Are Entry Wages Really (Nominally) Flexible?*

Gabriel Ehrlich
University of Michigan

Matthew Hall
Boston Consulting Group

Joshua Montes
Federal Reserve Board

September 1, 2018

*We would like to thank Charles Brown, Susan Collins, George Fulton, Chris House, Pawel Krowlikowski, Ryan Nunn, David Ratner, Matthew Shapiro, and seminar participants at the Econometric Society North America Summer Meetings, the University of Michigan, the University of Notre Dame, and the Federal Reserve Bank of Boston for helpful comments. All errors are our own. Please contact the authors by e-mail at gehrlich@umich.edu, mathall@umich.edu, or joshua.k.montes@frb.gov. The views expressed here do not necessarily reflect the views of the staff and members of the Federal Reserve Board or the Federal Reserve System as a whole.

Abstract

No, entry wages simply appear flexible because of composition bias. We show that although the wages of job finders are more elastic with respect to the business cycle than the wages of job stayers, both types of workers show substantial downward nominal wage rigidity as measured in aggregate wage change histograms. We reconcile this apparent contradiction in a model in which employed and unemployed workers both face Calvo-style downward nominal wage rigidity. 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. The estimated model reproduces the stylized fact that the observed wages of job finders are substantially more elastic with respect to the business cycle than the wages of job stayers, although the estimated (unobserved) reservation wages of unemployed workers are nearly as rigid as the wages of employed workers. Therefore, the standard wage elasticity regressions used in the literature are likely unreliable and will generate large wage elasticities for new hires even when the underlying reservation wages of all unemployed workers are substantially rigid. Thus, the large observed wage elasticities of job finders do not preclude downward nominal wage rigidity from playing an important role in determining the cyclical movements in unemployment.

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

I 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. A canonical set of models implies that the wages of new hires, and not those of incumbent workers, determine job creation over the business cycle. As a result, those models suggest that downward nominal wage rigidity (hereafter, wage rigidity) is unlikely to explain unemployment volatility.

We argue that the apparent flexibility of entry wages is an artifact of composition bias. If unemployed workers are heterogeneous in their ability or willingness to reduce their reservation wages, those workers who have flexible reservation wages will be more likely to become re-employed. Because workers with flexible reservation wages will disproportionately compose the pool of new hires, observed entry wages will appear flexible. Conversely, workers with rigid (unobserved) reservation wages will be more likely to remain unemployed.

We estimate worker wage elasticities with respect to unemployment and aggregate labor productivity 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. Yet, we show that histograms of nominal wage changes from the same survey data display substantial wage rigidity for both incumbent workers (hereafter, job stayers) and for workers with recent spells of non-employment (job finders).

To reconcile this apparently contradictory evidence, we construct a search and matching model of the labor market and show that entry 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. Measured wage elasticities generated from dynamic model simulations are substantially higher for job finders than for job stayers, just as in the observed data. 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 composition 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 job finding to measure wage responsiveness to the business cycle among potential new hires. Therefore, the standard wage elasticity regressions used in the literature are likely unreliable and will generate large wage elasticities for new hires even when the underlying reservation wages of all unemployed workers are substantially rigid.

Despite those large measured wage elasticities in the model, wage rigidity substantially amplifies and propagates negative economic shocks in the labor market. Layoffs rise immediately in response to a negative shock, followed by a persistent decrease in the job finding rate. The majority of the persistent decline in the job finding rate can be attributed to the rigid reservation wages of unemployed workers. The centrality of wage rigidity to flows into and out of unemployment in our model highlights the potential of rigid wages to explain 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.[1] Prominent examples include Hall (2005), who introduces real wage rigidity via a bargaining norm between workers and employers, Gertler et al. (2016), who model wage bargaining with staggered multi-period contracts, and Christiano et al. (2014), who endogenously derive wage rigidity from alternating offers in bargaining negotiations.

Several empirical studies, however, show that the wages of new hires seem much more responsive to the business cycle than the wages of longer-tenured workers. Bils et al. (2014), Shin (1994), Solon et al. (1994), Barlevy (2001), Devereux (2001), and Shin and Solon (2007) all find lower elasticities of wages with respect to the unemployment rate for job stayers than for others. Furthermore, Haefke et al. (2013) estimate that the aggregate wages of new hires are much more elastic with respect to labor productivity than are the wages of all workers. Kudlyak (2014) emphasizes that the user cost of labor, rather than the spot entry wage, drives firms' hiring decisions. She estimates that the user cost of labor is even more responsive to the business cycle than spot entry wages. 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."[2]

Notably, the time series evidence contrasts starkly with the direct survey evidence on unemployed workers' reservation wages reported by Krueger and Mueller (2016). They find that "self-reported reservation wages decline at a modest rate over the spell of unemployment" and argue that "many workers persistently misjudge their prospects or anchor their reservation wage on their previous wage."

Gertler et al. (2016) present evidence that the greater wage cyclicality of non-stayers relative to stayers reflects primarily job-to-job switchers, who are able to climb the "job ladder" more easily during economic expansions than during downturns. Schoefer (2016) shows that wage rigidity

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

[2]Elsby et al. (2016) are also skeptical of the role that downward nominal wage rigidity plays in unemployment fluctuations for similar reasons.

among incumbent workers can affect firm hiring decisions directly if firms are financially constrained. Our study complements those two studies by showing that substantial rigidity in the wages of all unemployed workers can coexist with observed entry wages that appear to be flexible over the business cycle.

The remainder of the paper proceeds as follows. Section 2 describes the data and presents descriptive statistics. In section 3, we estimate wage rigidity for both job stayers and job finders. In section 4, we build 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.

II Data and Descriptive Statistics

Our empirical analysis uses longitudinal data from two sources: the Panel Study of Income Dynamics (PSID) and the Current Population Survey (CPS). Both datasets have been widely used in this literature, and they each have advantages and disadvantages. We use the PSID to conduct analyses similar to those in Solon et al. (1994) and Devereux (2001) and 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). The PSID has the advantage of allowing us to follow workers over an extended history and to distinguish between job stayers and job switchers, while the CPS has the advantage of larger sample sizes and a survey designed to capture the labor market characteristics of the entire civilian noninstitutionalized population that is at least 16 years old.

II.A Panel Study of Income Dynamics

The PSID contains data on employment, salary, and hourly wages along with key demographic variables for household heads and their spouses over many years. We combine the 1980-1997 annual surveys with the 1999-2013 biannual surveys to construct an employment history for respondents that spans 1980-2013.[3] Additionally, the PSID includes job start and end dates, which allow us to determine worker tenure over several years. The unrestricted number of respondents in these surveys averages about 12,500 per year.

Our sample includes both household heads and spouses. Since the PSID codes household heads by gender, we include spouses in the analysis to ensure that the primary earner in a family is included in the analysis.[4] We restrict employed individuals in our sample to include only those that report as either salaried or hourly. The remainder of employed workers have a primary income

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

[4] 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.

source that is significantly affected by bonuses, commissions, or other variable rate pay; those workers make up about 15 percent of the unrestricted sample.

The first column of table I provides a description of some key PSID variables. The labor force participation rate is roughly 65 percent, and the unemployment rate averages 4.3 percent, reflecting the restriction of the sample to heads of household and spouses.[5] About 41 percent of employed workers are salaried, while about 44 percent are hourly employees. 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 comparisons of inferred hourly wages for those who switch jobs.

We partition the set of employed workers with valid wage observations in the current and prior surveys as job stayers, job switchers, and job finders. These categories are not exhaustive of the set of all employed workers because some workers do not have a valid wage in the prior survey. For example, an individual who is employed in the current survey, but who was either unemployed or out of the labor force in the prior survey, would not be classified in any of the three groups.

Job stayers are defined as workers who have continuous employment at their present job between the current and prior survey dates without spells of unemployment or time out of the labor force. We identify these individuals as either those providing a start date at their current job that is prior to the last time the person was surveyed, or, if the start date is unavailable, those providing a tenure length at their current job exceeding the time between survey dates. Job stayers make up the majority of employed workers—about 61 percent in each survey.

Job switchers are workers who are employed at the time of both the current and previous surveys and do not report any months as being unemployed or out of the labor force but who provide a start date at their current job between the two survey dates. These workers comprise 20 percent of employed workers in each survey.

Finally, 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. Job finders make up 11 percent of employed workers in each survey.

Figure I 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.[6] The histograms are truncated at -35 and 35 percent, with a dotted vertical line to indicate a zero percent nominal wage change.[7]

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

[6] 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.

[7] Individual-year histograms of wage changes for stayers, switchers, and finders are also shown in the appendix.

The first row of histograms in figure I contains a spike in the proportion of reported wage changes at nominal zero, which we interpret as one of the hallmarks of wage rigidity. There is a also a visually-evident asymmetry between the nominally positive and nominally negative portions of the distribution, with significantly fewer wage cuts compared to wage increases than a simple extrapolation from the nominally positive portion of the distribution would indicate. This asymmetry is especially visible in the two-year changes in the histogram for job stayers.[8] Negative wage changes are relatively uncommon in both histograms, as many wage changes have "piled up" to nominal zero and the nominally negative portion of the distribution appears to be "hollowed out".

The second and third rows of figure I show histograms for job switchers and job finders, respectively. Both of these histograms show more dispersion of wage changes than the histogram for job stayers. Nevertheless, the histograms share striking similarities with those for stayers: first, a spike at nominal zero shows that the most common wage change for both job switchers and job finders is no wage change at all ("the pile up"). Second, there is again an asymmetry between the nominally positive and nominally negative portions of the wage change distributions, with less mass in the nominally negative portions than would be implied by the nominally positive portions ("the hollowing out"). We take these histograms as visual evidence that job switchers and job finders exhibit some degree of wage rigidity, a notion we formalize in section III.

II.B Current Population Survey

In addition to the PSID, we use the CPS basic monthly micro files from 1984 through 2013. The CPS is administered each month to a probability-selected sample of roughly 60,000 households designed to represent the labor market activities of the U.S. civilian noninsitutional population 16 years and older. Survey questions reference the labor market activities of each member of the household, such as labor force participation and employment status, along with key demographic information.

Selected households participate in the survey for four months, rotate out of the survey temporarily for eight months, and return to the survey for another four months before rotating out permanently. Respondents in their fourth and eighth months participating in the survey are referred to as the "outgoing rotation group" since they are rotated out of the survey in the following month. The CPS includes additional questions for the outgoing rotation groups that reference wages and weekly hours worked. Given the four-eight-four month sampling scheme of the CPS, individuals can be linked longitudinally, allowing us to use the outgoing rotation group wage data to calculate

Each year exhibits the same basic pattern, with a spike at a wage change of nominal 0.

[8]The two-year wage changes contain sample years with lower inflation, among other factors, leading to smaller nominal wage increases.

year-over-year wage changes between an individual's fourth and eight months in the survey. To track individuals longitudinally across outgoing rotation groups, we use the merged datasets of Rivera Drew et al. (2014), who build on the methodology of Madrian and Lefgren (2000). That dataset is available from 1989 to 2013 and contains an average of 25,317 total wage changes per surveyed year.

We use usual hours worked per week to transform usual weekly earnings to an hourly wage for salaried workers.[9] Following the procedure of Haefke et al. (2013), we restrict the dataset to nonfarm, nonsupervisory, private-sector workers, trim outliers in hours worked, and impute top-coded earnings according to the procedure in Schmitt (2003).

The second column of table I presents summary statistics for the CPS. The labor force participation rate averages 66 percent during the sample period, while the unemployment rate averages 6.2 percent. Salaried workers make up about 60 percent of employed workers, and hourly workers make up about 40 percent of the employed.

The design of the CPS prevents us from distinguishing between job stayers and job switchers as we do in the PSID. The CPS does not contain any information regarding start dates or tenure of the current job for employed workers or the workers' employment and labor force status in any of the 8 months in between survey rotations. We cannot tell whether workers who report as employed in all months are employed with the same employer through that entire period or whether they switched employers without reporting time in unemployment or out of the labor force.

We partition the set of employed workers in the CPS who have valid wage observations in their outgoing rotation group months as job finders and non-job finders. A worker is defined as a non-job finder if he or she reports as employed in the outgoing rotation group and in each of the three months prior to being in the outgoing rotation group. Non-job finders make up about 87 percent of all workers in the sample.

We classify workers as job finders in the CPS if they report as employed while they are in the outgoing rotation group but reported as either unemployed or out of the labor force in any of the prior three months. This is consistent with the definition of job finders in Haefke et al. (2013). [10] Under that definition, job finders make up roughly 13 percent of all employed workers. Note that a worker can be classified as a non-job finder in month four in the survey but as a job finder in month eight of the survey or vice versa.

Figure II shows pooled wage change histograms for the years 1989 to 2013 for all workers, all

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

[10] The eight-month break in between survey rotations gives rise to a potential undercount of job finders. For instance, an individual may report as being employed for all months in each of the four-month rotations. Our partition would classify these workers as non-job finders. It is possible, though, that the worker experienced a spell of non-employment at some point during the eight-month survey break, and we would incorrectly classify the worker as a non-job finder rather than a job finder.

workers excluding job finders, and job finders who can be matched longitudinally between their fourth and eighth months in the survey.[11] These histograms are qualitatively similar to those in figure I.[12] There are large spikes at nominal zero and an asymmetry between the nominally positive and negative portions of the distributions, with the negative portion appearing to be "hollowed out". The job finders' wage change distribution displays weaker, but still suggestive, evidence of downward nominal rigidities than the distribution for other workers, as was the case in the PSID.

