mathrm{d}F(p'|p) \\
& + (1 - \mathbb{E}[f(\theta')](1-s_x))\beta \int \mathbb{E}[U(p', w)] \,\mathrm{d}F(p'|p) \Big\}. \qquad (14)
\end{aligned}
$$

The unemployed worker receives the unemployment benefit $b$ this period and a continuation value that reflects the probabilities of matching or failing to match next period. Since wages are always flexible upwards, it is optimal for an unemployed worker to set their reservation wage at the minimum possible value, for instance the minimum wage.[27] The reservation wage that solves

[26] Denoting the price level in period $t$ as $P_t$, the nominal wage in period $t$ is then $P_t w_t$, and the nominal wage in period $t-1$ is $P_{t-1}w_{t-1}$. Thus, a worker experiences a nominal wage cut if and only if $P_t w_t < P_{t-1}w_{t-1} \iff \frac{P_t}{P_{t-1}} w_t < w_{t-1} \iff (1+\pi)w_t < w_{t-1} \iff \frac{w_{t-1}}{1+\pi} > w_t$.

[27] As a result, the value function can be expressed using only $W^F(p')$ and $U^F(p')$: even if next period's wage is

the unemployed worker's degenerate maximization problem is denoted as $w^{\star}_{UF}(p)$.

The value function for unemployed workers with productivity $p$ and a downwardly-rigid reservation wage $w_{-1}$ is:

$$U^R(p, w_{-1}) = b + \mathbb{E}[f(\theta')](1 - s_x)\beta \int \mathbb{E}[W(p', \frac{w_{-1}}{1+\pi})] \,\mathrm{d}F(p'|p) \\ + (1 - \mathbb{E}[f(\theta')](1 - s_x))\beta \int \mathbb{E}[U(p', \frac{w_{-1}}{1+\pi})] \,\mathrm{d}F(p'|p). \tag{15}$$

This function follows the pattern of the function in the flexible wage case closely, except that it must account for the probability that wage rigidity will again be binding next period. Again, note that $w^{\star}_{UR}(p, w_{-1})$ is the larger of $w_{-1}$ and $w^{\star}_{UF}(p)$. Because the latter term is the lowest possible wage, an unemployed worker with a rigid wage will always set this period's reservation wage to equal last period's reservation wage. The wage schedule associated with this value function is denoted $w^{\star}_{UR}(p, w_{-1})$.

## 4.4 Stationary Equilibrium

To define an equilibrium of the model, we derive the equations for flows into and out of employment. The matching function dictates the number of unemployed workers who are matched to a vacant job each period, but not all matches will result in a flow into employment, because of exogenous separations and negotiation failures. Given the cumulative distribution of productivity and reservation wages across unemployed workers $G(p, w)$, with corresponding marginal distribution $G_w(w)$, the job creation flow of workers from unemployment to employment is determined by:

$$\text{Jobs Created} = \left[ f(\theta)(1 - s_x) \iint^{\tilde{w}(p)} \mathrm{d}G(p, w) \right] u = f(\theta)(1 - s_x)\mathbb{E}[G_w(\tilde{w}(p))]u \tag{16}$$

The number of jobs created is the number of unemployed workers times the matching rate for an interview $f$, the likelihood of continuation into negotiation $(1 - s_x)$, and the likelihood of a successful negotiation $\mathbb{E}[G_w(\tilde{w}(p))]$.

In order to determine the flow into unemployment, we define the stationary joint cumulative distribution of productivity levels and reservation wages across employed workers, $\Lambda(p, w)$. The

rigid, the rigidity will never bind. The simplified value function is

$$U^F(p) = b + \mathbb{E}[f(\theta')](1 - s_x)\beta \int W^F(p') \,\mathrm{d}F(p'|p) + (1 - \mathbb{E}[f(\theta')](1 - s_x))\beta \int U^F(p') \,\mathrm{d}F(p'|p).$$

mass of employed workers less than the cutoff wage function $\tilde{w}(p)$, expressed as $\Lambda_w(\tilde{w}(p))$, represents the number of workers who will continue in employment this period. Then the job destruction flow of workers from employment to unemployment is given by:

$$\begin{aligned}\text{Jobs Destroyed} &= \left[(1-s_x)\left(1-\iint^{\tilde{w}(p)} \mathrm{d}\Lambda(p,w)\right)+s_x\right](1-u) \\ &= \Big((1-s_x)\mathbb{E}[1-\Lambda_w(\tilde{w}(p))]+s_x\Big)(1-u)\,, \end{aligned} \tag{17}$$

where the stock of employed workers $1-u$ separates exogenously at rate $s_x$ and endogenously due to wage demands exceeding the firms' cutoff wage function.

The stationary unemployment rate that is consistent with these flows is therefore implicitly defined as the $u$ that equalizes the number of jobs created (equation 16) with the number of jobs destroyed (equation 17) :

$$u^\star = \frac{(1-s_x)\mathbb{E}[1-\Lambda_w(\tilde{w}(p))]+s_x}{f(\theta^\star)(1-s_x)\mathbb{E}[G_w(\tilde{w}(p))]+(1-s_x)\mathbb{E}[1-\Lambda_w(\tilde{w}(p))]+s_x} \tag{18}$$

where stationary labor market tightness $\theta^\star$ is defined as the ratio of the stationary vacancy level $v^\star$ to the stationary unemployment level $u^\star$.

Thus, a *recursive stationary equilibrium* of the model is a collection of value functions $\{V, J, W^F, W^R, U^F, U^R\}$, a collection of policy functions $\{\tilde{w}(p), w^\star_{EF}(p), w^\star_{ER}(p,w_{-1}), w^\star_{UF}(p), w^\star_{UR}(p,w_{-1})\}$, an unemployment level $u^\star$, and a vacancy level $v^\star$ such that:

- Firms maximize expected profits;
- Workers maximize their expected value functions taking firms' policies as given;
- Posting a vacancy has an expected value of zero; and
- Employment flows are consistent with firm and worker policy functions.

The appendix describes our numerical procedure for solving the model.

# 5 Model Estimation and Results

In this section we estimate the parameters of the model described in section 4 and describe some implications of the results. We also examine the model's response to one-time permanent shocks to aggregate productivity. We compare the results of both the steady-state model and the simulations with aggregate shocks to the empirical results from the literature and in this paper, and argue that the model is able to reconcile the observed facts.

## 5.1 Target Moments and Estimation

The theoretical model has 11 parameters: $\beta, \pi, \phi, A, \psi_p, \sigma_p, b, c, \lambda_E, \lambda_U$, and $s_x$. We set $\beta$ to 5 percent annually, as in Shimer (2005) and Hall (2005). Our model does not explicitly feature real productivity growth, so we set $\pi$ to 4 percent annually to capture both price inflation and productivity growth. Therefore, $\beta$ implicitly represents a discount factor that encompasses both pure time preference and trend growth in consumption.

We estimate eight of the nine remaining parameters, $\Theta = \{A, \psi_p, \sigma_p, b, c, \lambda_E, \lambda_U, s_x\}$, via indirect inference, in order to match a set of simulated moments, $\hat{\mu}^s(\Theta)$, to a set of real-world target moments $\mu$. The elasticity of the matching function with respect to the unemployment rate, $1-\phi$, is set to equal the resulting share of job surplus accruing to the worker (Hosios 1990).[28] The estimated parameters are the values that minimize $\hat{\Theta} = \arg\min_{\Theta}[\hat{\mu}^s(\Theta) - \mu]' W^{-1} [\hat{\mu}^s(\Theta) - \mu]$, where the weighting function $W$ is a diagonal matrix of the squares of the target moments. $W$ normalizes each moment to equalize the importance of squared percent deviations from their targets.

Estimating the model via indirect inference helps to correct for potential sources of error in our empirical approach. The first is mis-classification of job stayers and job finders. We simulate the data at a monthly frequency and then classify the simulated workers according to the same definitions we use in the actual PSID and CPS data. Therefore, any classification errors resulting, for instance, from the CPS sampling structure, will be the same in the simulated and observed data. The second is bias in our measurement of the fraction of counterfactual wage cuts prevented by downward nominal wage rigidity. Besides helping to correct for potential measurement error, the indirect inference procedure provides a tight link between the reduced form empirical estimates and their counterparts in the simulated data.

Table 5 displays the empirical moments that we target, along with the simulated moments that result from the estimated model. All moments were calculated over the years 1981 to 2013. The unemployment rate, $u = .064$, job-finding rate, $\tilde{f} = .42$, and median duration of unemployment, $D = 4.3$ months, are targeted to CPS quarterly averages.

The remainder of the target moments are derived from the PSID data.[29] Wage rigidity for incumbent workers ($\widehat{wr}_s = 0.53$ for job stayers) and new hires ($\widehat{wr}_f = 0.20$ for job finders), outlined in section 3 above, are derived from the PSID data for 1981-2013 using two-year wage changes. Differences between the 25th and 50th, as well as 75th and 50th, two-year wage change percentiles, are included for job finders and job stayers from the PSID data. The moments $\hat{\delta}$ and $\hat{\sigma}_\varepsilon$, are taken from the regression $\ln w_{it} = \alpha_0 + \alpha_t + \delta \ln w_{it-2} + \varepsilon_{it}$, and are estimated as $\hat{\delta} = 0.89$

[28] This condition ensures that the number of vacancies is efficient in an environment with flexible wages.

[29] We have also estimated this model using CPS-derived moments, with qualitatively similar results, but we highlight the PSID data because it is a superior dataset for multi-year analysis of the evolution of wages (as opposed to a single one-year change for each worker in the CPS).

and $\hat{\sigma}_\varepsilon = 0.20$.

The right-hand columns of table 5 show the simulated moments in the baseline model and in a constrained model in which $\lambda_U$ is required to equal $\lambda_E$. We first examine the unconstrained case. The model matches most of the target moments fairly well, but is unable to generate the observed dispersion in wages indicated by $\hat{\sigma}_\varepsilon$ and the wage change percentiles. We succeed in generating some of the asymmetry in the wage change percentiles that is evident in the data. The assumption of a common productivity process for job stayers and job finders, which neglects real-world considerations such as human capital formation, may be one reason that the wage dispersion of job finders in particular is smaller than in the observed data. As expected, the constrained model generates wage rigidity estimates for stayers and finders that are quite similar to each other, and in between the estimates in the unconstrained model. Its performance on the other moments is mixed but not substantially worse than that of the unconstrained model.

Although in principle all of the target moments can influence all of the estimated parameters, in practice some of the target moments have a larger influence on some parameters than on others. The Calvo parameters $\lambda_E$ and $\lambda_U$ are primarily determined by the wage rigidity target moments ($\lambda_U$ is also influenced by $D$). The parameters governing the productivity process, $\psi_p$ and $\sigma_p$, are heavily influenced by many of the targets, but $\psi_p$ is directly characterized by $\hat{\delta}$, while $\sigma_p$ is influenced more by $\hat{\sigma}_\varepsilon$ and $D$. The matching efficiency parameter $A$ and the exogenous separations rate $s_x$ are jointly determined by $u$ and $\tilde{f}$. The cost of vacancy creation $c$ and the flow unemployment benefit $b$ are characterized in part by the share of job surplus accruing to the worker.