III Estimating Wage Rigidity

In this section, we estimate wage rigidity for all workers, job finders, and job stayers in the PSID and for all workers, job finders, and non-job finders in the CPS. We use two complementary approaches to measuring wage rigidity. First, we estimate wage rigidity using the aggregate histograms presented in section II similar to that of Card and Hyslop (1997) and Ehrlich and Montes (2017). This estimate measures the fraction of wage changes that are "missing" in the nominally negative portion of the histogram. Second, we estimate wage elasticities similar to those of Solon et al. (1994), Devereux (2001), and Haefke et al. (2013). This approach estimates how wage changes vary with particular measures of the aggregate business cycle.

The two approaches to estimating wage rigidity give apparently contradictory results. Estimating wage rigidity in the histograms confirms the visual impression from section II: job finders display a substantial amount wage rigidity, as do job-stayers (PSID) and non-job finders (CPS). Estimating time series wage elasticities suggests that, while job-stayers' and job non-finders' wages display little covariance with the business cycle (indicating rigid wages), job finders' wages show substantial covariance with the business cycle (indicating flexible wages). We detail these estimates in sections III.A and III.B and then reconcile this apparent contradiction in sections IV and V.

III.A Measurement of Wage Rigidity in Histograms

In this section, we provide estimates of wage rigidity using the aggregate histograms in figures I and II by measuring the proportion of nominal wage cuts that would have occurred in an environment with perfectly flexible wages but are instead prevented by wage rigidity. Such analyses have typically focused on the wages of either job stayers or of all workers, but we extend the approach

[11] The classification of workers in the histograms corresponds to their status in their eighth month in the survey. Job finders make up about 4 percent of all wage changes in the total distribution. The appendix contains year-by-year histograms for each category of worker. The histograms for 1995 are omitted because a change in sampling design does not permit matches of worker wages to their employment histories.

[12] We again censor the histograms at -35 percent and 35 percent.

here to job finders (and job switchers in the PSID), as shown in the subsections below.

We measure the degree of wage rigidity in the histograms similarly to Card and Hyslop (1997) and Ehrlich and Montes (2017) by using the upper half of the observed wage change distribution to extrapolate what the lower half of the distribution would look like in the absence of rigidity (see appendix A.2 for more detail). The implied share of nominal wage cuts that would be expected based on the upper half of the wage change distribution is then compared to the actual share of nominal wage cuts. The statistic

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

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

The 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 is meant to 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 through either a layoff or a quit.

This measure of wage rigidity has two key identifying assumptions. The first assumption is that in absence of wage rigidity, the wage change distribution would be symmetric about its median. We view this as a reasonable assumption, particularly since the aggregate wage change distributions appear to be more symmetric in years of high inflation when the median wage change is considerably larger than zero—that is, when wage rigidity is unlikely to bind (see, for example, the wage change distributions for the early 1980s in figure A.7).

The second assumption is that the upper half of the wage change distribution is unlikely to be affected by wage rigidity. As shown in Elsby (2009), this assumption is less likely to be satisfied, as forward looking firms anticipate the inability to cut wages during future bad times by dampening the size of wage increases during good times. The result is a wage distribution that is compressed relative to its counterfactual in absence of wage rigidity. To the extent that this assumption is violated in practice, it should lead to a systematic underestimation of wage rigidity in the histogram approach—that is, our estimates should provide a lower bound on actual wage rigidity. However, our model estimation procedure descried in section V will correct for this potential source of bias.

Table II displays our estimates of the proportion of nominal wage cuts prevented by wage rigidity in both the PSID and CPS.[13] We provide PSID estimates for job stayers and job finders

[13]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 1,000 dollar value (see, for instance, Altonji and Williams (1997)). This rounding could lead to an overstatement of the

using one-year wage changes from 1980 to 1997 and two-year wage changes from 1981 to 2013. We show estimates using one-year wage changes in the CPS for job finders and non-job finders from 1989 to 2013. Separate estimates are provided for salaried and hourly workers.

We estimate that job finders in the PSID have approximately 48.9 percent counterfactual one-year wage cuts and 20.1 percent of counterfactual two-year wage cuts prevented due to wage rigidity. Even though the estimated degree of wage rigidity falls by more than half when moving from one-year to two-year wage changes, these estimates imply that wage rigidity prevents a substantial proportion of nominal wage cuts even over a period of two years.

Among job stayers in the PSID, we estimate that 53.5 percent of counterfactual nominal one-year wage cuts and 53.3 percent of two-year wage cuts are prevented due to 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 in 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 by one-year versus two-year wage changes.

The estimates using the CPS are qualitatively similar, particularly when compared to the one-year wage changes in the PSID. We estimate that among job finders, 40.3 percent of counterfactual nominal wage cuts were prevented by wage rigidity. For non-job finders, that estimated fraction is 46.9 percent. Again, the estimates for salaried and hourly workers do not systematically vary.

We interpret these estimates as indicating a substantial amount of estimated wage rigidity for both job finders and job stayers/non-job finders. Although the wages of job finders exhibit less rigidity than the wages of other workers, they are by no means perfectly flexible.

III.B Wage Elasticities for Job Stayers, Switchers, and Finders

Our second approach to measuring wage rigidity extends the literature on estimating wage elasticities for job finders, job stayers/non-job finders, and all workers with respect to different measures of the business cycle. These estimates suggest that wages for job finders are much more flexible than the estimates implied by the histogram approach, generating an apparent contradiction between the two approaches.

The literature estimates the time series wage elasticities in two ways, and we estimate and extend these approaches. The first approach is to regress individual-level real wage changes on

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.

changes in the aggregate unemployment rate using regressions of the form:

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

where w_{ijt} is the real hourly wage for individual i in group j in year t, y_t is a measure of the business cycle in year t, and X_{ijt} is a polynomial measure of job tenure and potential work experience for individual i in group j in year t.[14] This regression reflects the specifications in Solon et al. (1994) and Devereux (2001), who estimate these elasticities in the PSID and use the aggregate unemployment rate as their measure of the business cycle. The estimated coefficient $\beta_{1,j}$ is therefore the semi-elasticity of real wage changes with respect to the unemployment rate.[15] We use both the dependent variable in Solon et al. (1994)—all earnings in the surveyed year—as well as that in Devereux (2001)—earnings in the worker's primary job. Although Solon et al. (1994) and Devereux (2001) restrict their samples to men only, we include both men and women in our sample.

A second approach, pioneered by Haefke et al. (2013), estimates the elasticity of aggregate average real hourly wages with respect to a measure of the business cycle for both job finders and for all workers in the CPS. To account for composition bias in each group, they remove demographically explainable wage determinants for all workers via a first-stage Mincer regression. The main regression specification then takes the following form:

$$\Delta \ln w_{jt} = \beta_{0,j} + \beta_{1,j} \Delta y_t + \varepsilon_{jt}, \tag{3}$$

where w_{jt} is the average residualized real hourly wage series for group j (i.e. job finders or all workers) in the calendar quarter t and y_t is the measure of the business cycle in quarter t. In Haefke et al. (2013), the business cycle measure is the log of aggregate labor productivity, defined as real output per hour worked in the nonfarm business sector. The estimated coefficient $\beta_{1,j}$ is therefore the elasticity of real wage changes with respect to labor productivity.[16]

Note that the the histogram measurement of wage rigidity in section III.A focuses on nominal

[14] We use a standard measure of work experience: age minus years of school minus 6.

[15] 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 2 directly.

[16] Haefke et al. (2013) estimate this equation by quarter for each subgroup j of workers from 1984 to 2006q1. Wages are deflated by the Bureau of Labor Statistics (BLS) private nonfarm business sector implicit price deflator. Both the implicit price deflator and real output per hour series in Haefke et al. (2013) are from the 2006q1 vintage of the BLS productivity and costs release. They exclude 1995q3 and 1995q4 from the analysis because of a change in sample design that makes it difficult to match workers. They also add quarter dummies to account for seasonality and add a dummy for 2003q1 to reflect a change in occupation classification in 2003 that increases the fraction of supervisory workers. Their definition of job finders and non-job finders is the same as we use in section II.B and, therefore, suffers the same limitation of being able to look back over only three months of work history to determine whether an individual experienced a spell of non-employment.

wage rigidity—as will our theoretical model in sections IV and V—whereas the time series elasticity measurements of wage rigidity in this section focus on real wage changes. In a low inflation environment, this distinction is minimal. We view the combined evidence from the two approaches as implying that nominal downward wage rigidities are an important cause of real wage rigidities. For example, the spikes and asymmetries in the wage change histograms are consistently at wage changes of nominal zero, not real zero (see appendix figures A.1-A.9). We will maintain the distinction between real and nominal wage changes consistently when estimating the model below.

We build on and extend the wage elasticity literature in two ways. First, we longitudinally link individuals across their fourth and eighth months in the CPS to calculate individual-level, year-over-year real wage changes. We then estimate equation 2 in the CPS using aggregate labor productivity as the business cycle measure.[17] 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.[18]

Second, we estimate the wage elasticities through 2013. This extension is economically important because inflation has been systematically lower over the past 20 years than it was in years prior, pushing the economy-wide median year-over-year nominal wage change closer to zero. To the extent that wage rigidity is more binding in lower inflation environments, we would expect wages to be less responsive to the business cycle when inflation is low and more responsive when inflation is high. Thus, a large estimated wage elasticity in a high inflation environment does not necessarily imply that nominal wages are downwardly flexible. If wage rigidity is indeed binding, then estimated wage elasticities may be smaller when periods of low inflation are more represented in the sample.

Tables III and IV show estimates of the wage regressions from equations 2 and 3 in the PSID and CPS, respectively. Altogether, we estimate four specifications for the relevant groups. We estimate equation 2 in the PSID with the aggregate unemployment rate as our measure of the business cycle, using either the hourly wage in an individual's main job (specification 1) or the average hourly wage across all of an individual's jobs as the dependent variable (specification 2). We report estimates of both specifications using both one-year wage changes (through 1997) and two-year wage changes (through 2013) to account for the switch to the biannual surveys. We estimate equations 2 and 3 in the CPS using aggregate labor productivity as our measure of the business cycle (specifications 3 and 4). We report results of regressions extending through 2006q1 to be consistent with Haefke et al. (2013), and through 2013 to capture more recent data.

[17] Specifically, we use the merged datasets of Rivera Drew et al. (2014), who build on the methodology of Madrian and Lefgren (2000) to link individuals across surveys.

[18] 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 Rivera Drew et al. (2014).

The PSID estimates using the individual-level wage changes in equation 2 show that job finders have uniformly larger wage elasticities in absolute value compared to job stayers and all workers across each of our specifications. Moreover, the estimated wage elasticities for job finders are all greater than 1 in absolute value (ranging from -1.09 to -2.85)—suggesting that wages for job finders are quite responsive to the business cycle—whereas the estimated wage elasticities for job stayers are all less than 1 in absolute value (ranging from -0.03 to -0.84). The CPS estimates using either the individual-level wage changes or the group-level average hourly wage changes in equation 3 show similar results: the estimated wage elasticities with respect to labor productivity for job finders are uniformly larger than for all workers and non-job finders. Although the estimates for job finders are less than 1, they are still relatively large (ranging from 0.57 to 0.86), again suggesting that wages for job finders are quite responsive to the business cycle.[19]

Our results differ from previous studies in that our wage elasticity estimates tend to be smaller in absolute value. Table IV shows CPS results both for the period 1984 through 2006q1–the same period as the Haefke et al. (2013) analysis–and for the 1984 through 2013 period. The elasticity estimates using the sample through 2013 are clearly smaller than those using the sample through 2006q1.[20] One potential explanation for our smaller estimates is that the extended sample covers more quarters in a lower inflation environment than previous studies that estimate these elasticities. As discussed above, if wage rigidity is more binding in low inflation environments than in high inflation environments, then wage elasticity estimates encompassing the later lower inflation period should be smaller.

Still, the estimates in this section confirm the key patterns in the previous literature: the observed wages of job finders are roughly twice as responsive to changes in labor market conditions as the wages of other workers. These results stand in no small contrast to the histogram results in section III.A, which indicate that the wages of job finders display very substantial wage rigidity.

In the next section, we build a a search and matching model of the labor market that attempts to reconcile this apparent contradiction. The model's key insight is that the seeming flexibility of the wages of job finders stems from composition bias in the pool of newly hired workers. Once we correct for that composition bias, our model provides estimates that the (unobserved) reservation wages of the pool of unemployed workers are nearly as rigid as the observed wages of job stayers.

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

[20]Though we use the same procedure as Haefke et al. (2013) to calculate the elasticities in table IV, our results differ from theirs in the 1984 through 2006q1 period because we data for labor productivity from the June 2016 BLS Productivity and Costs release, whereas Haefke et al. (2013) use data from the May 2006. This series, as well as others from the BLS Productivity and Costs release, is subject to regular and sometimes major revisions. When we use the same vintage data as Haefke et al. (2013) (not reported), we obtain the same estimates reported in their paper.

IV Model

We build 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. We assume, as in Barattieri et al. (2014) 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 in which a fraction of workers are constrained from reducing their nominal wage demands in each period. The model allows that fraction to differ for employed and unemployed workers.

IV.A Model Environment

We consider the stationary equilibrium of a discrete time model with no aggregate shocks. Workers face idiosyncratic productivity shocks and receive a probabilistic draw each period that determines whether they can lower their nominal wage demands that period. Each firm has one job that is either vacant or filled and producing output. Workers in a filled job supply exactly one unit of labor, L, each period—that is, there is no intensive margin of labor supply. There is a unit mass of workers who are either employed in a job or unemployed and searching for a job.

Firms and workers are infinitely lived with a common discount rate β and have linear preferences over profits and consumption, respectively. The economy lacks a storage technology, so workers consume their entire incomes each period. Employed workers receive a wage, w, each period, and 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:

$$Y = pL = p \tag{4}$$

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

$$\pi(p, w) = p - w. \tag{5}$$

Firms that are not in a match and that wish to meet with a worker must post a vacancy at a 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 the matching function $m(v, u)$, where v is the number of vacancies and u is the number of workers who are unemployed.[21] We assume that the matching function has the Cobb-Douglas form:

$$m(v,u) = Av^{\phi}u^{1-\phi} \tag{6}$$

where A is a parameter that governs matching efficiency and ϕ is the elasticity of the matching function with respect to the number of vacancies. Denoting "labor market tightness", v/u, as θ, 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 $q(\theta) = m(v,u)/v = A\theta^{\phi-1}$.[22]

There is no on-the-job search, and job matches end with exogenous probability s_x each period. The model also features endogenous job separations, which 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 to a level that is between the maximum that the firm is willing to pay and the minimum that the worker would accept in an environment with flexible wages. Thus, a bilaterally inefficient endogenous separation is a match that would have resulted in production if worker wages were not downwardly rigid.

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 λ_E and λ_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. Employed and unemployed workers draw realizations on whether they can reduce their reservation wages in the period.

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

3. Firms post vacancies; unemployed workers match with vacancies.

   Not every match between an unemployed worker and a vacancy will result in the formation of a new job, both because exogenous separations occur between matching and production, 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

[21] 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.

[22] 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. Upon meeting, workers and firms enter an "interview", as described below. We denote the probability of finding a job as $\tilde{f}$ and the probability of filling a vacancy as $\tilde{q}$.

call a match between an unemployed worker and a firm with a vacancy 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; unemployed workers set their reservation wages.

6. Firms decide whether to accept matched workers' wage demands and either 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.[23]

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

8. The period ends.

A firm 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 those states as V and J, respectively. We define the value functions for the firm's states in section IV.B.

A worker can find him or herself 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^F, and W^R, respectively. We define the value functions for the worker's states in section IV.C.

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

$$\ln p = (1 - \psi_p) \ln \bar{p} + \psi_p \ln p_{-1} + \varepsilon_p, \ \varepsilon_p \sim N\left(0, \sigma_p^2\right). \tag{7}$$

Productivity is a time-varying, mean-reverting characteristic of the individual worker. Further, a worker's productivity process persists in unemployment; the main results would not change if instead the productivity process were match-specific. The productivity distribution of employed 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.[24]

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

[24] 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.

IV.B Firm's Problem

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

$$V = -c + q(\theta)(1-s_x)\iint J(p,w)\,\mathrm{d}G(p,w) + (1-q(\theta)(1-s_x))\beta\mathbb{E}[V'], \tag{8}$$

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

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

$$\begin{aligned} J(p,w) = \max_{\text{discontinue,continue}} \Big\{ & \beta\mathbb{E}[V'], \\ & p - w + \beta(1-s_x)\iint J(p',w')\,\mathrm{d}F(p'|p)\mathrm{d}H(w'|p',w) \Big\}. \end{aligned} \tag{9}$$

where $F(p'|p)$ 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 demand for a worker in a filled job given the current wage, w, and next-period's productivity level, p'.[25] 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).

Given equation 9, 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 schedule, denoted as $\tilde{w}(p)$, solves the equation:

$$\beta\mathbb{E}[V'] = p - w + \beta(1-s_x)\iint J(p',w')\,\mathrm{d}F(p'|p)\mathrm{d}H(w'|p',w). \tag{10}$$

IV.C Worker's Problem

We define the worker's value functions at step 5 in the timeline, after matching and exogenous separations have occurred and when the worker must decide on a reservation wage. At this point

[25] 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.

in the timeline, workers know whether they are constrained in lowering their wage demands.

The value of an employed worker negotiating with a flexible wage is a function of this period's productivity level, whereas the value of an employed worker negotiating with a rigid wage depends on both this period's productivity and last period's wage demand. We denote these value functions as $W^F(p)$ and $W^R(p, w_{-1})$, respectively. 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 $\mathbb{E}[W(p', w)] = \mathbb{E}[(1-\lambda_E)W^F(p') + \lambda_E W^R(p', w)]$.

The value to the worker of being in a negotiation with a flexible wage and productivity p is given by:[26]

$$\begin{aligned} W^F(p) = \max_w \Big\{ &\mathbb{1}\Big(w \leq \tilde{w}(p)\Big)\Big(w + \beta \int \big\{(1-s_x)\mathbb{E}[W(p', w)] + s_x \mathbb{E}[U(p', w)]\big\}\, \mathrm{d}F(p'|p)\Big) \\ &+ \mathbb{1}\Big(w > \tilde{w}(p)\Big)\Big(b + \beta \int \Big(f(\theta)(1-s_x)\mathbb{E}[W(p', w)] \\ &+ (1 - f(\theta)(1-s_x))\mathbb{E}[U(p', w)]\Big)\, \mathrm{d}F(p'|p)\Big)\Big\}. \end{aligned} \tag{11}$$

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 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 nominal wage is given by:

$$\begin{aligned} W^R(p, w_{-1}) = &\mathbb{1}\Big(\frac{w_{-1}}{1+\pi} \leq w^\star_{EF}(p)\Big)W^F(p) + \mathbb{1}\Big(\frac{w_{-1}}{1+\pi} > w^\star_{EF}(p)\Big) \times \cdots \\ &\Big\{\mathbb{1}\Big(\frac{w_{-1}}{1+\pi} \leq \tilde{w}(p)\Big)\Big(\frac{w_{-1}}{1+\pi} + \beta \int \Big[(1-s_x)\mathbb{E}[W(p', \frac{w_{-1}}{1+\pi})] + s_x \mathbb{E}[U(p', \frac{w_{-1}}{1+\pi})]\Big)\Big]\, \mathrm{d}F(p'|p)\Big) \\ &+ \mathbb{1}\Big(\frac{w_{-1}}{1+\pi} > \tilde{w}(p)\Big)U^R(p, w_{-1})\Big\}. \end{aligned} \tag{12}$$

The previous period's real wage, w_{-1}, divided by $1+\pi$, where π is the deterministic rate of inflation,

[26]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.

represents the new real wage that corresponds with a downwardly rigid nominal wage.[27] The first term in the value function represents the state in which the optimal wage demand is at least the value of 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, that wage 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 to the firm, the worker receives the payoff associated with unemployment, which we will define below. Implicit in $W^R(p, w_{-1})$ is an optimization problem because workers always have the freedom to raise their wage demands. 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 maximum of w_{-1} and $w^\star_{EF}(p)$.

Similar to the employed, the value of being unemployed at step 5 with a flexible reservation wage is a function of this period's productivity level, whereas the value of being unemployed with a rigid reservation wage is a function of both this period's productivity and last period's wage demand. We denote these value functions as $U^F(p)$ and $U^R(p, w_{-1})$, respectively. 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 unemployed with productivity p and a flexible reservation wage is given by:

$$\begin{aligned} U^F(p) = \max_w \Big\{ & b + \mathbb{E}[f(\theta')](1-s_x)\beta \int \mathbb{E}[W(p', w)]\,\mathrm{d}F(p'|p) \\ & + (1-\mathbb{E}[f(\theta')](1-s_x))\beta \int \mathbb{E}[U(p', w)]\,\mathrm{d}F(p'|p) \Big\}. \end{aligned} \tag{13}$$

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.[28] The reservation wage that solves 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 nom-

[27] 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 $P_t w_t < P_{t-1}w_{t-1} \iff \frac{P_t}{P_{t-1}} w_t < w_{t-1} \iff (1+\pi)w_t < w_{t-1} \iff \frac{w_{t-1}}{1+\pi} > w_t$.

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

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

inal reservation wage is:

$$U^R(p, w_{-1}) = b + \mathbb{E}[f(\theta')](1 - s_x)\beta \int \mathbb{E}[W(p', \frac{w_{-1}}{1+\pi})] \, \mathrm{d}F(p'|p)$$
$$+ (1 - \mathbb{E}[f(\theta')](1 - s_x))\beta \int \mathbb{E}[U(p', \frac{w_{-1}}{1+\pi})] \, \mathrm{d}F(p'|p). \tag{14}$$

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 $w^\star_{UF}(p)$. Since the latter term is the lowest possible wage, an unemployed worker with a rigid wage will always set this period's reservation wage equal to last period's reservation wage. The wage schedule associated with this value function is denoted $w^\star_{UR}(p, w_{-1})$.

IV.D Stationary Equilibrium

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

$$\text{Jobs Created} = \left[f(\theta)(1 - s_x) \iint^{\tilde{w}(p)} \mathrm{d}G(p, w) \right] u = f(\theta)(1 - s_x)\mathbb{E}[G_w(\tilde{w}(p))]u \tag{15}$$

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

Second, we characterize flows into unemployment. The firms' cutoff wage schedule, $\tilde{w}(p)$, and exogenous separations, s_x, largely dictate the number of jobs destroyed each period. Let $\Lambda(p, w)$ be the stationary joint cumulative distribution of productivity levels and reservation wages across employed workers. The number of workers who will continue in employment each period can be expressed as $\Lambda_w(\tilde{w}(p))$—that is, the mass of employed workers less than the cutoff wage function,

$\tilde{w}(p)$. Then the job destruction flow of workers from employment to unemployment is given by:

$$\text{Jobs Destroyed} = \left[(1-s_x)\left(1-\iint^{\tilde{w}(p)} \mathrm{d}\Lambda(p,w)\right)+s_x\right](1-u)$$
$$= \Big((1-s_x)\mathbb{E}[1-\Lambda_w(\tilde{w}(p))]+s_x\Big)(1-u)\,, \tag{16}$$

where the stock of employed workers, $1-u$, can separate either endogenously—due to wage demands exceeding the firms' cutoff wage function—or exogenously at rate s_x.

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 15) and the number of jobs destroyed (equation 16) :

$$u^\star = \frac{(1-s_x)\mathbb{E}[1-\Lambda_w(\tilde{w}(p))]+s_x}{f(\theta^\star)(1-s_x)\mathbb{E}[G_w(\tilde{w}(p))]+(1-s_x)\mathbb{E}[1-\Lambda_w(\tilde{w}(p))]+s_x} \tag{17}$$

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.

V Model Estimation and Results

In this section, we estimate the parameters of the model described in section IV and discuss the results. The estimated model matches the moments in the data well. The estimated Calvo parameters for the employed and unemployed are of similar magnitudes and statistically indistinguishable from each other.

We also examine the model's response to one-time permanent shocks to aggregate productivity and show that wage rigidity for both employed and unemployed workers is critical in explaining observed unemployment dynamics. Comparing the results of both the steady-state model and the simulations with aggregate shocks to the empirical facts about wage rigidity, we argue that the model reconciles the apparently contradictory evidence documented in section III.

V.A 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 β to 5 percent annually, as in Shimer (2005) and Hall (2005). Our model does not explicitly feature real productivity growth, so we set π to 4 percent annually to reflect both price inflation and productivity growth. Therefore, β 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 observed target moments, μ. The ninth parameter, 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).[29] 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 provides a tight link between our empirical estimates and the theoretical model, but it also helps to correct for potential sources of misspecification in our empirical approach. The first is the potential misclassification of job stayers and job finders. To correct for that misclassification, 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 the potential bias in our measurement of the fraction of counterfactual wage cuts prevented by wage rigidity. As discussed in section III.A, the two identifying assumptions in the histogram approach for measuring wage rigidity are that the underlying distribution of wage changes is symmetric around the observed median and that the upper half of the distribution is unaffected by wage rigidity. Although we argue that the first assumption is reasonable, the assumption that the upper half of the distribution is unaffected by wage rigidity may be violated. As argued by Elsby (2009), forward looking agents may moderate wage increases today knowing that they might not be able to cut wages in response to future negative shocks, thus compressing the wage change distribution. However, that forward looking behavior is also feature of our model.

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

Accordingly, applying the same measure in the observed data to the simulated data will correct for that misspecification, making the histogram measures of wage rigidity for both job finders and job stayers appropriate target moments.