Table 6 lists the estimated parameter values and their standard errors for the baseline and constrained models. The values for $\lambda_E$ and $\lambda_U$ could not be determined to be different from each other at the 5 percent significance level, and they both correspond to a probability of experiencing rigid wages of greater than 90 percent per month. The exogenous separations rate $s_x$ corresponds to a little more than half of the total separations implied by the stationary unemployment and finding rates. The elasticity of the matching function with respect to unemployed workers $1 - \phi$ is 0.73, reflecting the "take-it-or-leave-it" nature of the wage demands of workers in our model, which causes the majority of the match surplus to accrue to the workers. Nonetheless, because workers realize that they may be unable to cut their wage demands in the future, they moderate their wage demands in the present, leaving a non-trivial share of the match surplus to the firm.[30] The flow benefit of unemployment, $b$, is estimated to be quite low at 0.32, or approximately 30% of the average wage, which helps to moderate their wage demands. The estimated parameters in the constrained model are remarkably similar to the estimates from the baseline case, with the exception that the single $\lambda$ is estimated to be between the estimated $\lambda_E$ and $\lambda_U$. The relatively large standard error

[30]This result is reminiscent of Elsby (2009), who argues that firms will respond to downward nominal wage rigidity by compressing wage increases in good times.

on the estimate of $\lambda_E$ prevents us from distinguishing statistically between those estimates.

## 5.2 Simulation Results

We use our estimated model to simulate a dynamic economy that experiences shocks to aggregate productivity. Each simulation features one permanent shock to aggregate productivity, which is entirely unanticipated by the agents in the model. However, upon the shock arriving, it is common knowledge among all agents that the shock will be permanent. We run 500 simulations of the economy containing 10,000 workers over 8 years (96 months). The aggregate productivity shock arrives in month 60, with equal probabilities of being a 1-percent increase or a 1-percent decrease. We discard the first 4 years of each simulation as a burn-in period. The resulting simulated data represents 500 unique simulations of 12 months of data using the baseline aggregate productivity level and 36 months of data responding to the permanently changed aggregate productivity level.

To facilitate computation, we assume that workers and firms use the policy functions that correspond to the eventual new steady state of the model beginning immediately after the aggregate productivity shock hits. We argue that this assumption approximates the transition from one steady-state to another reasonably well for two reasons. First, following Shimer (2005) and Pissarides (2009), the model will converge quickly to the new steady state after the aggregate shock because the hiring and job separation probabilities are quite large in the model.[31] Additionally, employment relationships are on average long-lasting (49 months in the steady-state model). Thus, firms' hiring and workers' wage posting decisions in the new steady state are likely to be a close proxy for their behavior in transition between states. The number of vacancies each period is not determined using steady state relationships, but is instead set by the free-entry condition using the labor market flows consistent with the assumed policy functions.

Figure 3 shows the impulse responses of the unemployment rate following positive and negative shocks to aggregate productivity. The unemployment rate behaves asymmetrically with regards to the productivity shocks, with a negative shock having a larger effect on unemployment than a positive shock. This asymmetry results from wages being downwardly rigid but upwardly flexible in our model. Figure 3 also decomposes unemployment into its various sources in the model. Exogenous separations and rigidity-based separations are the proximate causes of a little less than half the total unemployment in any given period, while rigid wages for unemployed workers and failures to match with a vacancy account for the remainder. In the event of a negative shock, unemployment due to rigid wages for both the employed and the unemployed increases significantly,

[31] In the baseline steady state, the job finding probability is 0.372 and the separation probability is .021, implying a half-life for the deviation of unemployment from its steady state value of 1.8 months using the approximation $\frac{\ln(2)}{s+f}$. In our simulations, the unemployment rate takes approximately 9 months from its peak or trough following the shock to return halfway to its new steady state.

but after the initial period (during which many workers flow from the employed to unemployed states) the effect of rigidity for unemployed workers dominates the effect of rigidity for employed ones.

The first panel of figure 4 shows the impulse responses of average productivity among all workers and among workers whom we would classify as job finders in the CPS. The observed labor productivity of job finders also responds asymmetrically to positive and negative productivity shocks. Because idiosyncratic productivity evolves as a Markov process independent of firm and employee behavior, these changes are driven entirely by compositional changes. The new hiring spurred by a positive productivity shock brings more marginal employees into employment, leading to a gradual rise in average observed productivity. Wage rigidity for new hires binds much more strongly in the event of a negative shock than a positive one, causing the share of new hires that have flexible wages to rise dramatically in recessions. Thus, a negative shock leads to a rapid decline in average productivity among finders, from which it gradually recovers.

This pattern is also evident in the wage demands of job finders versus all workers, shown in the second row of figure 4. Real wages follow the same qualitative patterns as productivity, but with smaller magnitudes because of the dampening effect of wage rigidity. In the model, unemployed workers, from whom the pool of new hires is selected, do not exhibit this kind of flexibility on average. The ratio of the reservation wage to the idiosyncratic productivity level of the unemployed, shown in the third row of figure 4, does not respond any more dramatically than the wage-to-productivity ratio of employed workers. The gap between these ratios constitutes a major barrier to unemployed workers' chances of becoming re-employed.

The bottom two panels of figure 4 display the impulse responses of the job finding and job separation probabilities. In response to a positive shock, the job finding probability rises roughly 7 percentage points on impact before declining gradually, while the job separation probability falls approximately 0.6 percentage points on impact before beginning to rise. Measured using the log change decomposition of Elsby, Michaels, and Solon (2009), changes in the job finding probability account for 58 percent of the fluctuations in the unemployment rate in the two years after a positive shock. In response to a negative shock, the job finding rate falls almost 5 percentage points on impact, while the separation probability rises 1.6 percentage points, a 70 percent increase from its steady state value. The separation probability returns more quickly than the finding probability towards its new steady state value, but because the initial proportional rise in the separation probability is so large, changes in the job separation probability account for 65 percent of the fluctuations in the unemployment rate in the two years after a negative shock. We view these results as consistent with Elsby et al.'s (2009) argument that "a complete understanding of cyclical unemployment requires an explanation of countercyclical unemployment inflow rates as well as procyclical outflow rates."

Table 7 illustrates individual and aggregate wage elasticities for different worker types estimated from the simulated data in the spirit of the empirical work in section 2. The top panel displays the elasticities of the real wages of individual workers with respect to aggregate productivity and unemployment. Therefore, the elasticities with respect to productivity are analogous to the results in the right-hand columns of table 3, while the elasticities with respect to unemployment are roughly analogous to the results in table 2.[32] Individual wage elasticities with respect to productivity are higher in the simulated data than in the CPS, but the model reproduces the pattern in the CPS that the wages of job finders are more elastic than the wages of non-finders. Elasticities with respect to unemployment are smaller in magnitude than in table 2, but are again consistent with the regularity that the wages of job finders display an elevated responsiveness to business cycle conditions.

The bottom panel of table 7 displays the wage elasticities for aggregate groups of workers. The elasticities with respect to productivity are analogous to the left-hand columns of table 3, which themselves build on the results of Haefke et al. (2013). Simulated elasticities with respect to productivity are substantially higher for all workers and non-finders, and somewhat higher for job finders, than in the CPS. Nonetheless, the simulated data re-creates the key stylized pattern in the literature, that the wages of job finders are substantially more elastic than the wages of other workers. Quantitatively, the simulated wage elasticity with respect to productivity for job finders, 0.79, is nearly twice as large as the elasticity for non-finders, 0.42. Table 2 does not provide a direct analog to the aggregate elasticities with respect to unemployment in table 7, but these elasticities display the same pattern as the others: observed wages of job finders appear more responsive to labor market conditions than do the wages of other workers.

Comparing the individual and aggregate wage elasticities in table 7 shows that the aggregate elasticities are smaller in magnitude than the individual elasticities. This pattern is the same as in the CPS data reported in table 3. It reflects the compositional shifts between worker types in response to business cycle shocks first documented by Solon et al. (1994). For instance, a positive aggregate shock pushes more unemployed workers into employment. Those workers have productivity that is lower on average than the productivity of the previously employed workers, dragging down average wages relative to what they would be in the absence of compositional shifts. A negative shocks works similarly but in reverse. Although the model was not designed to produce this pattern, it arises naturally from the model's structure.

The simulation results demonstrate that a model in which unemployed workers have reservation wages that are nearly as downwardly rigid as the wages of incumbent workers can generate

[32] The aggregate elasticities in table 7 are calculated using quarterly averages of monthly simulated data. The individual elasticities are calculated using year-over-year changes in individual wages. Both sets of elasticities use CPS definitions of workers types.

measured wage elasticities that are substantially higher for job finders than for other workers.[33] It is important to note that although the model does not precisely match the wage elasticities in the data, none of those elasticities were targets of the estimation process, which focused entirely on steady state values. The model is additionally able to generate other stylized features of the labor market data emphasized by Solon et al. (1994) and Elsby et al. (2009). We therefore conclude that the labor market data are consistent with an important role for downward nominal wage rigidity among unemployed workers.

# 6 Conclusion

This paper demonstrates that composition bias can account for the apparent flexibility of the wages of newly hired workers. Newly hired workers are disproportionately likely to have flexible reservation wages relative to the pool of unemployed workers. Analyses that neglect the possible heterogeneity of wage rigidity among unemployed workers may therefore lead to incorrect conclusions. Of course, because reservation wages are not regularly measured in most economic datasets, this problem is inherently difficult to solve.

Using a model that explicitly ascribes high degrees of nominal wage rigidity to both incumbent workers and new hires, we are able to reconcile several disparate patterns in the empirical data. Most importantly, the simulated wages of newly hired workers appear to be much more elastic with respect to business cycle conditions than the wages of other workers, yet cross-sectional measures of wage rigidity are non-trivial both for finders and for non-finders. A negative productivity shock leads to a persistent increase in unemployment attributable to wage rigidity among the unemployed, but the aggregate wages of new hires appear flexible because of selection effects. Therefore, we argue that downward nominal wage rigidity may account for a substantial share of the fluctuations in the unemployment rate during recessions.

[33]The constrained model, in which the reservation wages of unemployed workers are precisely as rigid as the wages of incumbent workers, generates similar results, which are omitted for space.

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Table 1: Descriptive Statistics, PSID and CPS

| | PSID | CPS |
|---|---|---|
| Sample Period | 1980-2013 | 1984-2013 |
| Survey Frequency | Annual/Biannual | Monthly |
| Average Respondents per Survey | 12,513 | 116,071 |
| Wages Used per Survey | 6,142 | 14,056 |
| | | |
| LFPR | 0.649 | 0.659 |
| Unemployment Rate | 0.043 | 0.062 |
| | | |
| Salaried Workers: | | |
| Share of Employed Workers | 0.407 | 0.602 |
| Average Salary ($000s per year) | 40.2 | 41.9 |
| | | |
| Hourly Workers: | | |
| Share of Employed Workers | 0.440 | 0.398 |
| Hourly Wage ($/hr.) | 12.1 | 11.7 |
| | | |
| Proportion Job Finders | 0.113 | 0.126 |
| Proportion Job Stayers | 0.610 | – |
| Proportion Job Switchers | 0.197 | – |
| Proportion Non-Job Finders | – | 0.874 |

Note: PSID switched from annual to biannual surveys after the 1997 survey. Wages used in PSID came from household heads and spouses whose primary compensation was hourly or salaried (i.e., not significantly commission- or bonus-based); see text for more details. Wages used in CPS come from workers in Outgoing Rotation Groups who were between 25 and 60 years old in nonfarm and nonsupervisory occupations. See text for definitions of Job Stayers and Non-Job Finders.