We target moments from both the CPS and PSID, and all moments are calculated over the years 1981 to 2013 (see the first column in table V).[30] 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. In the PSID, we target wage rigidity as measured in the histogram approach from section III.A using two-year wage changes for both incumbent workers ($\widehat{wr}_s = 0.53$ for job stayers) and new hires ($\widehat{wr}_f = 0.20$ for job finders). To match the full shape of the observed wage change histograms in addition to the mass missing below nominal zero, we target the difference between the 25th and 50th percentiles as well as the difference between the 75th and 50th percentiles of the two-year wage change histograms for both job finders and job stayers. Finally, we target the moments $\hat{\delta}$ and $\hat{\sigma}_\varepsilon$ from the regression $\ln w_{it} = \alpha_0 + \alpha_t + \delta \ln w_{it-2} + \varepsilon_{it}$. Those moments are estimated in the PSID as $\hat{\delta} = 0.89$ and $\hat{\sigma}_\varepsilon = 0.20$.

We estimate two versions of the model: an unconstrained (baseline) model, in which the Calvo parameter is allowed to vary between employed and unemployed individuals, and a constrained model, in which λ_U is required to equal λ_E. The unconstrained model matches most of the target moments fairly well (see the second column of V), but generates less dispersion in wages than is observed in the data, reflected both in a smaller simulated $\hat{\sigma}_\varepsilon$ than in the data and in smaller differences in the wage change percentiles for job finders and job stayers. The model does succeed in generating some of the asymmetry observed in the wage change distribution. 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 is smaller than in the observed data.

The constrained model generates simulated wage rigidity estimates for job stayers and job finders that are quite similar to each other—about 30 percent of wage cuts prevented for both stayers and finders. Similar measured wage rigidity moments for stayers and finders are not surprising in the constrained model given that both groups draw wage adjustment realizations from the same Calvo parameter. The constrained model's performance on the other moments is mixed but not substantially worse than that of the unconstrained model.

Although all of the target moments can influence all of the estimated parameters, certain target moments have a larger influence on some parameters than on others. The Calvo parameters λ_E and λ_U are primarily determined by the wage rigidity target moments (λ_U is also influenced by D).

[30] We have also estimated this model using entirely CPS-derived moments. The results and qualitatively similar, 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).

The parameters governing the productivity process, ψ_p and σ_p, are heavily influenced by many of the targets, but ψ_p is directly characterized by $\hat{\delta}$, while σ_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.

The estimation results for the unconstrained model show that the Calvo parameters for the unemployed and employed are similar in magnitude and not statistically distinguishable from each other at the 5 percent significance level (see the first column of table VI). Both estimates correspond to a probability of experiencing rigid wages of greater than 90 percent per month, suggesting a significant degree of wage rigidity for both job stayers and job finders.

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. As a result, 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.[31]

The exogenous separations rate, s_x, is estimated at 0.12 and corresponds to a little more than half of the total separations in the stationary model. 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 worker wage demands.

In the constrained model, the single Calvo parameter is estimated to be about 0.37 (see the second column of table VI). This estimate falls directly in the middle of the 0.40 and 0.34 point estimates of the Calvo parameters for employed and unemployed workers in the unconstrained case. The remaining estimated parameters in the constrained model are similar to the estimates from the baseline case.

Overall, the model estimates suggest a substantial degree of wage rigidity for both job stayers and job finders. In the next two sections, we examine the estimated level of wage rigidity's ability to explain observed unemployment fluctuations in the model. We also reconcile the apparent contradiction between significant measured wage rigidity in the aggregate wage change histograms and the apparent flexibility of entry wages as measured in the wage elasticity regressions.

V.B Simulation Results

We use our estimated model to simulate a dynamic economy that experiences shocks to aggregate productivity. These dynamic simulations allow us to estimate equations 2 and 3 summarizing

[31] 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.

how responsive wages are to business cycle shocks in the estimated model, similarly to Solon et al. (1994), Devereux (2001), and Haefke et al. (2013).

Each simulation features one permanent shock to aggregate productivity, which is entirely unanticipated by the agents in the model. However, the shock's arrival and permanence becomes common knowledge to all agents in the economy immediately upon its arrival. We run 500 simulations of the economy containing 10,000 workers over 8 years (96 months) per simulation. The aggregate productivity shock arrives in month 60 of each simulation, 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.[32] Second, 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. It is instead set by the period-by-period free-entry condition using the labor market flows consistent with the assumed policy functions.

Figure III shows the impulse responses of the unemployment rate following positive and negative shocks to aggregate productivity. The unemployment rate behaves asymmetrically with regard 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.

We also decompose unemployment into its various sources in the model. The unemployment rate rises immediately upon the arrival of a negative shock to productivity, driven primarily by wage rigidity among job stayers. Decreases in the number of matches—driven by a decline in the number of firms posting vacancies—and rigid reservation wages among the unemployed contribute only a small amount to the increase in the unemployment rate immediately after impact.

[32]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.

The unemployment rate stays elevated well after the immediate impact of the shock passes, however, driven primarily by the rigid reservation wages of unemployed workers. The increase in unemployment due to layoffs from the rigid wages of job stayers mostly abates, and the contribution from a decline in job matches increases further by only a small amount. The share of the increase in the unemployment rate due to the rigid reservation wages of job seekers, however, increases considerably. Wage rigidity among job seekers is therefore the largest contributor to an elevated unemployment rate as the model converges towards its new steady state.

Figure IV shows the impulse response functions from a shock to aggregate productivity for all workers and for job finders. Similarly to the unemployment rate, the observed labor productivity of job finders responds asymmetrically to positive and negative productivity shocks. This asymmetry is driven entirely by compositional changes in the pool of employed workers, as idiosyncratic worker productivity evolves as a Markov process independent of firm and worker behavior. 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. Thus, a negative shock leads to a rapid decline in average productivity among job finders, from which it gradually recovers. The response of wage demands to an aggregate productivity shock is similar to the response of observed labor productivity, as shown in the second row of figure IV, but with smaller magnitudes due to the dampening effect of wage rigidity.

The average reservation wage increases relative to productivity following a negative shock because some workers' reservation wages are downwardly rigid. That increase persists over time, as seen in the third row of figure IV. The decline of productivity beneath some workers' reservation wages following a negative aggregate shock poses a lasting obstacle to those workers' prospects for re-employment.

The bottom two panels of figure IV 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 et al. (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 towards its new steady state value than the job finding probability. However, because the initial rise in the job separation probability is so large, changes in the separation probability account for 65 percent of the fluctuations in the unemployment rate in the two years after a negative shock.

Elsby et al. (2009) argue that "a complete understanding of cyclical unemployment requires an explanation of countercyclical unemployment inflow rates as well as procyclical outflow rates." Based on these simulation results, we believe our model provides a parsimonious explanation for the cyclical unemployment flows based on an empirically documented friction in the labor market.

V.C Wage Elasticity Regressions in the Simulated Data

We now return to reconciling the apparently contradictory evidence on wage rigidity in section III. We estimate the wage elasticity regressions from section III.B on the simulated data to understand why the empirical time series wage elasticities suggest flexible entry wages even though the wage change elasticities suggest substantial wage rigidity.

The top panel of table VII shows the elasticities of the real wages of individual workers with respect to aggregate productivity and unemployment.[33] 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 observed wages of job finders are much more elastic than the wages of non-finders. Elasticities with respect to unemployment are smaller in magnitude than in table III, 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 VII displays the wage elasticities for aggregate groups of workers. 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 III does not provide a direct analog to the aggregate elasticities with respect to unemployment in table VII, 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.

These simulation results show that the model produces entry wages that are substantially more elastic than other wages, despite unemployed workers having only slightly more flexible reservation wages than incumbents.[34] Those elasticities were not targets in the estimation procedure, which focused entirely on steady state values. The model's ability to produce elastic observed

[33] The aggregate elasticities in table VII 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 worker types.

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

wages for new hires, despite rigid reservation wages for the pool of unemployed workers, stems naturally from the selection induced by heterogeneity in unemployed workers' ability to cut their wage demands. Unemployed workers with flexible wages will make up a disproportionate share of new hires, for whom wage changes can be observed.

An interesting final way in which the model matches the observed wage data is that the aggregate wage elasticities in table VII are smaller in magnitude than the individual wage elasticities. This pattern matches the CPS data reported in table IV, reflecting compositional shifts among worker types over the business cycle first documented by Solon et al. (1994).[35] Although the model was not designed to produce this pattern, it arises from the tension between workers' wage demands and firms' cutoff rules at the heart of the model.

In sum, the model is able to reproduce several stylized features of the labor market data: substantial downward nominal wage rigidity as measured by the "histogram approach" for both incumbent workers and new hires; entry wages that are more elastic over the business cycle than other wages; countercyclical unemployment inflow rates and procyclical outflow rates; and less elastic aggregate wage changes than individual wage changes. We therefore conclude that the labor market data are consistent with an important role for downward nominal wage rigidity among employed and unemployed workers.

VI 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 an estimated model that assigns 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 composition effects. Therefore,

[35] 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.

we argue that downward nominal wage rigidity may account for a substantial share of the increase in unemployment during recessions.

References

Altonji, J. G. and N. Williams (1997). Do wages rise with job seniority? A reassessment. Working Paper 6010, National Bureau of Economic Research.

Barattieri, A., S. Basu, and P. Gottschalk (2014). Some evidence on the importance of sticky wages. *American Economic Journal: Macroeconomics 6*(1), 70–101.

Barlevy, G. (2001). Why are the wages of job changers so procyclical? *Journal of Labor Economics 19*(4), 837–878.

Bils, M., Y. Chang, and S.-B. Kim (2014). How sticky wages in existing jobs can affect hiring. Working Paper 19821, National Bureau of Economic Research.

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

Card, D. and D. Hyslop (1997). Does inflation "grease the wheels of the labor market"? In *Reducing inflation: Motivation and strategy*, pp. 71–122. University of Chicago Press.

Christiano, L. J., M. Eichenbaum, and C. L. Evans. (2014). Understanding the great recession. Working Paper 20040, National Bureau of Economic Research.

Daly, M. C. and B. Hobijn (2014). Downward nominal wage rigidities bend the phillips curve. *Journal of Money, Credit and Banking 46*(S2), 51–93.

Devereux, P. J. (2001). The cyclicality of real wages within employer-employee matches. *ILR Review 54*(4), 835–850.

Ehrlich, G. and J. Montes (2017). Wage rigidity and employment outcomes. *Mimeograph, University of Michigan*.

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

Elsby, M. W., R. Michaels, and G. Solon (2009). The ins and outs of cyclical unemployment. *American Economic Journal: Macroeconomics 1*(1), 84–110.

Elsby, M. W., D. Shin, and G. Solon (2016). Wage adjustment in the great recession and other downturns: Evidence from the United States and Great Britain. *Journal of Labor Economics 34*(S1), S249–S291.

Gertler, M., C. Huckfeldt, and A. Trigari (2016). Unemployment fluctuations, match quality, and the wage cyclicality of new hires. Working Paper 22341, National Bureau of Economic Research.

Haefke, C., M. Sonntag, and T. Van Rens (2013). Wage rigidity and job creation. *Journal of monetary economics 60*(8), 887–899.

Hall, R. E. (2005, March). Employment fluctuations with equilibrium wage stickiness. *American Economic Review 95*(1), 50–65.

Hosios, A. (1990). On the efficiency of matching and related models of search and unemployment. *The Review of Economic Studies 57*(2), 279–298.

Krueger, A. B. and A. I. Mueller (2016). A Contribution to the Empirics of Reservation Wages. *American Economic Journal: Economic Policy 8*(1), 142–179.

Kudlyak, M. (2014). The cyclicality of the user cost of labor. *Journal of Monetary Economics 68*, 53–67.

Madrian, B. C. and L. J. Lefgren (2000). An approach to longitudinally matching current population survey (CPS) respondents. *Journal of Economic and Social Measurement 26*(1), 31–62.

Mortensen, D. T. and C. A. Pissarides (1994). Job creation and job destruction in the theory of unemployment. *The Review of Economic Studies 61*(3), 397–415.

Pissarides, C. A. (2000). *Equilibrium unemployment thoery*. MIT Press.

Pissarides, C. A. (2009). The unemployment volatility puzzle: Is wage stickiness the answer? *Econometrica 77*(5), 1339–1369.

Rivera Drew, J. A., S. Flood, and J. R. Warren (2014). Making full use of the longitudinal design of the current population survey: Methods for linking records across 16 months. *Journal of Economic and Social Measurement 39*(3), 121–144.

Schmitt, J. (2003). Creating a consistent hourly wafe series from the current population survey outgoing rotation group, 1979-2002. *Mimeograph, CEPR*.

Schoefer, B. (2016). The financial channel of wage rigidity. *Mimeograph, University of California, Berkeley*.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *The American Economic Review 95*(1), 25–49.

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

Shin, D. and G. Solon (2007). New evidence on real wage cyclicality within employeremployee matches. *Scottish Journal of Political Economy 54*(5), 648–660.

Solon, G., R. Barsky, and J. A. Parker (1994). Measuring the cyclicality of real wages: how important is composition bias? *The Quarterly Journal of Economics 109*(1), 1–25.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics Letters 20*(2), 177–181.

Van Kerm, P. et al. (2003). Adaptive kernel density estimation. *The Stata Journal 3*(2), 148–156.

Table I: 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 II: 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 III: 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 IV: 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 et al. (2013). Individual wage changes come from workers linked across Outgoing Rotation Groups by Rivera Drew et al. (2014), 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 V: 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 λ_E and λ_U; constrained model imposes equality.

Table VI: Model Parameters

Parameter	Description	Unconstrained Model Value	Constrained Model Value
β	Time Preference	0.950	0.950
π	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)
ψ_p	Persistence of Productivity Process	0.899	0.901
		(0.043)	(0.510)
σ_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)
λ_U	Probability of Rigid Wages - Unemployed Worker	0.340	
		(0.004)	0.368
λ_E	Probability of Rigid Wages - Employed Worker	0.401	(0.110)
		(0.112)	

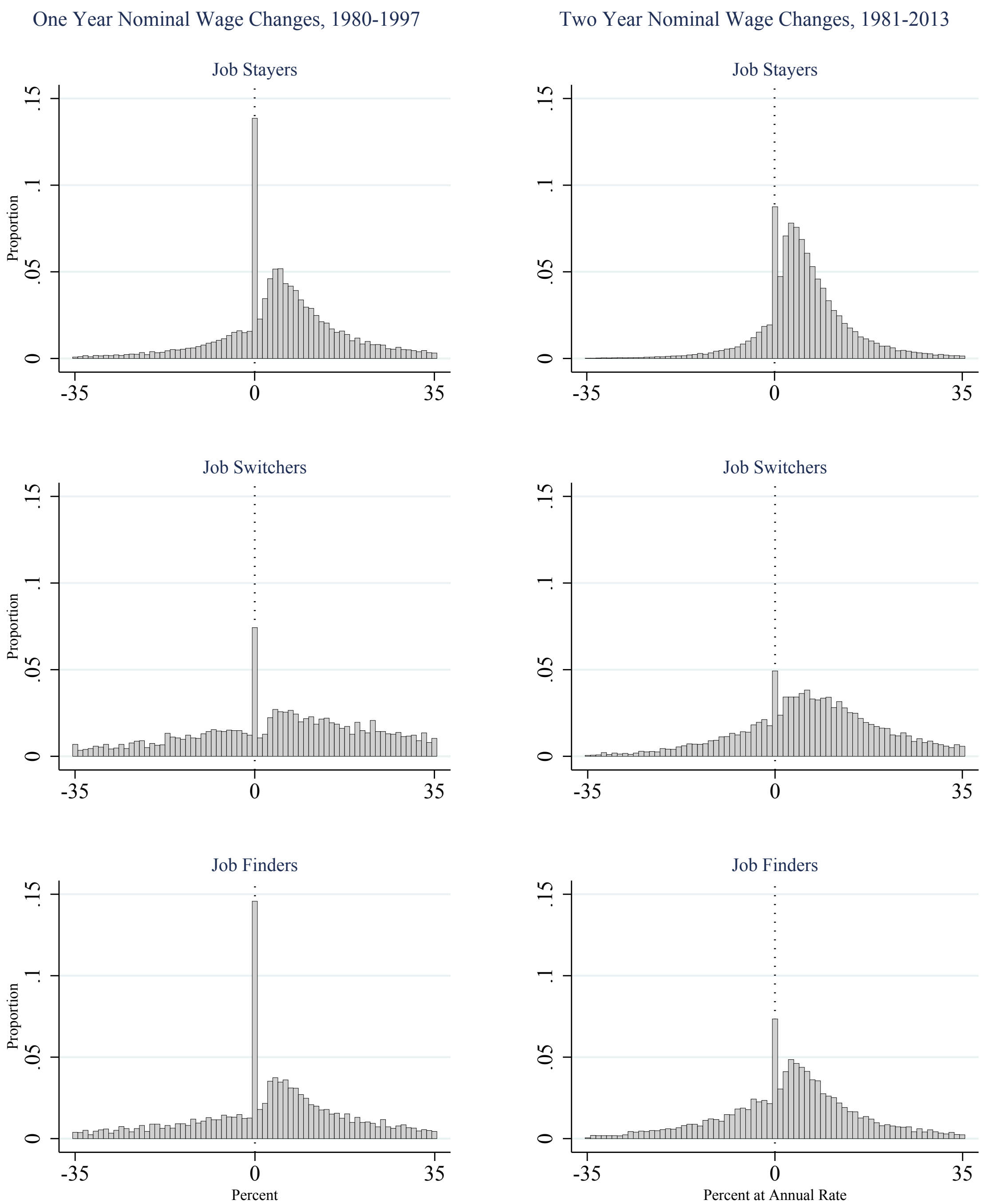
Note: β, π, and $\bar{p}$ are fixed externally; other parameters are estimated as described in the text. β, π, $\bar{p}$, ψ_p, λ_U, and λ_E are annual values; A, ψ_p, σ_p, b, and c are monthly values. Unconstrained model estimates separate λ_E and λ_U; constrained model imposes equality. Standard errors in parentheses.

Table VII: 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)

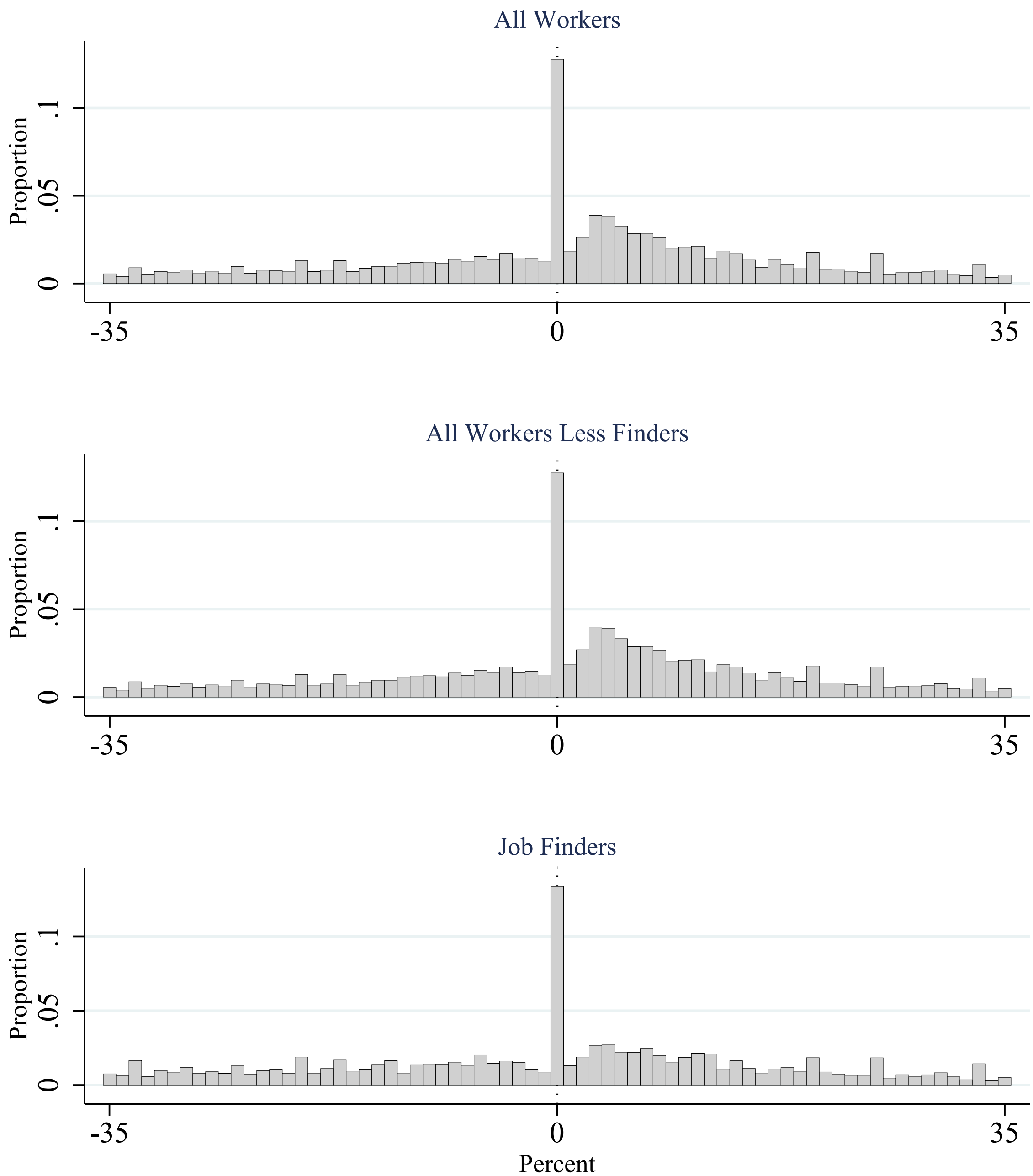
Note: The aggregate elasticities are calculated using quarterly averages of monthly simulated data. The individual elasticities are calculated using year-over-year changes in individual wages. Reported values with respect to unemployment are semi-elasticities. Both sets of elasticities use CPS definitions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

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



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

Figure II: 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 III: Sources of Unemployment

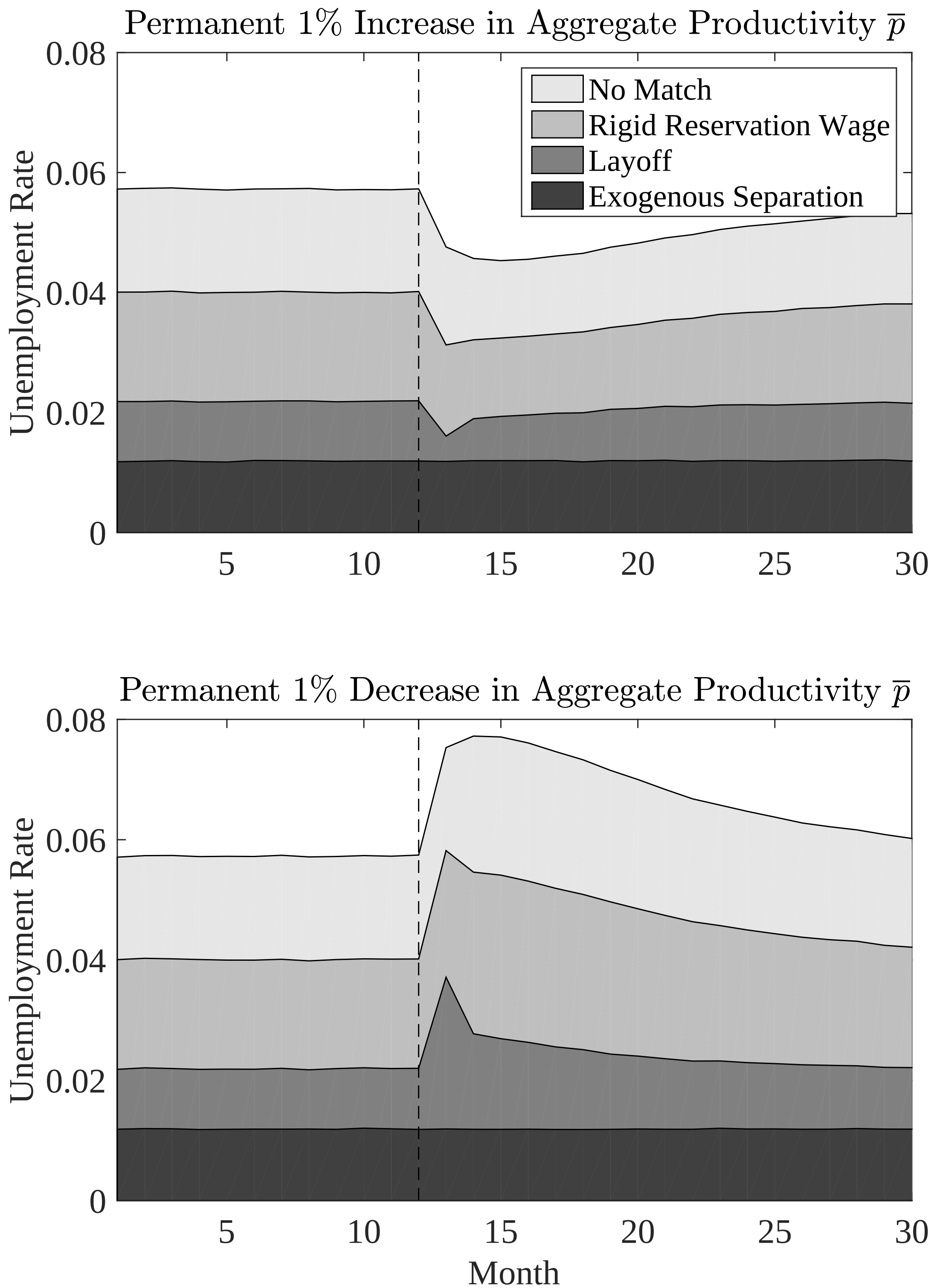
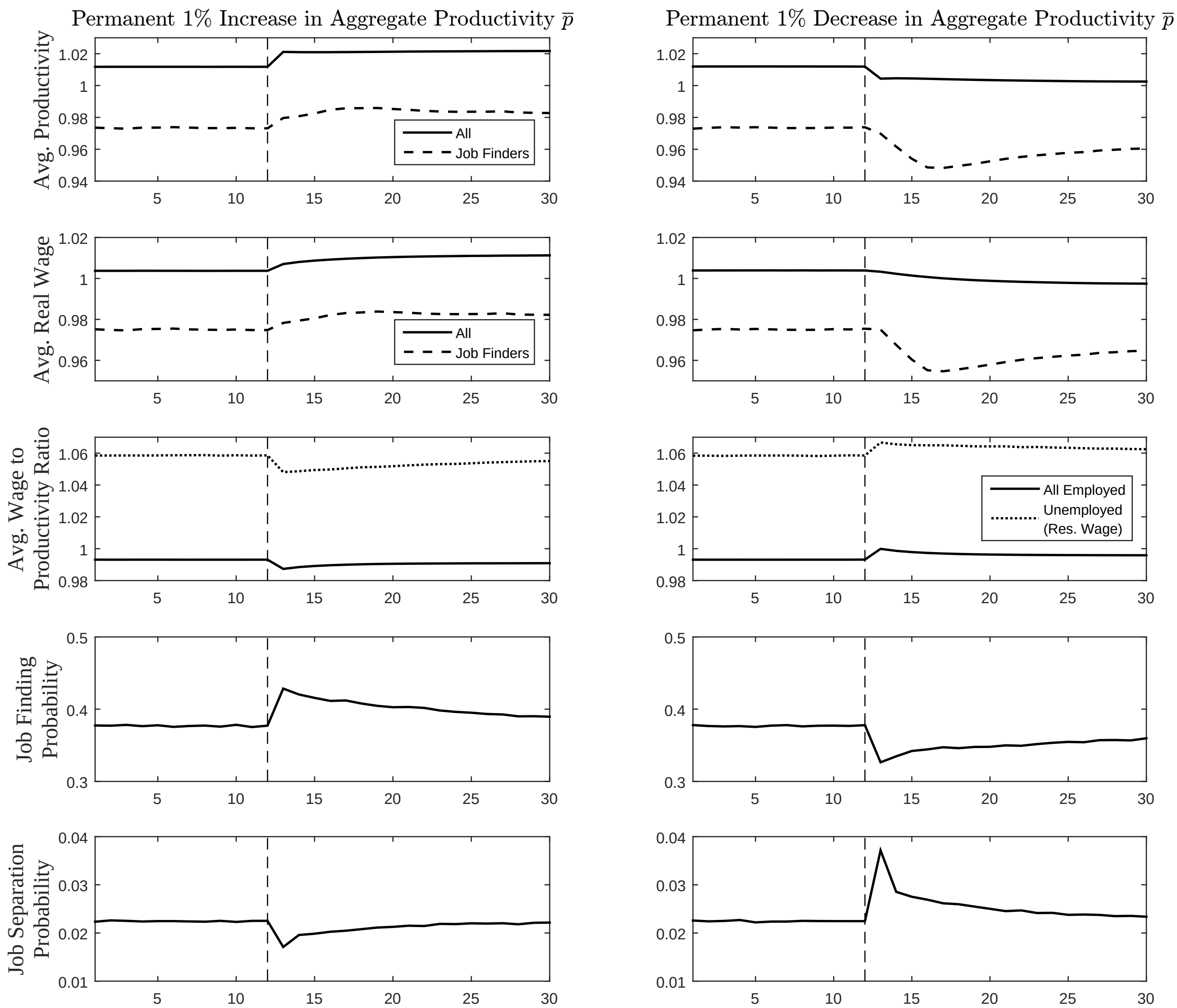