Table 2: Elasticity of Real Wages with Respect to Unemployment in the PSID

| | Wage of Primary Job | | Average Wage | |
|---|---|---|---|---|
| | 1-Year Changes | 2-Year Changes | 1-Year Changes | 2-Year Changes |
| All Workers | -0.83 | -0.36 | -0.70 | -1.19 |
| | (0.46) | (0.51) | (0.19) | (0.54) |
| Job Stayers | -0.56 | -0.03 | -0.49 | -0.84 |
| | (0.53) | (0.49) | (0.13) | (0.46) |
| Job Switchers | -1.80 | -1.59 | -0.59 | -3.53 |
| | (1.16) | (0.82) | (0.70) | (0.68) |
| Job Finders | -1.82 | -1.09 | -1.65 | -2.85 |
| | (0.36) | (0.79) | (0.79) | (1.38) |
| Sample Years | 1980-1997 | 1981-2013 | 1980-1997 | 1981-2013 |

Note: Standard errors are clustered by year. We use two measures of wages: 1) hourly wage in primary job at time of survey, and 2) average hourly wage in surveyed year across all jobs. Elasticities come from individual-level wage regressions that include year dummies, polynomial controls for experience, and, for job stayers, job tenure. The job tenure variable is adjusted using the procedure in Altonji and Williams (1997). We define finders as workers who are employed at the time of the survey date, but who responded that they had experienced unemployment at some point during the surveyed year. Stayers are defined similarly as continuously employed workers with the same employer between surveys. Switchers are defined as continuously employed workers who are not with the same employer as the prior survey. All workers includes household heads and spouses who have valid wages in consecutive surveys. Analysis includes only workers who are primarily hourly employees or salaried employees.

Table 3: Elasticity of Real Wages with Respect to Productivity in the CPS

| | Group Wage Changes | | Individual Wage Changes | |
|---|---|---|---|---|
| | 1984-2006q1 | 1984-2013 | 1989-2006q1 | 1989-2013 |
| All Workers | 0.15 | 0.05 | 0.45 | 0.38 |
| | (0.29) | (0.22) | (0.20) | (0.15) |
| All Workers Less Finders | 0.01 | -0.01 | 0.43 | 0.37 |
| | (0.22) | (0.18) | (0.20) | (0.15) |
| Job Finders | 0.72 | 0.57 | 0.86 | 0.69 |
| | (0.42) | (0.39) | (0.48) | (0.35) |

Note: Group wage changes are imputed as in Haefke, Sontag, and van Rens (2013). Individual wage changes come from workers linked across Outgoing Rotation Groups by Drew et al. (2014). Productivity series in regressions is from the June 2016 Productivity and Costs release. Nominal wages are deflated by the implicit price deflator for the private nonfarm business sector from the same release. Standard errors are clustered by the year level for individual wage changes. We define job finders as workers who are employed at the time of the survey date, but who responded that they had experienced nonemployment at some point during the prior 3 months. Analysis includes only nonfarm, non-management workers between the ages 25 and 60 who are primarily hourly employees or salaried employees.

Table 4: Measured Wage Rigidity in the PSID and CPS

| | PSID | | | | CPS | |
|---|---|---|---|---|---|---|
| | 2-Year Changes | | 1-Year Changes | | 1-Year Changes | |
| Category of Worker | Stayers | Finders | Stayers | Finders | Non-Finders | Finders |
| All Workers | 0.533 | 0.201 | 0.535 | 0.489 | 0.469 | 0.403 |
| | (0.010) | (0.033) | (0.009) | (0.024) | (0.003) | (0.015) |
| Salaried Workers | 0.466 | 0.319 | 0.467 | 0.397 | 0.424 | 0.471 |
| | (0.016) | (0.068) | (0.013) | (0.079) | (0.006) | (0.058) |
| Hourly Workers | 0.585 | 0.165 | 0.591 | 0.515 | 0.501 | 0.417 |
| | (0.015) | (0.034) | (0.012) | (0.029) | (0.003) | (0.015) |
| Sample Period | 1981-2013 | | 1980-1997 | | 1989-2013 | |

Note: Wage rigidity estimates measure the proportion of counterfactual wage cuts missing from the observed wage change distribution as described in Appendix A. Standard errors from 500 bootstrap replications in parentheses.

Table 5: Empirical and Simulated Moments

| Target Moments | Description | Target Values | Unconstrained Model | Constrained Model |
|---|---|---|---|---|
| $\hat{wr}_s$ | Wage Rigidity for Stayers - 2 year wage changes | 0.533 | 0.439 | 0.329 |
| $\hat{wr}_f$ | Wage Rigidity for Finders - 2 year wage changes | 0.201 | 0.145 | 0.297 |
| $u$ | Average Monthly Unemployment Rate | 0.064 | 0.056 | 0.057 |
| $\tilde{f}$ | Average Monthly Job Finding Hazard Rate | 0.417 | 0.372 | 0.362 |
| $D$ | Mean Duration (months) unemployed | 4.324 | 4.017 | 4.126 |
| $\Phi_s^{-1}(.25) - \Phi_s^{-1}(.5)$ | 25th Pctile-50th Pctile Real Log Wage Changes for Stayers | -0.031 | -0.021 | -0.028 |
| $\Phi_s^{-1}(.75) - \Phi_s^{-1}(.5)$ | 75th Pctile-50th Pctile Real Log Wage Changes for Stayers | 0.042 | 0.026 | 0.039 |
| $\Phi_f^{-1}(.25) - \Phi_f^{-1}(.5)$ | 25th Pctile-50th Pctile Real Log Wage Changes for Finders | -0.080 | -0.024 | -0.022 |
| $\Phi_f^{-1}(.75) - \Phi_f^{-1}(.5)$ | 75th Pctile-50th Pctile Real Log Wage Changes for Finders | 0.081 | 0.027 | 0.039 |
| $\hat{\delta}$ | AR(1) Coefficient on Log Wages | 0.886 | 0.794 | 0.894 |
| $\hat{\sigma}_\varepsilon$ | Std. Dev. Of AR(1) Log Wage Innovations | 0.201 | 0.063 | 0.049 |

Note: All target moments come from the PSID 1981-2013 except for $u$, $\tilde{f}$, and $D$, which come from the CPS over the same period. All wage change moments from PSID refer to two-year wage changes. Log wage change percentiles are for all workers. Unconstrained model estimates separate $\lambda_E$ and $\lambda_U$; constrained model imposes equality.

Table 6: Model Parameters

| Parameter | Description | Unconstrained Model Value | Constrained Model Value |
|---|---|---|---|
| $\beta$ | Time Preference | 0.950 | 0.950 |
| $\pi$ | Trend Nominal Wage Growth | 0.040 | 0.040 |
| $\bar{p}$ | Average Productivity Level (Normalized to 1) | 1.000 | 1.000 |
| $1-\phi$ | Elasticity of Matching Function w.r.t. unemployment | 0.730 | 0.731 |
| $A$ | Efficiency of Matching Function | 0.772 | 0.760 |
| | | (0.112) | (0.204) |
| $s_x$ | Exogenous Separations Rate | 0.012 | 0.012 |
| | | (0.006) | (0.013) |
| $\psi_p$ | Persistence of Productivity Process | 0.899 | 0.901 |
| | | (0.043) | (0.510) |
| $\sigma_p$ | Standard Deviation of Productivity Shock | 0.018 | 0.018 |
| | | (0.002) | (0.006) |
| $b$ | Flow Benefit of Unemployment | 0.323 | 0.319 |
| | | (0.015) | (0.039) |
| $c$ | Flow Cost of Vacancy Posting | 0.165 | 0.163 |
| | | (0.012) | (0.051) |
| $\lambda_U$ | Probability of Rigid Wages - Unemployed Worker | 0.340 | |
| | | (0.004) | 0.368 |
| $\lambda_E$ | Probability of Rigid Wages - Employed Worker | 0.401 | (0.110) |
| | | (0.112) | |

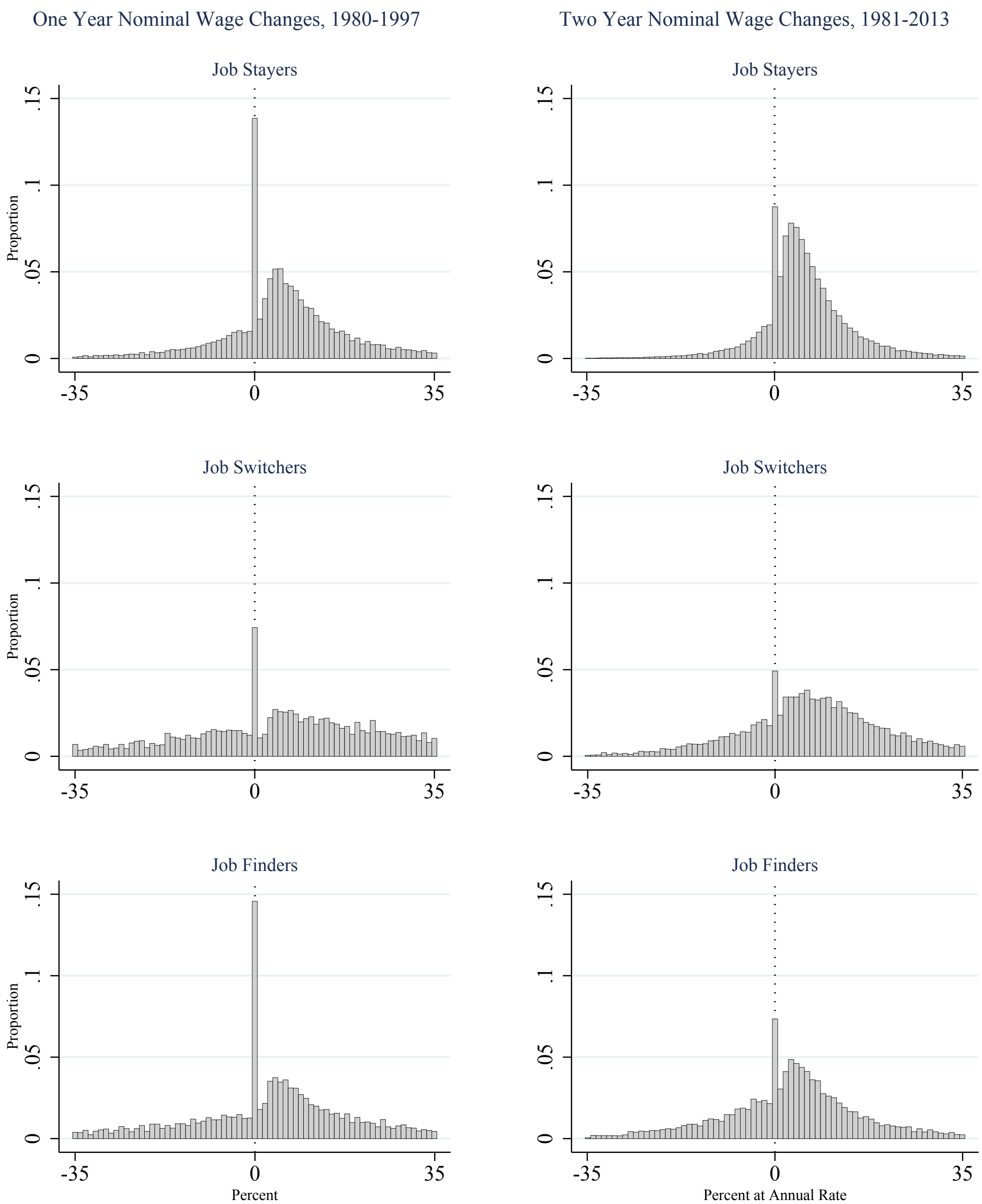
Note: $\beta$, $\pi$, and $\bar{p}$ are fixed externally; other parameters are estimated as described in the text. $\beta$, $\pi$, $\bar{p}$, $\psi_p$, $\lambda_U$, and $\lambda_E$ are annual values; $A$, $\psi_p$, $\sigma_p$, $b$, and $c$ are monthly values. Unconstrained model estimates separate $\lambda_E$ and $\lambda_U$; constrained model imposes equality. Standard errors in parentheses.