Figure IV: Labor Market Responses to Aggregate Productivity Shocks



A Appendix

A.1 Technical Appendix on Data

This section of the appendix details the methods employed in sections III.B and III 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 (2017), 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.[36] 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 et al. (2003), and K is a kernel function.[37] 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.[38] 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 $\hat{F}_t^{obs}(0^-)$.[39] Denote the proportion of wage cuts in the estimated counterfactual distribution as $\hat{F}_t^{cf}(0^-)$. Let the

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

[37] 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.

[38] 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 (2017). Those years are then excluded when averaging the upper tails, but are included when calculating the counterfactual wage cuts prevented by wage rigidity.

[39] 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.[40]

A.3 Computational Methods

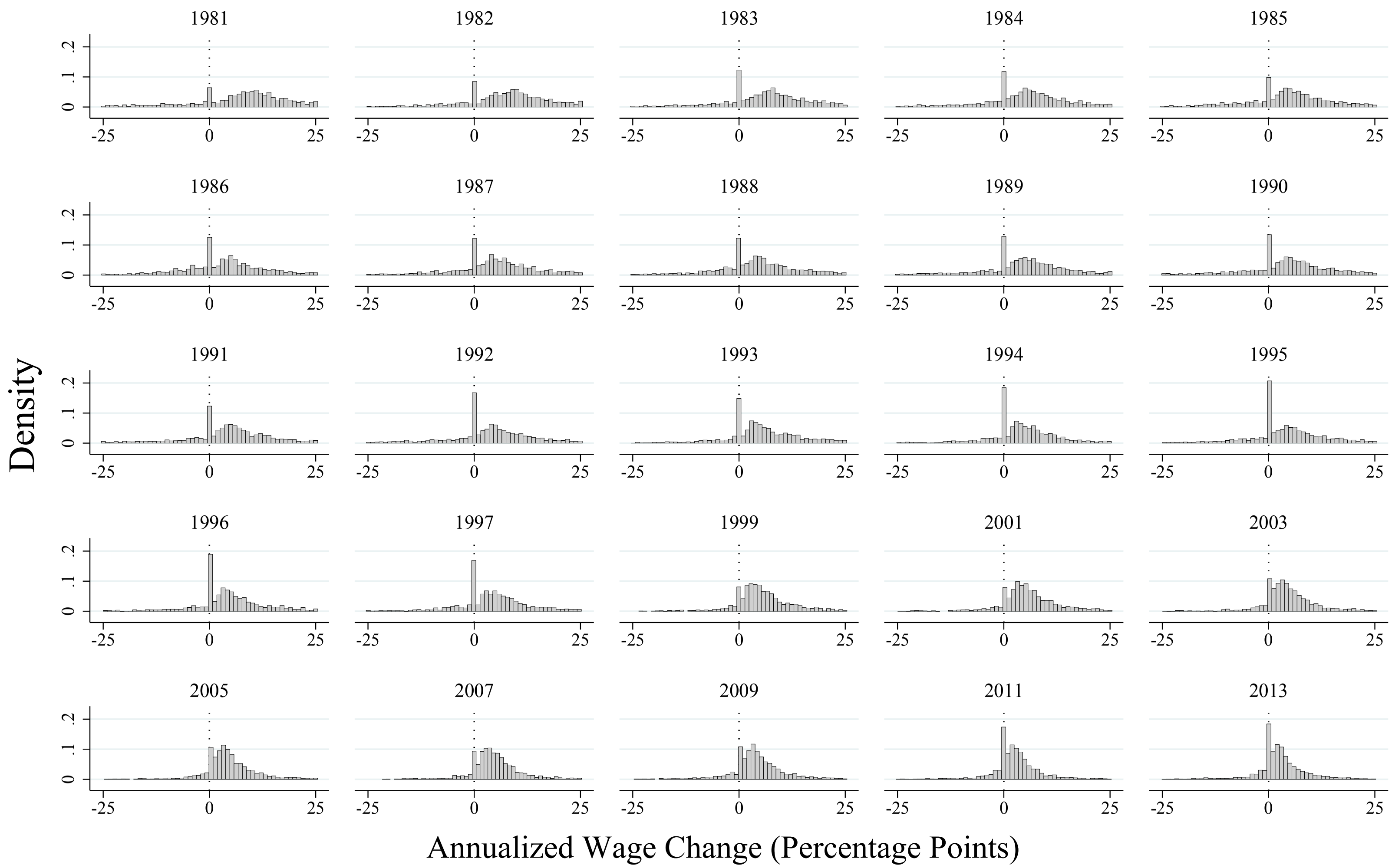
We approximate the value functions for firms and workers using standard value function iteration techniques. We approximate the productivity process using the method of Tauchen (1986), using a productivity grid with 200 nodes. The nodes are spaced evenly in log terms, ranging from two standard errors below the mean to two standard errors above. At the estimated values for persistence of the productivity process ψ_p and innovation σ_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 Θ, and average them.

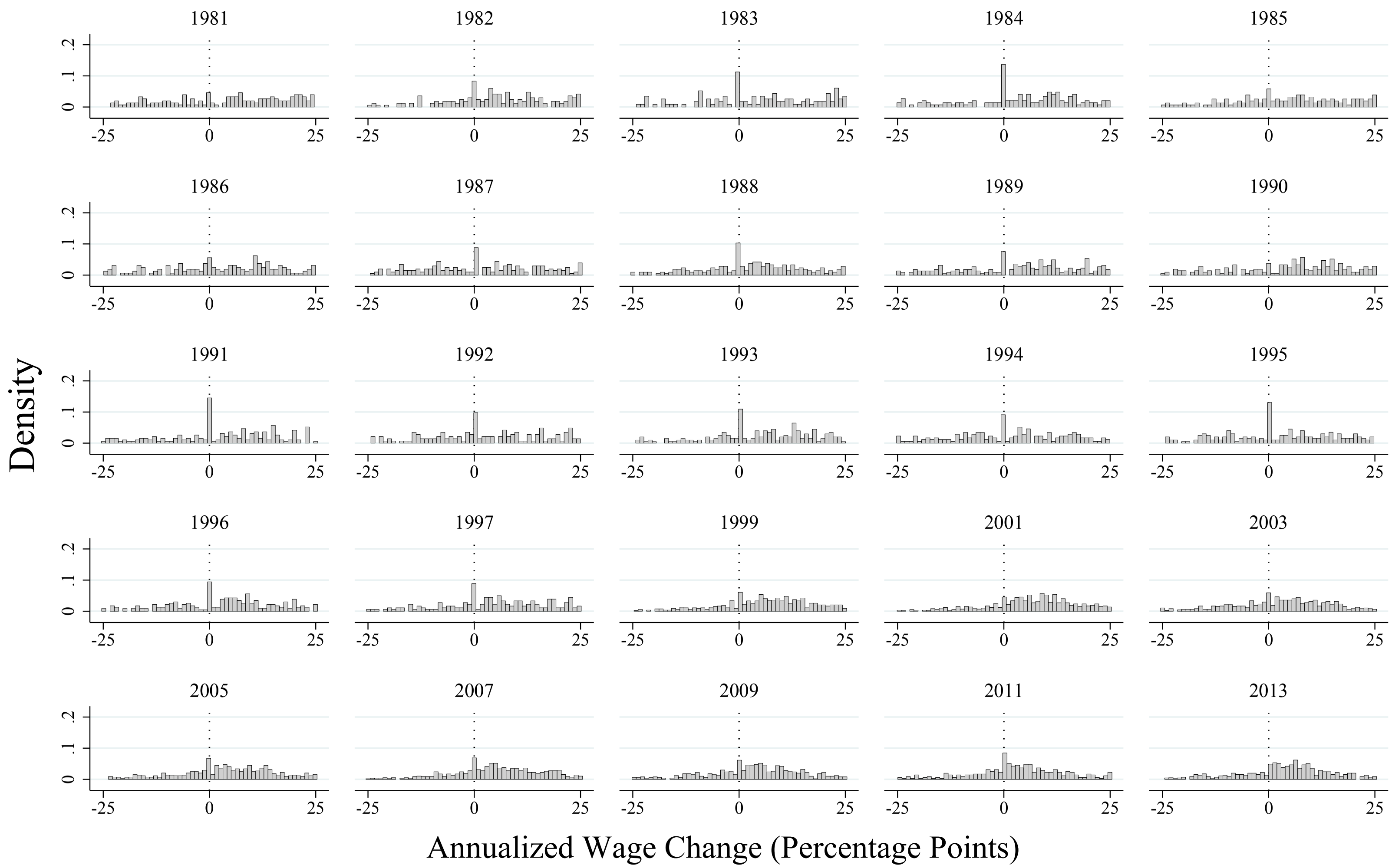
[40]Nothing in this procedure prevents $\widehat{wr}_i$ from being negative. A value for $\widehat{wr}_i$ of -0.25 would imply that there are 25 percent more wage cuts in the data than would be predicted by the distribution of nominally positive wage changes.