Table 7: Simulated Real-Wage Elasticities

| Wage Elasticity with Respect to: | All | All Less Finders | Finders |
|---|---|---|---|
| | | Individual Wages | |
| Productivity | 0.773 | 0.744 | 0.898 |
| | (0.003) | (0.003) | (0.013) |
| Unemployment | -0.549 | -0.528 | -0.639 |
| | (0.002) | (0.002) | (0.009) |
| | | Aggregate Wages | |
| Productivity | 0.445 | 0.421 | 0.790 |
| | (0.005) | (0.005) | (0.040) |
| Unemployment | -0.234 | -0.222 | -0.406 |
| | (0.003) | (0.003) | (0.022) |

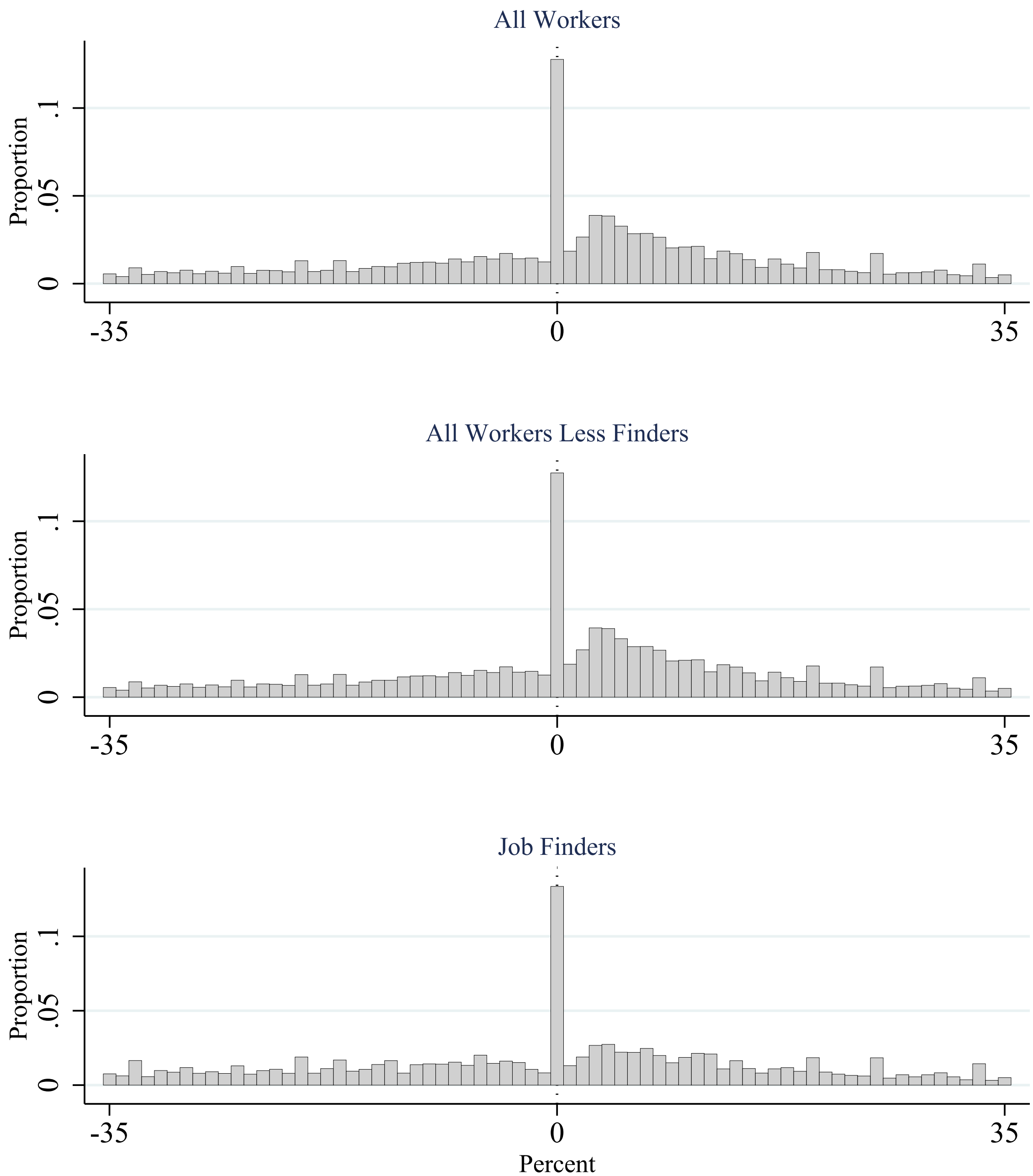
Note: The aggregate elasticities are calculated using quarterly averages of monthly simulated data. The individual elasticities are calculated using year-over-year changes in individual wages. Reported values with respect to unemployment are semi-elasticities. Both sets of elasticities use CPS definitions of workers types.

Figure 1: Nominal Wage Changes in the PSID by Worker Category




Note: distributions are truncated at plus and minus 35 percent.

Figure 2: Nominal Wage Changes in the CPS by Worker Category




Notes: Data range from 1989 to 2013.
Years 1995-1996 are excluded because of a sample design change in 1995 that hinders matching.
Graphs are truncated at -35 and 35 percent.

Figure 3: Sources of Unemployment

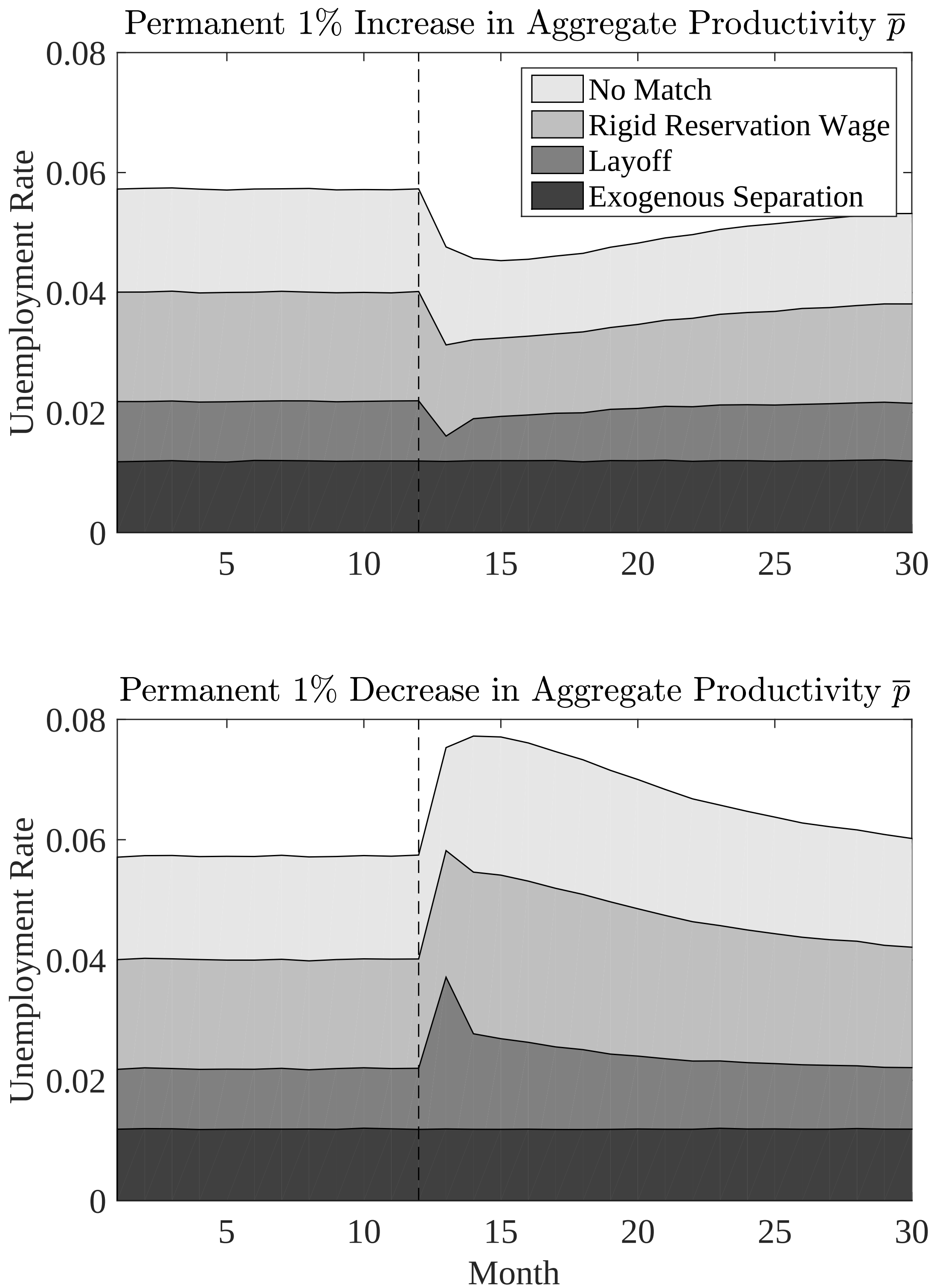
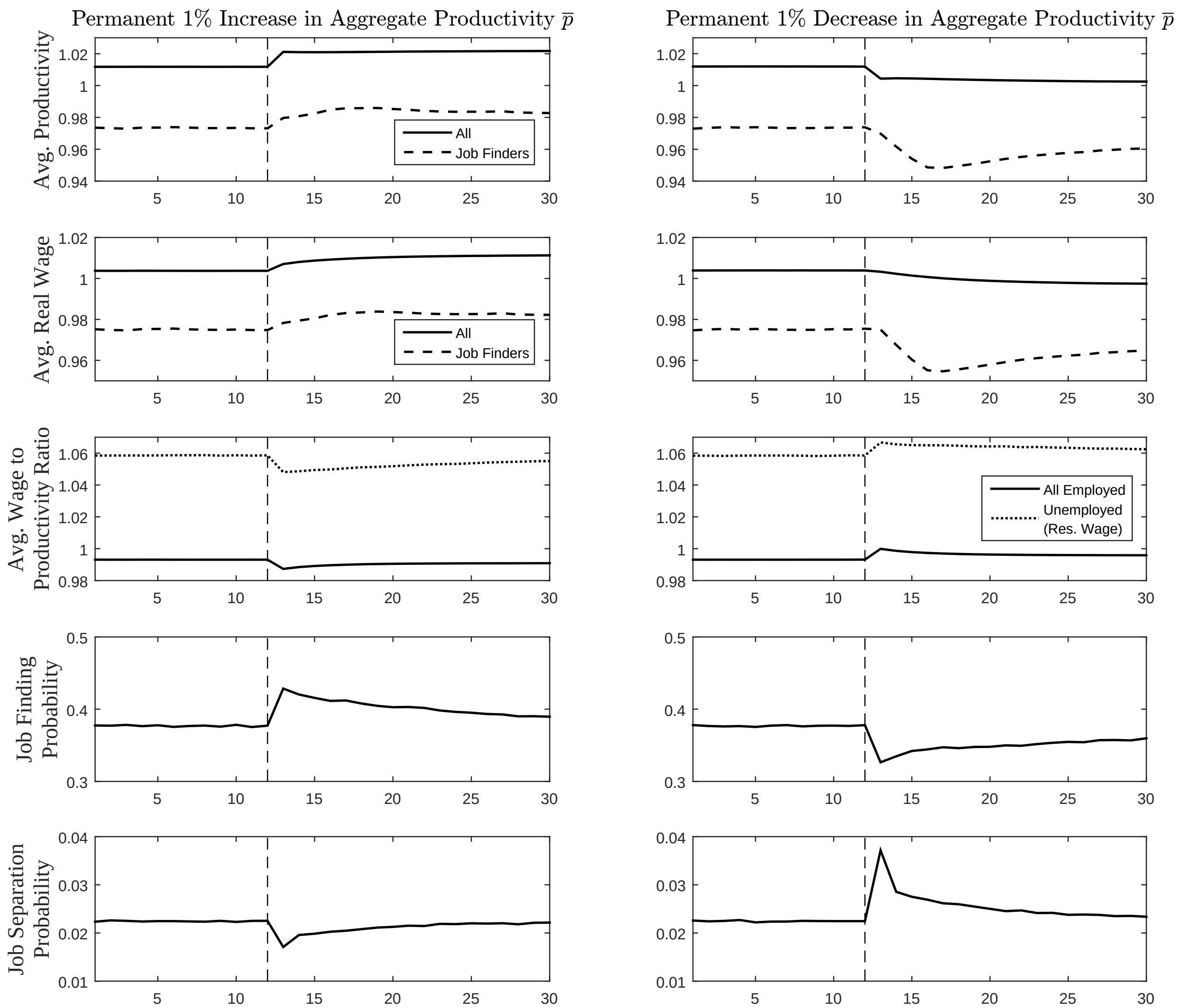


Figure 4: Labor Market Responses to Aggregate Productivity Shocks



# A Appendix

## A.1 Technical Appendix on Data

This section of the appendix details the methods employed in sections 2 and 3 to analyze real wage elasticities and nominal wage rigidity, respectively, in both PSID and CPS data.

### A.1.1 PSID

We extract employment, wage, and demographic information from each of the 1980-2013 family-level surveys for both the head of household and, where available, spouse. Because the PSID uses primarily gender-based assignment of "head of household," the primary earner of each family might be either the head or the spouse according to that family's particular economic situation.

These data are used to create an individual dataset, whereby each family-level entry is merged onto the individual file to obtain an individual weight corresponding to each record. The resulting file contains an average of 12,513 records per year.

The hourly nominal wage for each respondent is calculated using his or her primary job only, as this best suits our understanding of where wage rigidity manifests and is most economically relevant. For hourly employees, we use the current reported hourly wage; for salaried workers, we use the hourly wage when it is reported, but the more common response is to report pay over a longer horizon such as "per month" or "per year" values. In these cases, we assume 52 working weeks per year, 40 hours per week, to assign an hourly wage. We exclude all top-coded data, which applies to hourly wages at or above 100 dollars per hour before 1993 and 1,000 dollars per hour from 1993 to 2013. Salaried employees are top-coded above 1 million dollars from 1980 to 1993 and 10 million dollars thereafter. We exclude workers who earn significant money from bonus or incentive-laden schemes from our analysis.

In alternate specifications we use the PSID-generated hourly imputed wage, which adds the earnings of the surveyed year (not the wages at the time of the survey) and divides by the imputed hours spent working. This measure is not our preferred specification because it potentially involves a host of relationships between each worker and his or her various employers, but as expected, the level of wage rigidity decreases modestly using the imputed wage relative to our preferred hourly wage measure.

We calculate a tenure measure for all respondents who are currently employed. This measure is used both to categorize workers as "job stayers" versus "job switchers" and as a regressor to control for job-specific productivity gains in our elasticity measures. The tenure variable is constructed from a series of questions that ask how long the respondent has been with his or her current employer, with the answers converted into years. Job stayers are then distinguished from switchers by the time between surveys for each respondent; if the time elapsed between surveys is longer than the reported tenure, the respondent is deemed a switcher (unless he or she has experienced a month or more of non-employment). Otherwise, the respondent is deemed a stayer. We clean the tenure variable according to the procedure in Altonji and Williams (1997) by allowing tenure to increment by only 1 year at a time for each respondent and re-setting it whenever the raw tenure measure indicates that the respondent is either a switcher or a finder.

It is important to note that our definition of a job finder excludes some respondents who might nonetheless be best described as such. In both our direct measure of wage rigidity and our estimates of the various wage elasticities for job finders, we require that finders have a wage in both the previous and current survey dates to be included in the sample. A respondent who was not working in the prior year at the time of their survey date, but who nonetheless found a job in time for the current year's survey date, would be excluded from the analysis. Therefore, the job finder sample skews towards those who had shorter spells of unemployment. In addition, the worker who experiences multiple rounds of unemployment will find his or her current wages compared to the wages at the job held at the time of the previous survey rather than to those in the immediately preceding job.

We attempted two other methods to categorize workers. In the first, we augmented the tenure versus time elapsed between surveys comparison with the additional restriction that occupational codes and industry codes could not switch from one year to the next. In the second, we directly compared start dates with previous survey dates. We prefer the original method because a) responses to length of time on the job are more frequently given (or perhaps known) than start dates, and b) occupational codes and industry codes are not always comparable between years.

### A.1.2 CPS

We use the CPS basic monthly files from 1984 to 2013 and the Integrated Public Use Microdata Series (IPUMS) from 1989-2013. We use the basic monthly files to calculate aggregate wage elasticities with respect to productivity, in the spirit of Haefke et al. (2013). The IPUMS data are used when it is necessary to link individual workers' wages across outgoing rotation groups. We restrict our analysis to nonfarm, nonsupervisory workers between the ages of 25 and 60, so we exclude agricultural and managerial occupations. In addition, we evaluate only workers who were either paid by a flat salary or hourly wage.

The top-coding of hourly and salaried workers is more severe in the CPS than in the PSID, so for the aggregate wage elasticity regressions we impute earnings for top-coded workers following the procedure of Schmitt (2003), also used by Haefke et al. (2013). In the linked individual data, we exclude observations with top-coded earnings entirely from the analysis.

We construct a measurement of hours for salaried workers that is equal to their typical hours worked per week when available, substituted for hours worked in the past week if it is not. We then trim the sample of outliers (totaling 1 percent of workers) to address concerns that the previous week may have been atypical. To create an hourly wage for salaried workers, we divide weekly earnings by weekly hours worked. Employees who were paid an hourly wage have it reported as such. Real hourly wages are trimmed symmetrically at the 0.5 and 99.5 percentiles as well.

We exclude intervals that span 1995q3 and 1995q4 from our analysis because a change in sample design renders us unable to match workers across that break.

We are unable to create an analog to job stayers and job switchers in CPS data, as we have an incomplete employment history of each respondent. The limited employment history allows us to categorize a worker as a job finder, but this definition is more restrictive than the one used in the PSID. A worker who has a job in the outgoing rotation group but reports a month of non-employment at any point in the 3 months prior is called a job finder in analysis performed with

CPS data.

As in the PSID, wage changes are the unit of analysis. As such, workers who were unemployed in the outgoing rotation group either the first or second time do not have measurable wage changes and are excluded from the analysis.

We weight each record in our sample according to the earnings weight variable EARNWT.

## A.2 Measuring Wage Rigidity

This paper measures the fraction of counterfactual nominal wage cuts prevented by downward nominal wage rigidity using the approach in Ehrlich and Montes (2015), which builds on the approach of Card and Hyslop (1997). We present a brief overview here.

For each year $t$, estimate the distribution of observed wage changes using kernel density estimation.[34] The estimate of the density at a point $x$ is

$$\hat{f}_t(x) = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{h_j}K\left(\frac{x-x_j}{h_j}\right) \tag{A.1}$$

where $n$ is the number of observations, $x_j$ for $j \in \{1, ..., n\}$ denotes a point in the observed distribution, $h_j$ is an adaptive bandwidth following the procedure of Van Kerm (2003), and $K$ is a kernel function.[35] The specific kernel function used in the estimation is an Epanechnikov kernel of the form

$$K(z) = \begin{cases} \frac{3}{4}\left(1-z^2\right) & \text{if } |z| < 1 \\ 0 & \text{otherwise.} \end{cases} \tag{A.2}$$

Denote the estimated distribution of observed wage changes as $\hat{f}_t^{obs}$, and let $m_t$ represent the median wage change from year $t-1$ to year $t$ expressed in percentage points.

Next, construct a counterfactual wage change distribution $\hat{f}^{cf}$ for establishment $i$ by averaging the upper tails of the estimated observed distributions $\hat{f}_t^{obs}$ across each year. In constructing the average, first normalize the observed distribution for each year around its median.[36] Then, reflect the averaged distribution of the upper tails around the median each year.

The estimated proportion of wage cuts prevented by wage rigidity is then calculated by comparing the implied proportion of counterfactual wage cuts to the number observed. For year $t$, denote the proportion of wage cuts in the estimated observed wage change distribution as $\hat{F}_t^{obs}(0^-)$.[37] Denote the proportion of wage cuts in the estimated counterfactual distribution as $\hat{F}_t^{cf}(0^-)$. Let the

[34] The estimation procedure focuses on wage changes within 15 percentage points of the median wage change each year to avoid the influence of outliers.

[35] The global bandwidth is set to be 0.005. The adaptive bandwidths are calculated as the product of the global bandwidth and a local bandwidth factor that is proportional to the square root of the underlying density function at the sample points. The adaptive bandwidths have the property that their geometric average equals the global bandwidth.

[36] In practice, in situations in which the observed median is negative and there are more observed wage cuts than wage increases, recalculating the median by excluding observed wage changes between -0.25% and 0.25% helps to correct for the "sweep-up" of counterfactual wage cuts to zero. This adjustment improves the accuracy of the procedure in the Monte Carlo simulations discussed in Ehrlich and Montes (2015). Those years are then excluded when averaging the upper tails, but are included when calculating the counterfactual wage cuts prevented by wage rigidity.

[37] The notation $0^-$ indicates that the measured proportion does not include wage changes of exactly zero.

sum across years of these proportions be denoted $\hat{F}^{obs}(0^{-})$ and $\hat{F}^{cf}(0^{-})$. The measure of wage rigidity is then the proportion of counterfactual wage cuts that are "missing" from the data and is calculated as

$$\widehat{wr} = 1 - \frac{\hat{F}^{obs}(0^{-})}{\hat{F}^{cf}(0^{-})}. \tag{A.3}$$

Therefore, the wage rigidity estimate in equation (A.3) is time-invariant. $\widehat{wr}$ has the natural interpretation that a value of 0.25 implies that 25 percent of counterfactual nominal wage cuts were prevented by downward nominal wage rigidity over the sample period.[38]