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



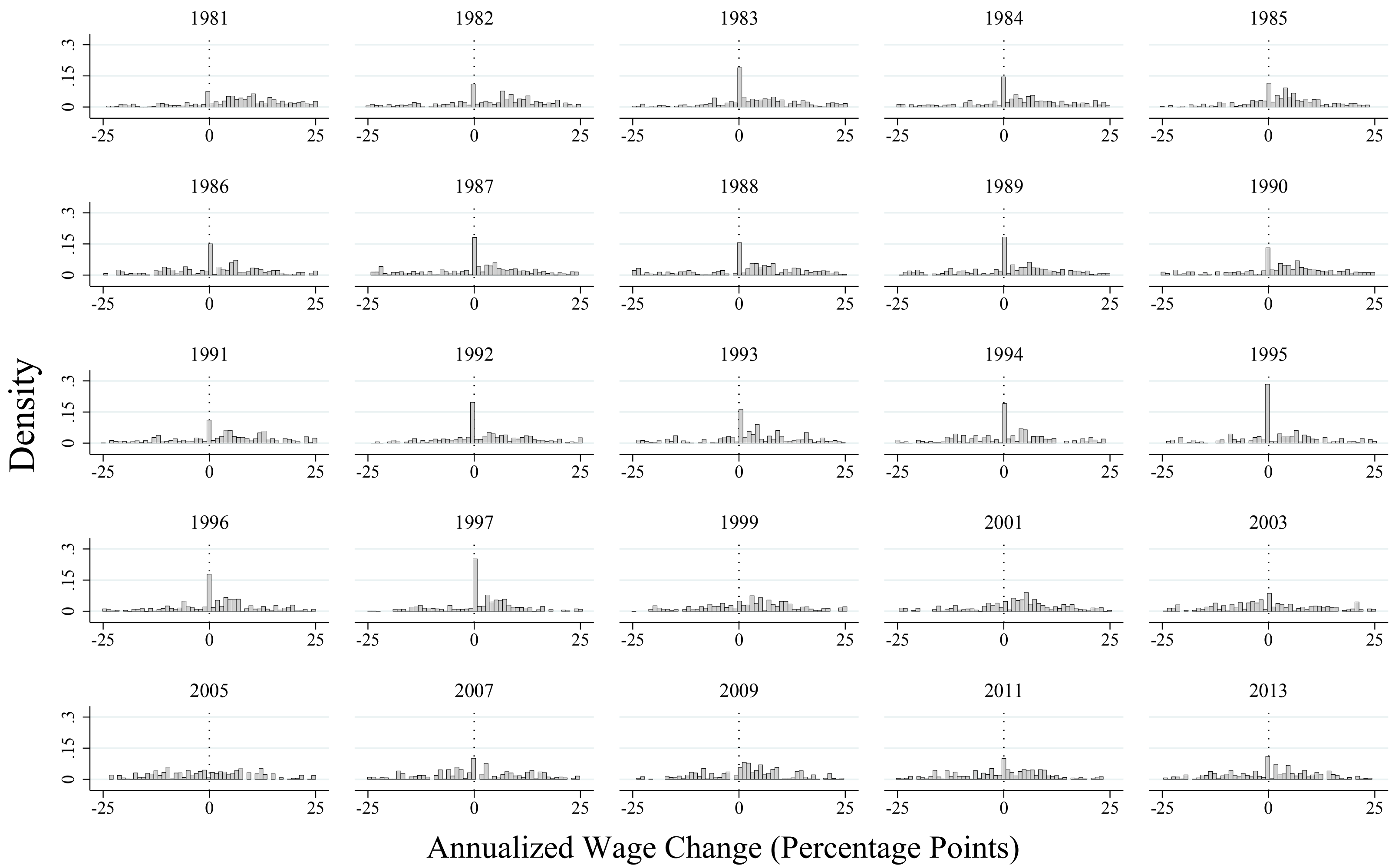
Notes:
Years 1981-1997 show the annual wage change from the previous year.
Years 1999-2013 show the annualized two-year wage change from two years previously.
Distributions are truncated at -25 and 25 percent.

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



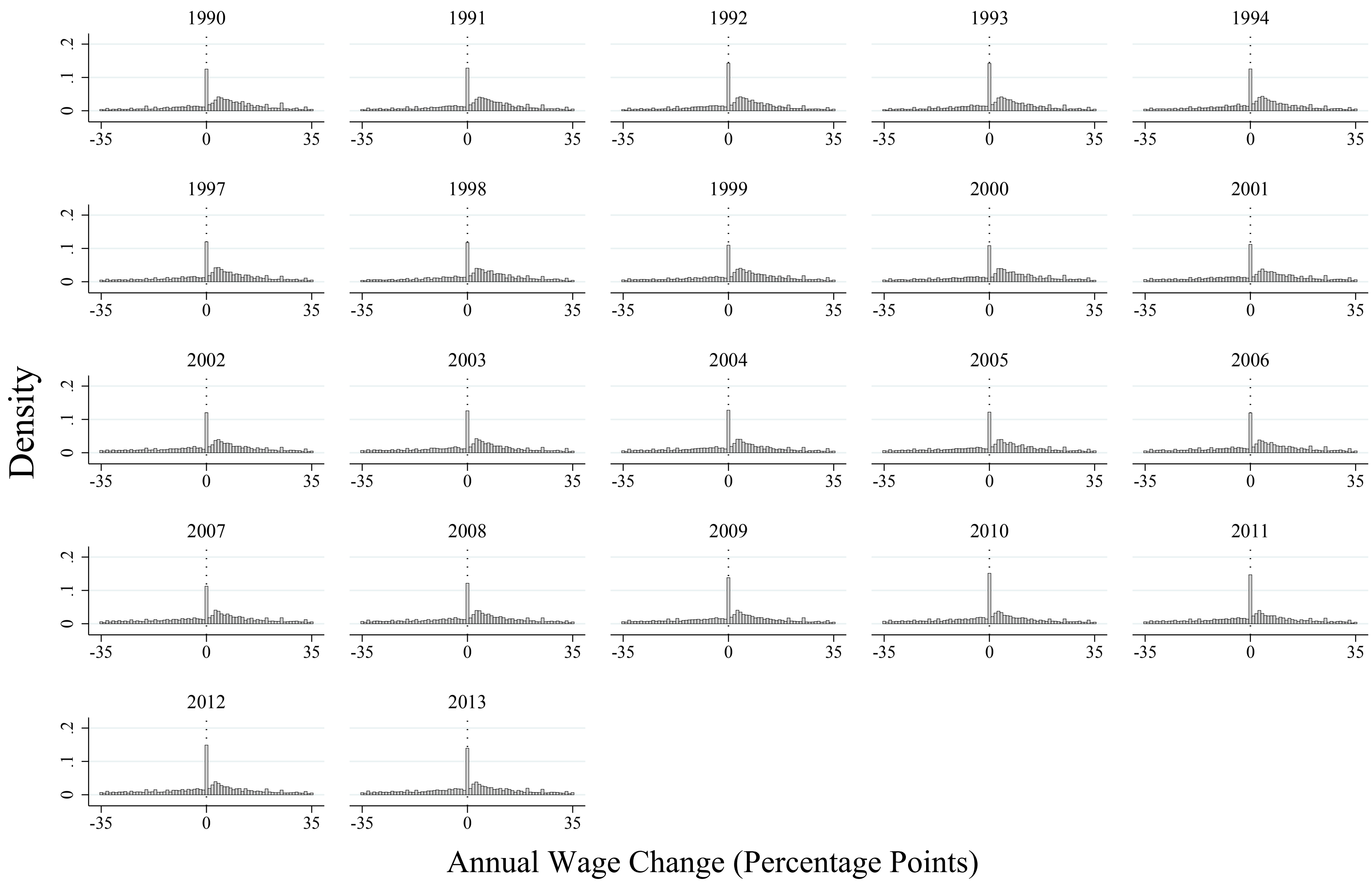
Notes:
Years 1981-1997 show the annual wage change from the previous year.
Years 1999-2013 show the annualized two-year wage change from two years previously.
Distributions are truncated at -25 and 25 percent.

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



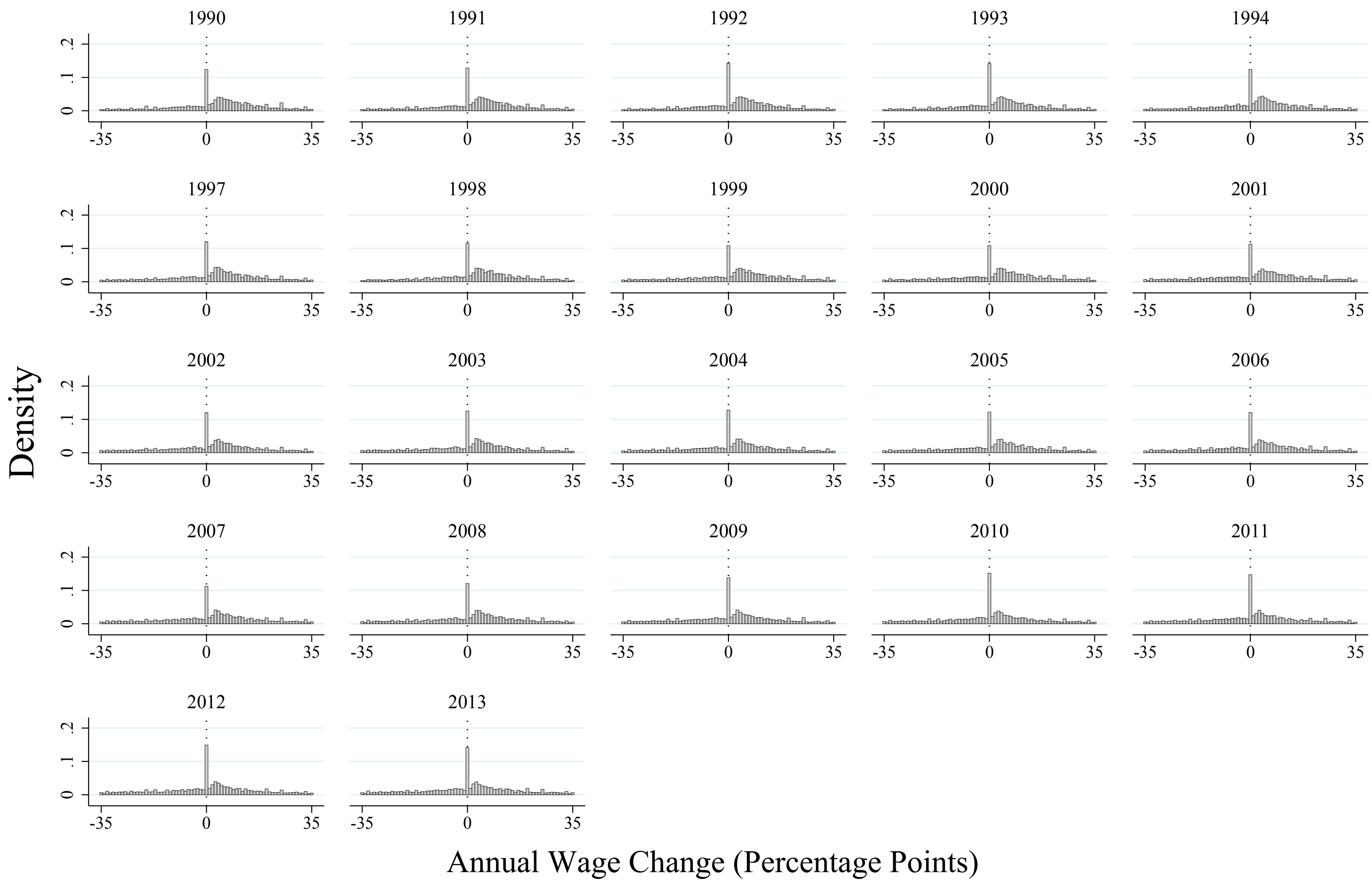
Notes:
Years 1981-1997 show the annual wage change from the previous year.
Years 1999-2013 show the annualized two-year wage change from two years previously.
Distributions are truncated at -25 and 25 percent.

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



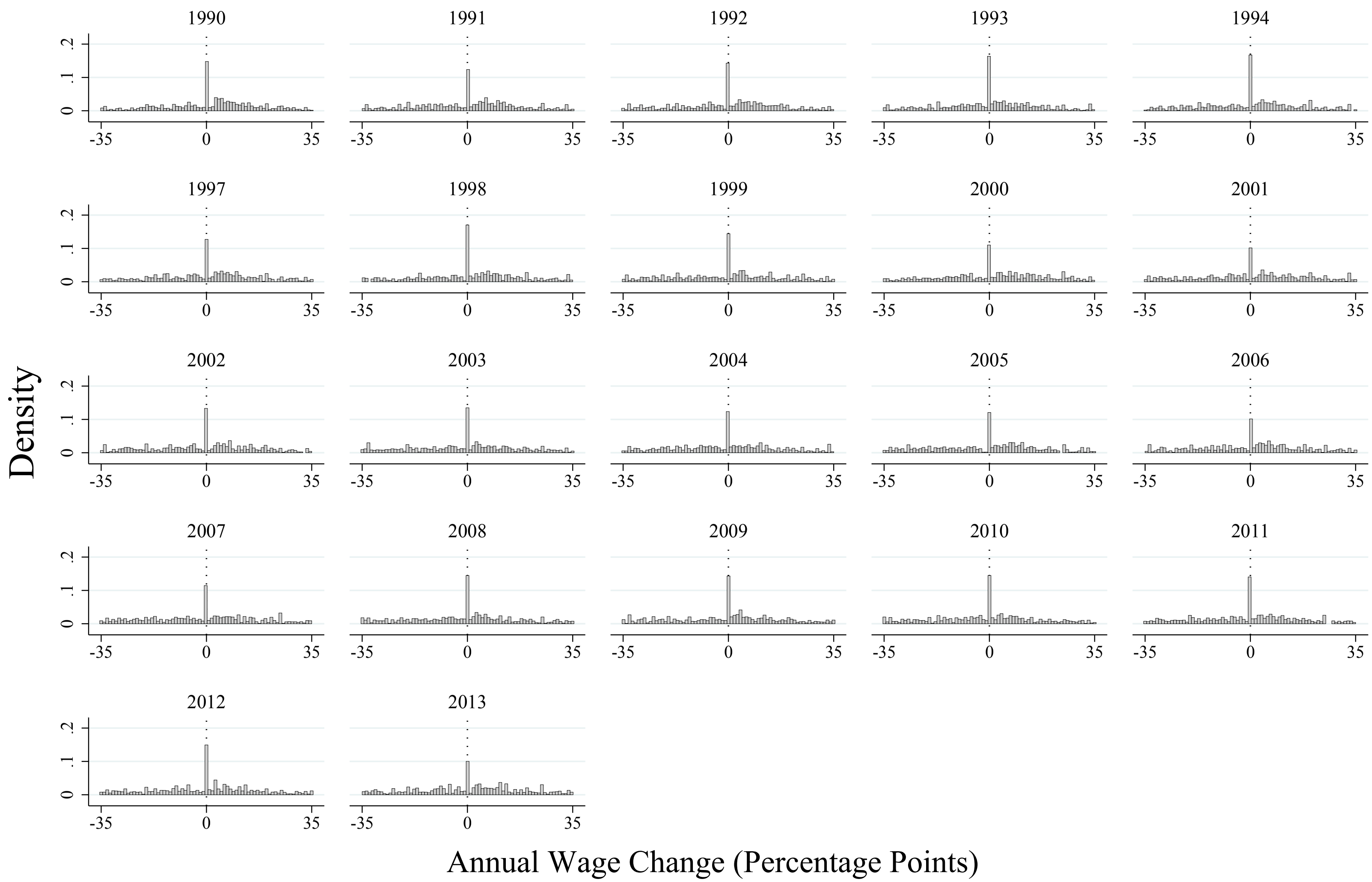
Notes:
Years 1995-1996 are exluded because of a sample design change in 1995 that hinders matching.
Distributions are truncated at -35 and 35 percent.