## A.3 Computational Methods

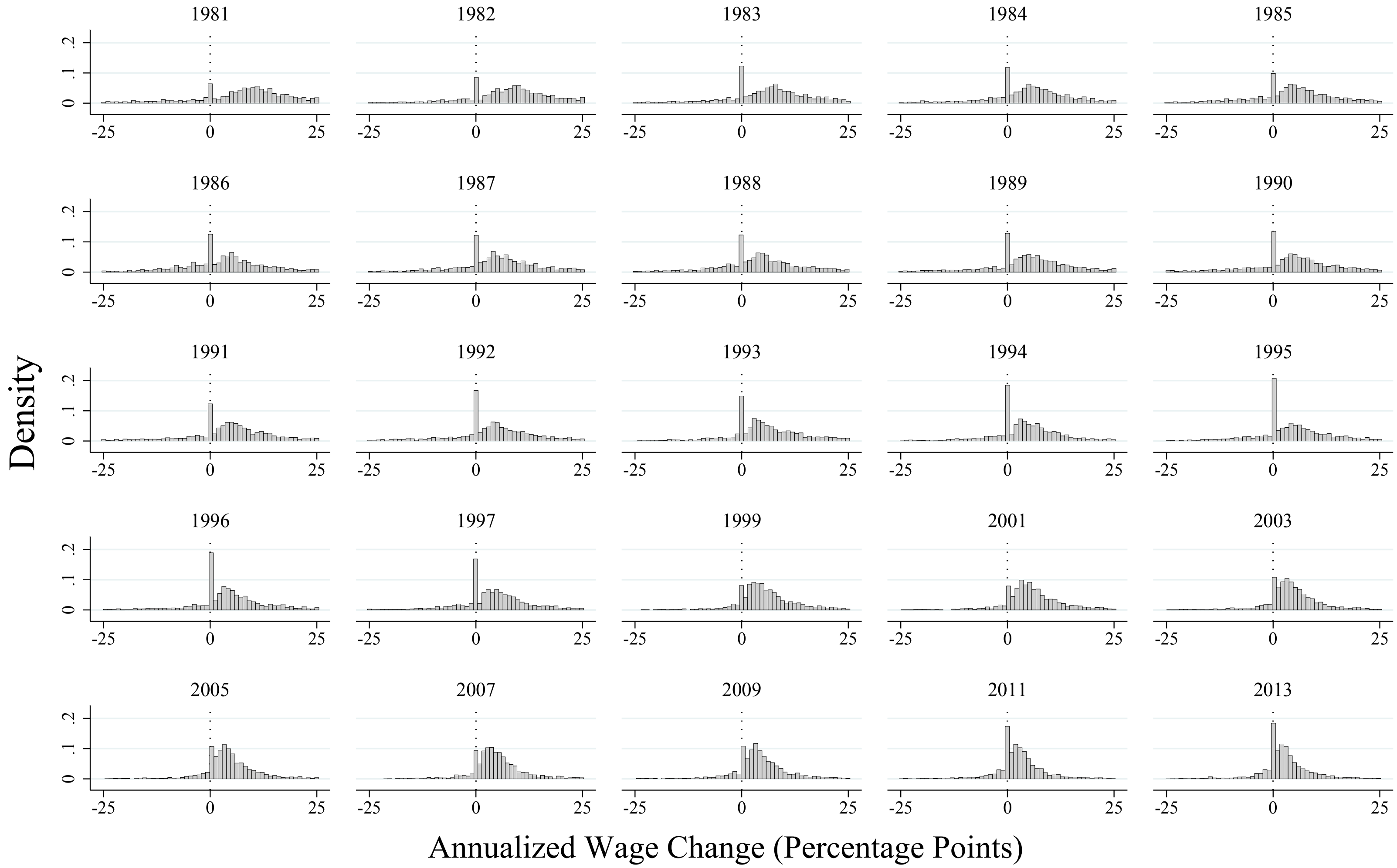
We approximate the value functions for firms and workers using standard value function iteration techniques. We approximate the productivity process using the method of Tauchen (1986), using a productivity grid with 200 nodes. The nodes are spaced evenly in log terms, ranging from two standard errors below the mean to two standard errors above. At the estimated values for persistence of the productivity process $\psi_p$ and innovation $\sigma_p$, the minimum grid value for $p$ is 0.761 and the maximum value is 1.314. We allow workers to choose reservation wages along an evenly-spaced 250-point grid with a minimum value of 0.723 and a maximum value of 1.380; these extrema represent a range that encompasses that of $p$ and extends an additional 5 percent in either direction.

The period for the model simulations is taken to be one month. We draw one set of random shocks to use in every simulation. We simulate 2500 workers for 60 years, or 720 periods, discarding the first 10 years (120 periods) for burn-in. We sample workers' simulated wages annually, except where noted otherwise in the text, for the purpose of measuring individual and aggregate elasticities and wage rigidities.

In order to reduce the numerical error associated with the calculation of the standard errors in table 6, we use three different step sizes, 1%, 3%, and 5%, to calculate the derivatives of the simulated moments $\hat{\mu}^s(\Theta)$ with respect to the model parameters $\Theta$, and average them.

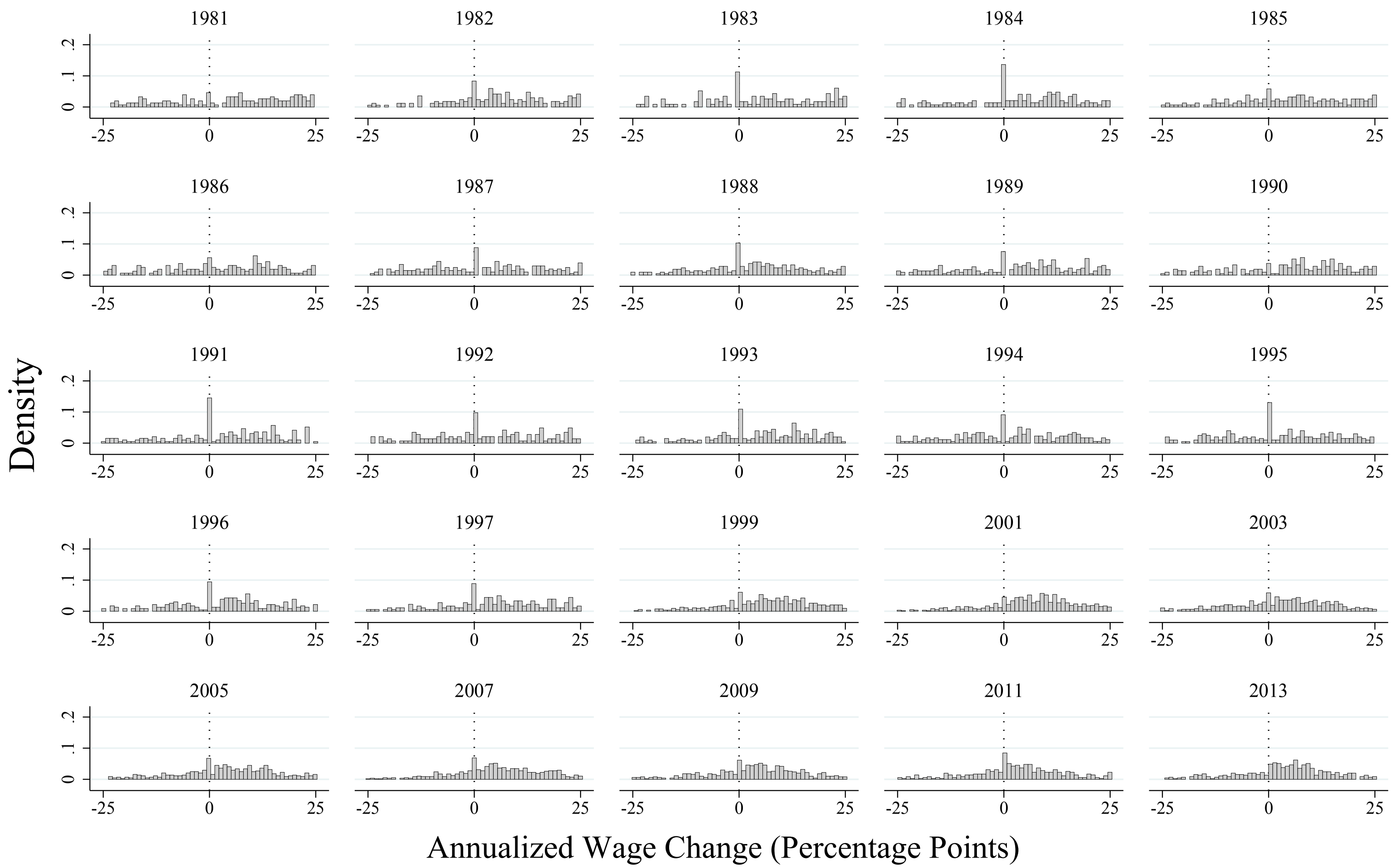
[38]Nothing in this procedure prevents $\widehat{wr}_i$ from being negative. A value for $\widehat{wr}_i$ of -0.25 would imply that there are 25 percent more wage cuts in the data than would be predicted by the distribution of nominally positive wage changes.

Figure A.1: Nominal Wage Growth Among Job Stayers in the PSID by Year



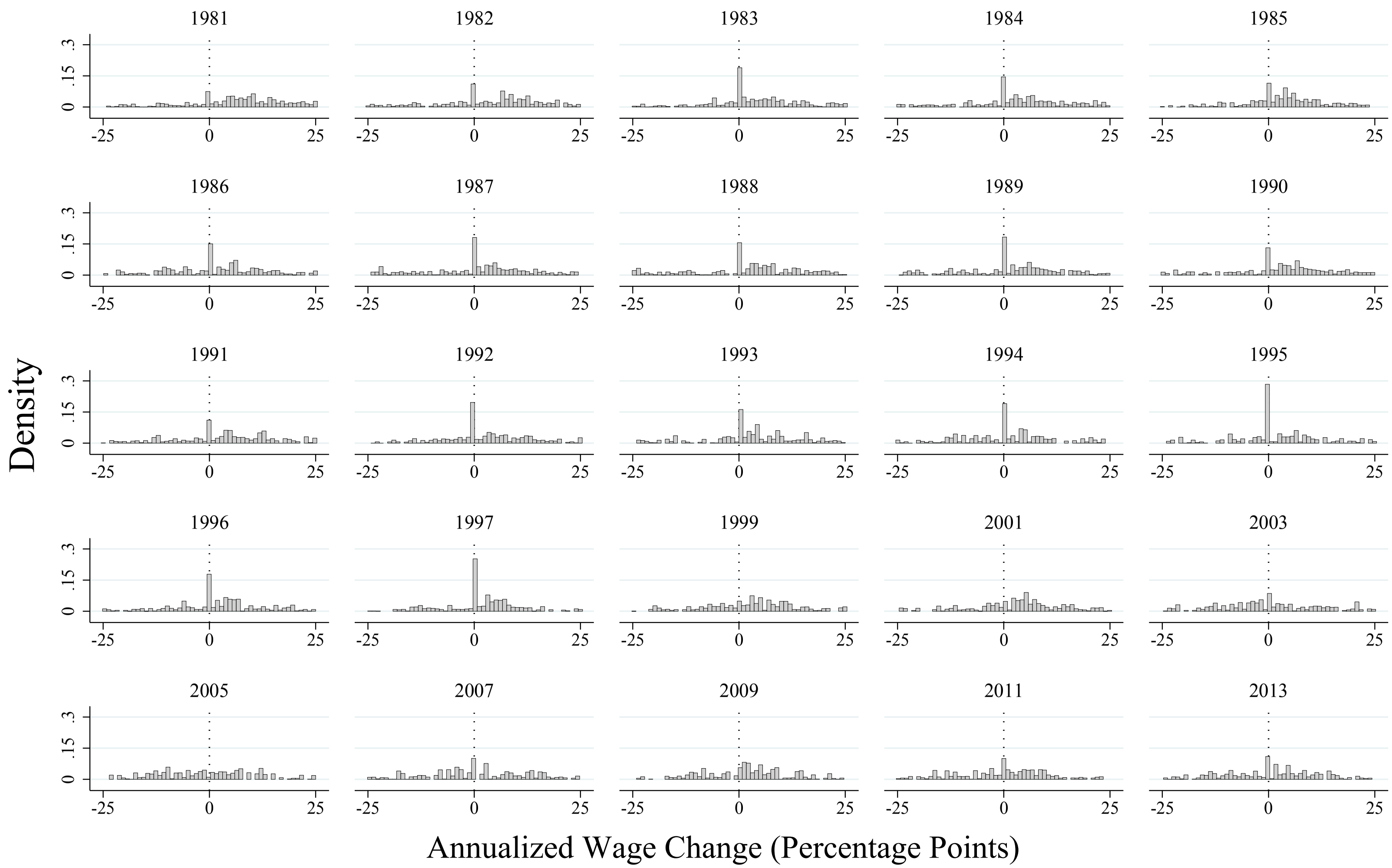

Notes:
Years 1981-1997 show the annual wage change from the previous year.
Years 1999-2013 show the annualized two-year wage change from two years previously.
Distributions are truncated at -25 and 25 percent.

Figure A.2: Nominal Wage Growth Among Job Switchers in the PSID by Year



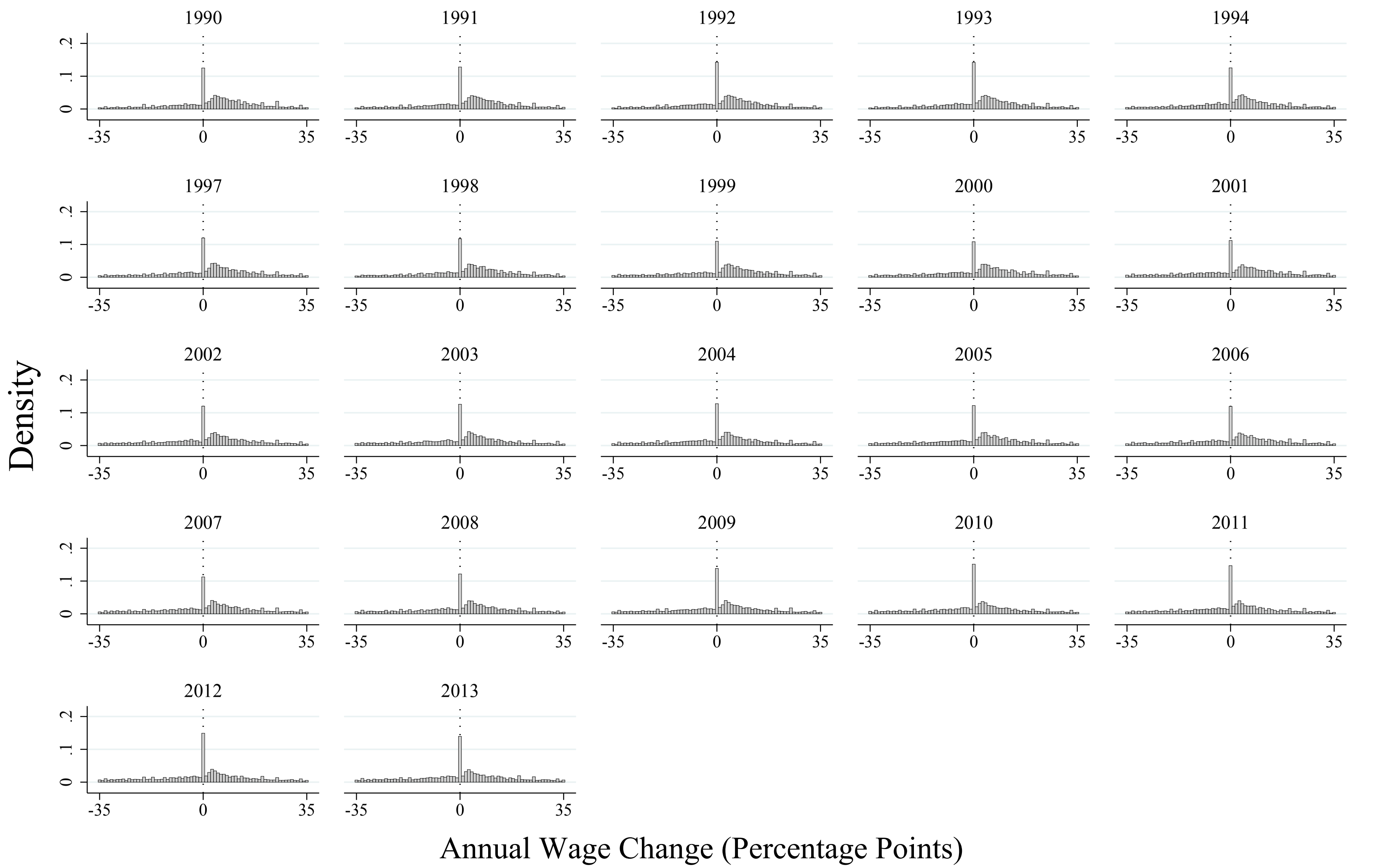

Notes:
Years 1981-1997 show the annual wage change from the previous year.
Years 1999-2013 show the annualized two-year wage change from two years previously.
Distributions are truncated at -25 and 25 percent.

Figure A.3: Nominal Wage Growth Among Job Finders in the PSID by Year



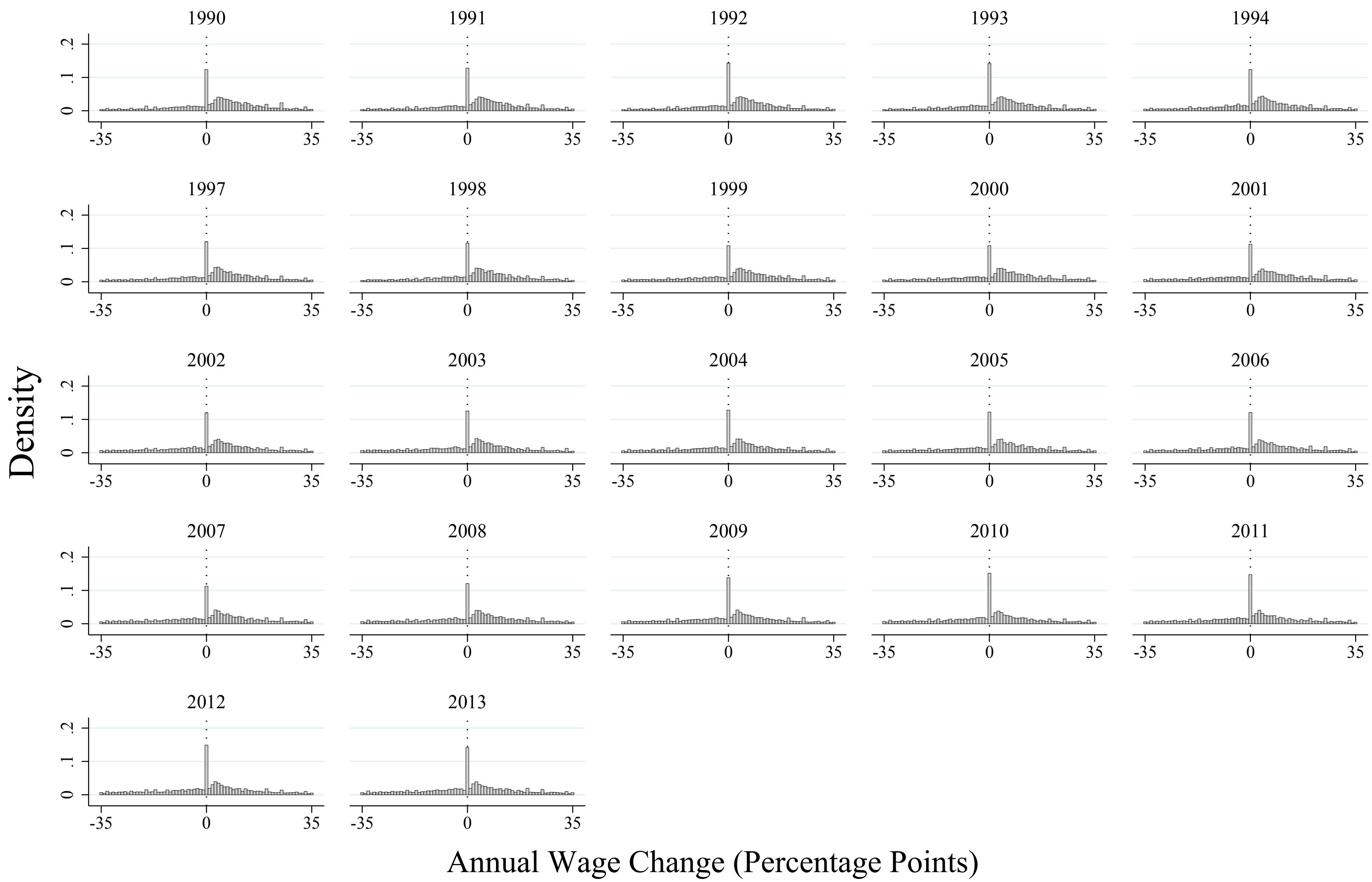

Notes:
Years 1981-1997 show the annual wage change from the previous year.
Years 1999-2013 show the annualized two-year wage change from two years previously.
Distributions are truncated at -25 and 25 percent.

Figure A.4: Nominal Wage Growth Among All Workers in the CPS by Year



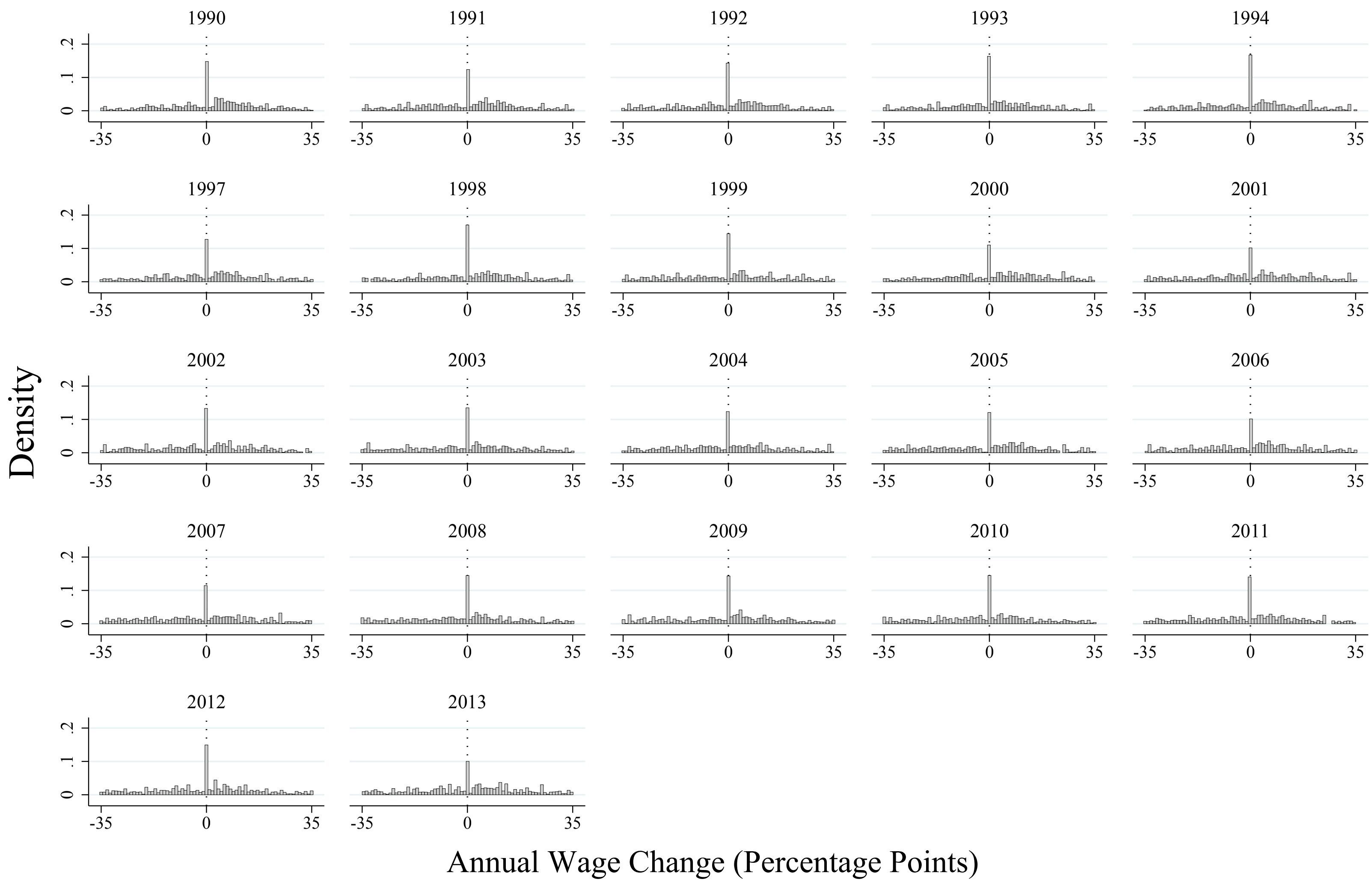

Notes:
Years 1995-1996 are exluded because of a sample design change in 1995 that hinders matching.
Distributions are truncated at -35 and 35 percent.