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



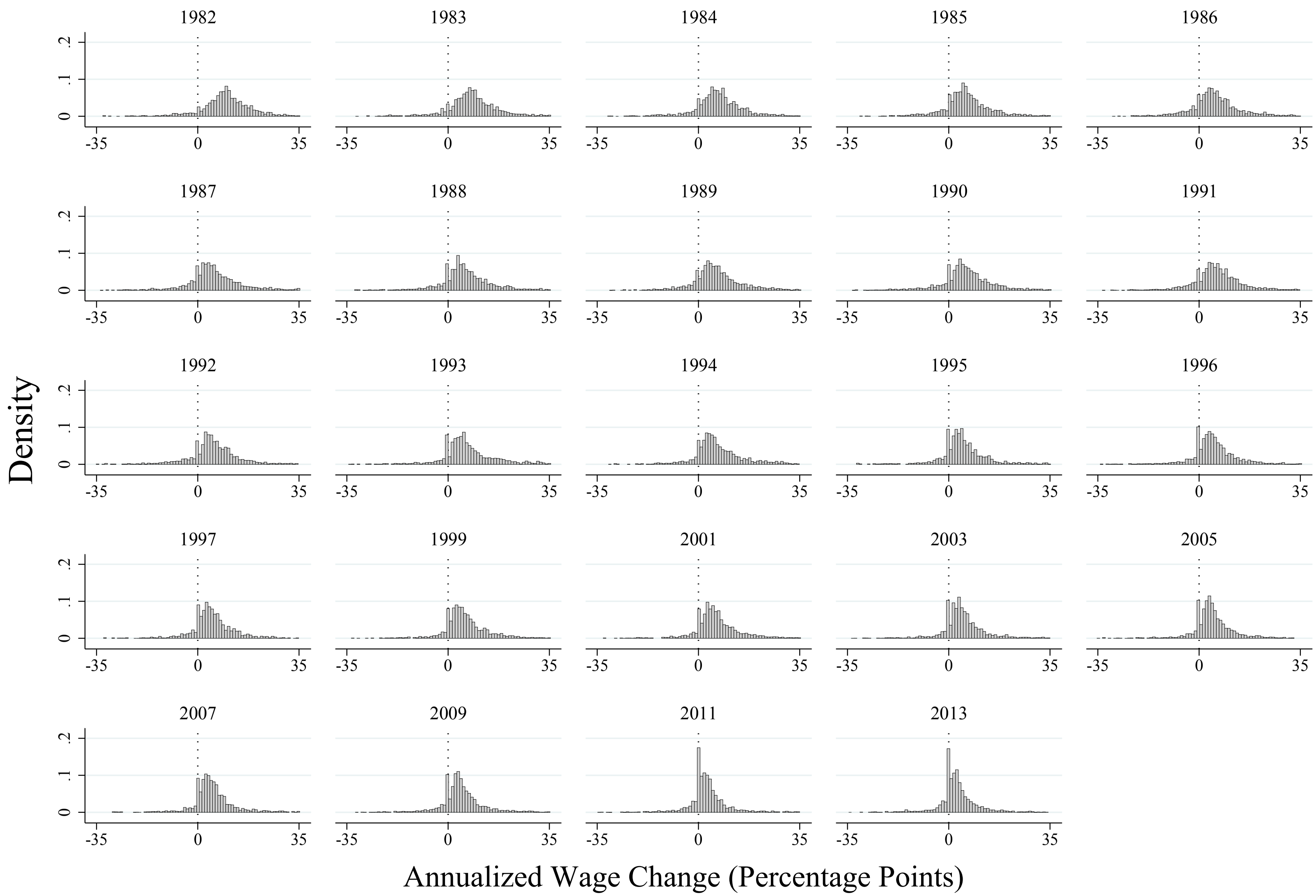
Notes:
Years 1995-1996 are exluded because of a sample design change in 1995 that hinders matching.
Distributions are truncated at -35 and 35 percent.

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



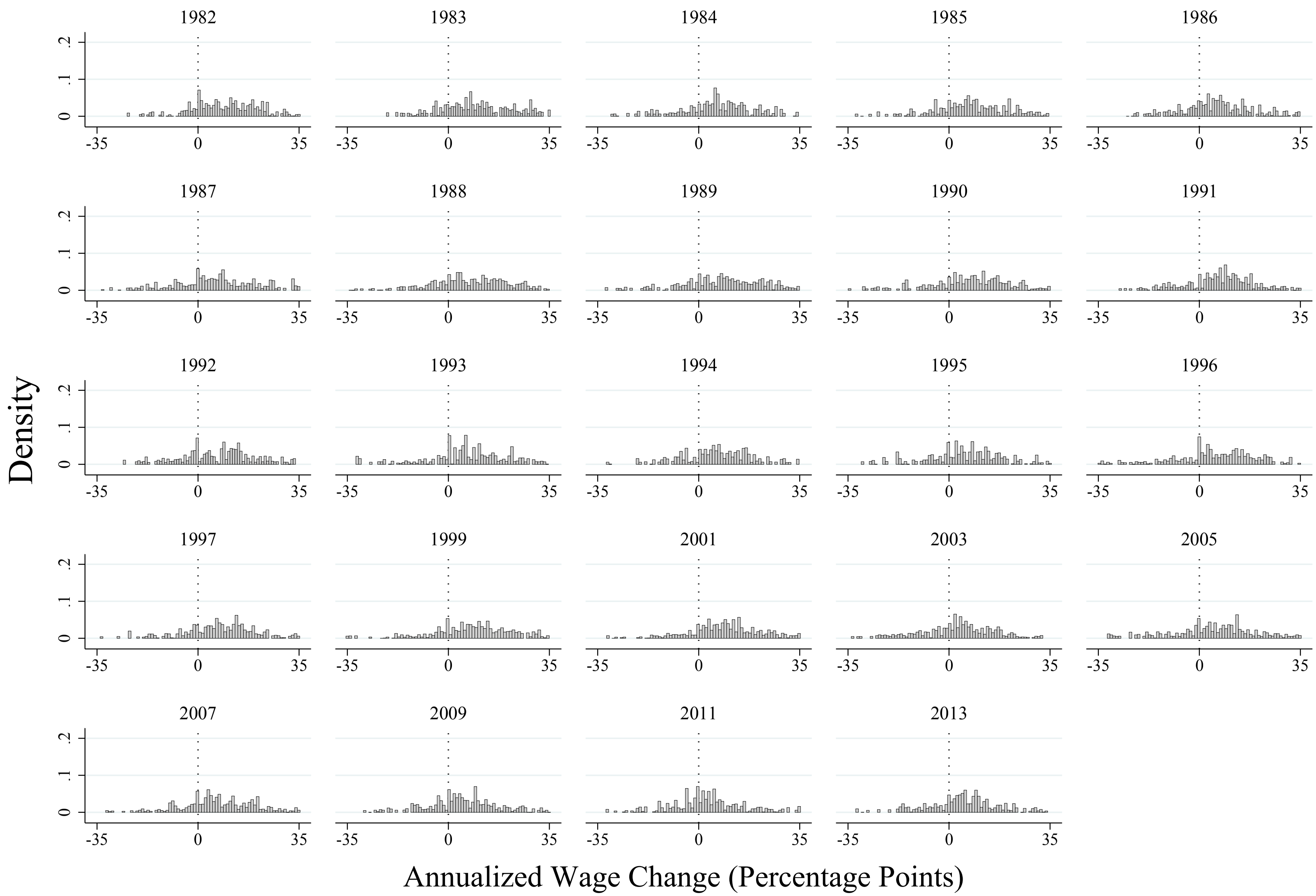
Notes:
Years 1995-1996 are exluded because of a sample design change in 1995 that hinders matching.
Distributions are truncated at -35 and 35 percent.

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



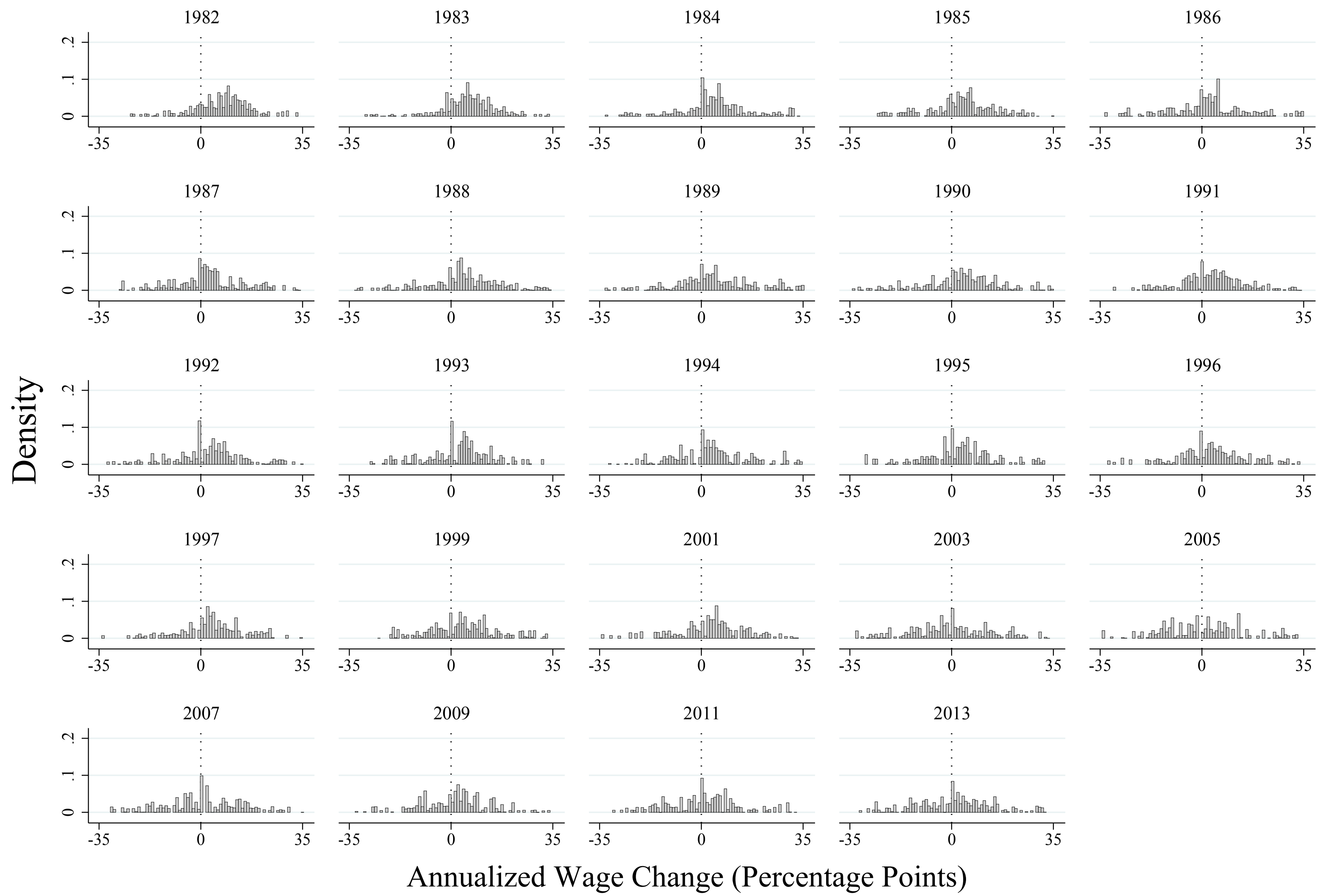
Note: Years show the annualized two-year wage growth rate from two years previously.

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.