Figure A.5: Nominal Wage Growth Among Workers, Excluding Finders, in the CPS by Year



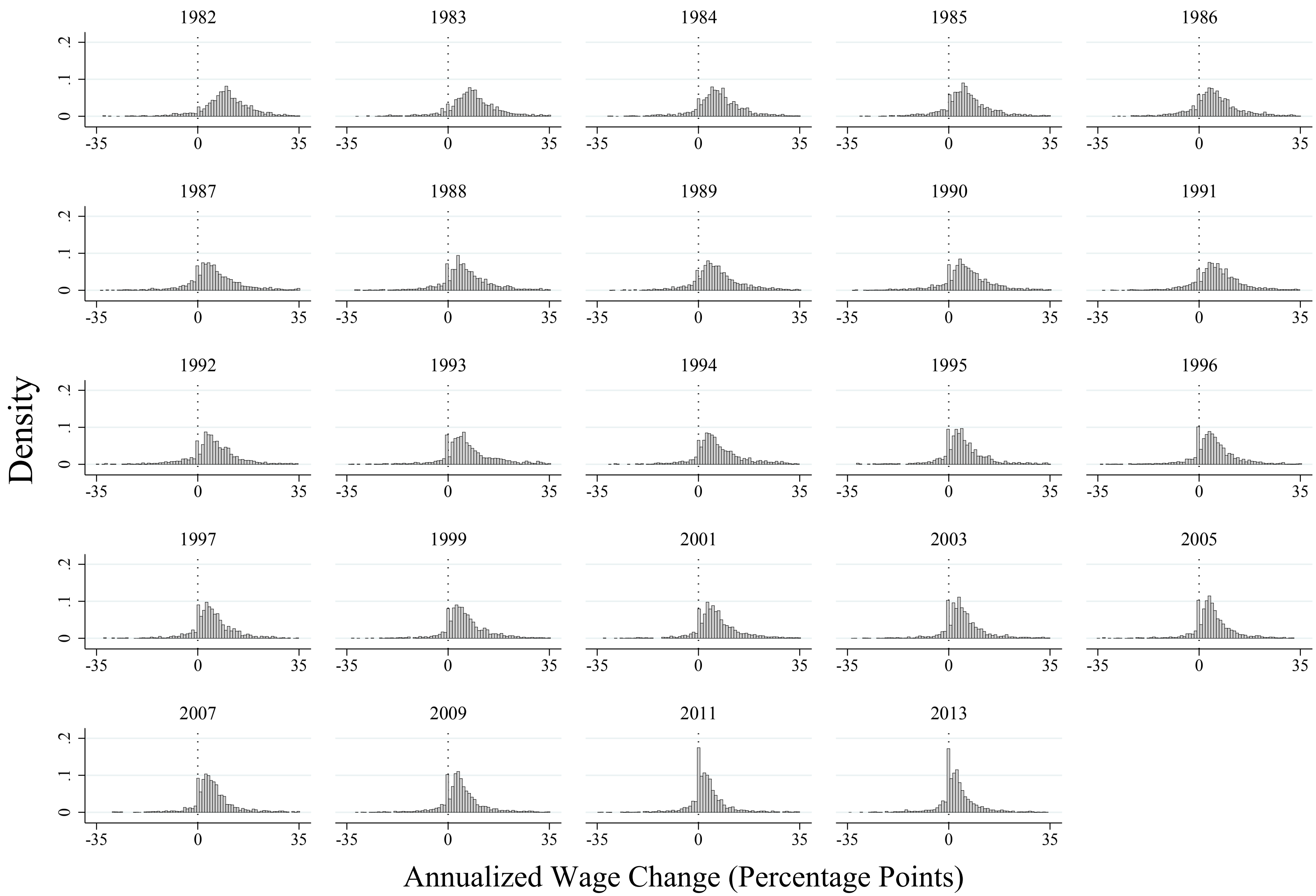

Notes:
Years 1995-1996 are exluded because of a sample design change in 1995 that hinders matching.
Distributions are truncated at -35 and 35 percent.

Figure A.6: Nominal Wage Growth Among Job Finders in the CPS by Year



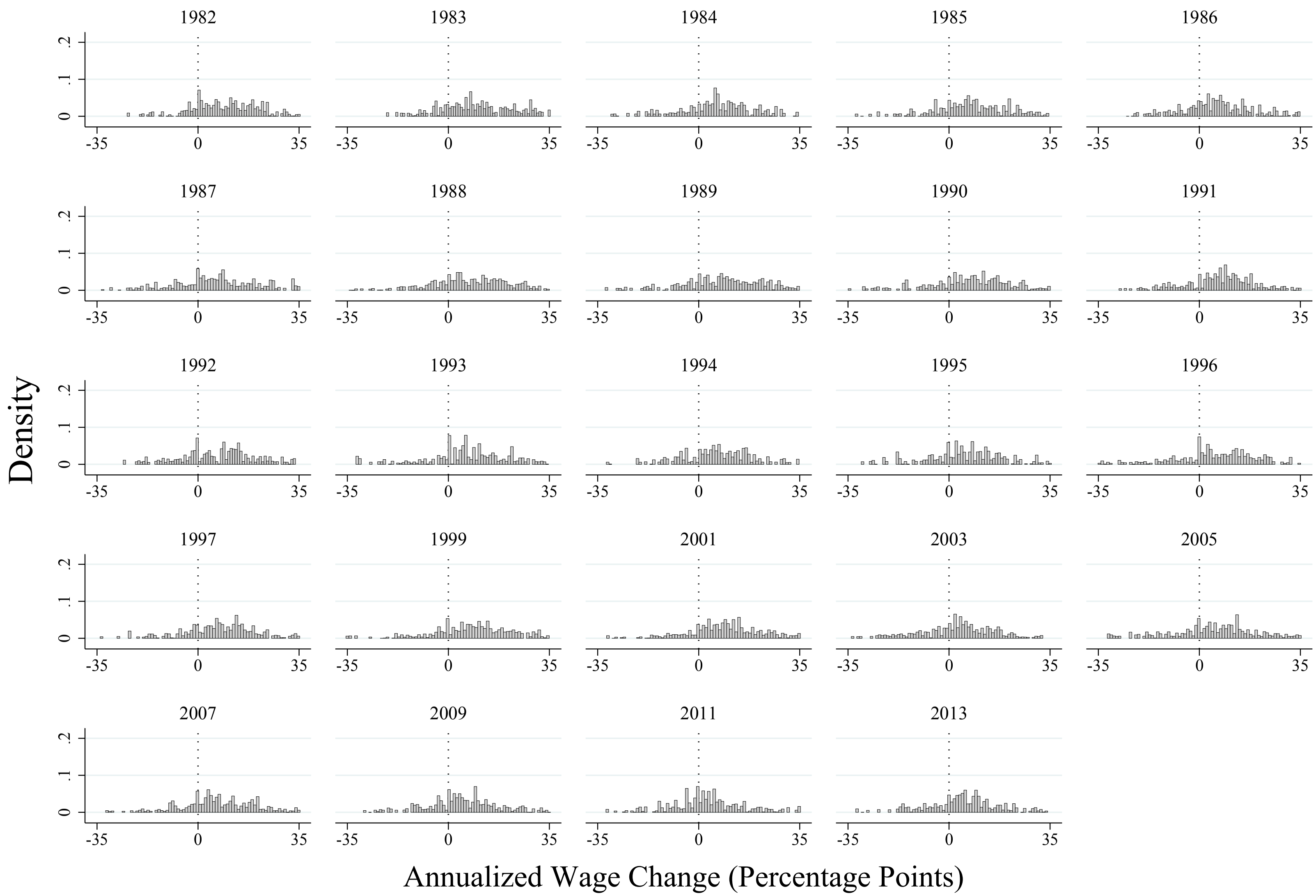

Notes:
Years 1995-1996 are exluded because of a sample design change in 1995 that hinders matching.
Distributions are truncated at -35 and 35 percent.

Figure A.7: 2-Year Nominal Wage Growth Among Job Stayers in the PSID by Year



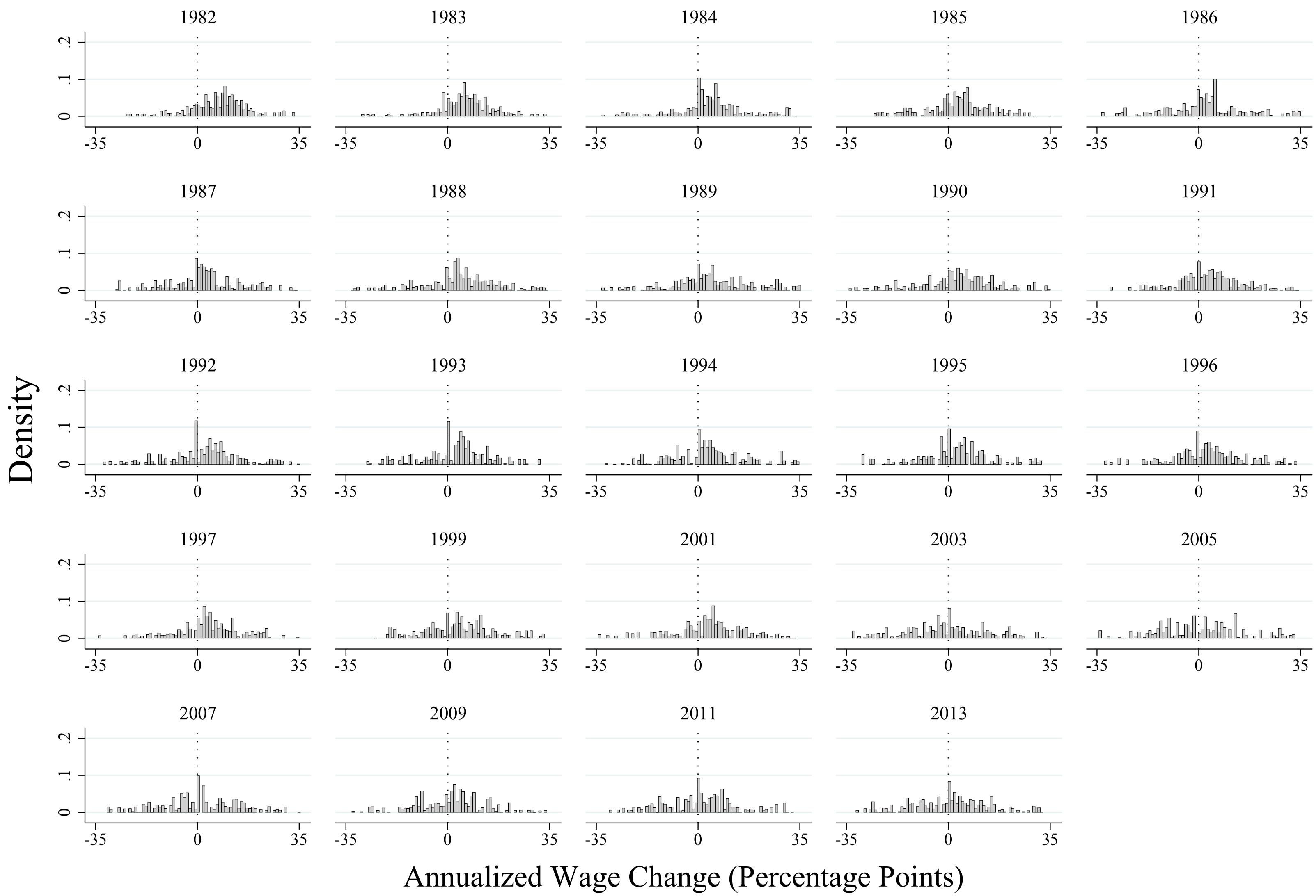

Note: Years show the annualized two-year wage growth rate from two years previously.

Figure A.8: 2-Year Nominal Wage Growth Among Job Switchers in the PSID by Year




Note: Years show the annualized two-year wage growth rate from two years previously.

Figure A.9: 2-Year Nominal Wage Growth Among Job Finders in the PSID by Year




Note: Years show the annualized two-year wage change from two years previously.