

# ONLINE APPENDIX TO “THE LABOR DEMAND AND LABOR SUPPLY CHANNELS OF MONETARY POLICY”

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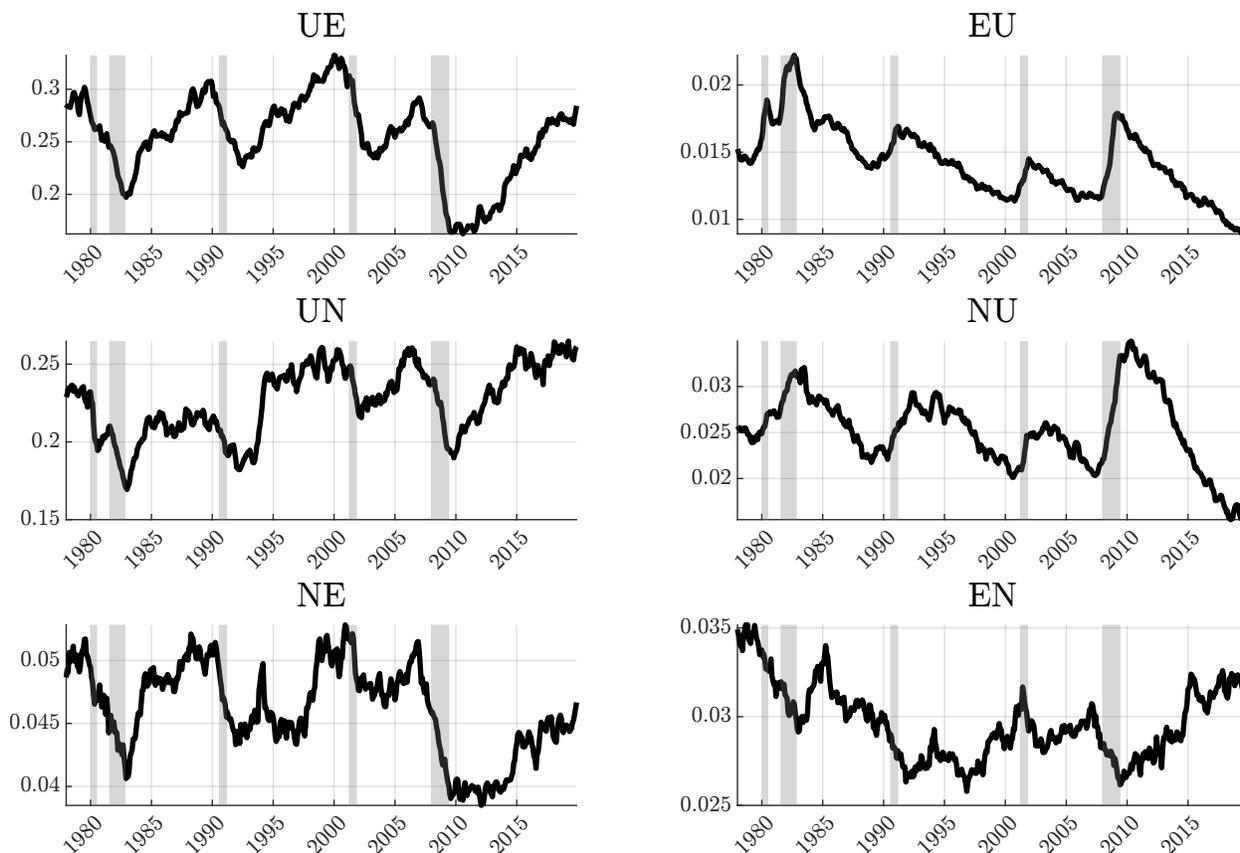
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The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or any other person associated with the Federal Reserve System. *Graves*: University of Cambridge, sg566@cam.ac.uk. *Huckfeldt*: Board of Governors of the Federal Reserve System, chris.huckfeldt@frb.gov. *Swanson*: University of California, Irvine, and NBER, eric.swanson@uci.edu. First version: February 2023. This version: October 9, 2024.

## APPENDIX A. TIME SERIES: LABOR MARKET FLOWS AND INTENSIVE MARGINS OF JOB SEARCH

FIGURE A.1. Time Series of Labor Market Flows



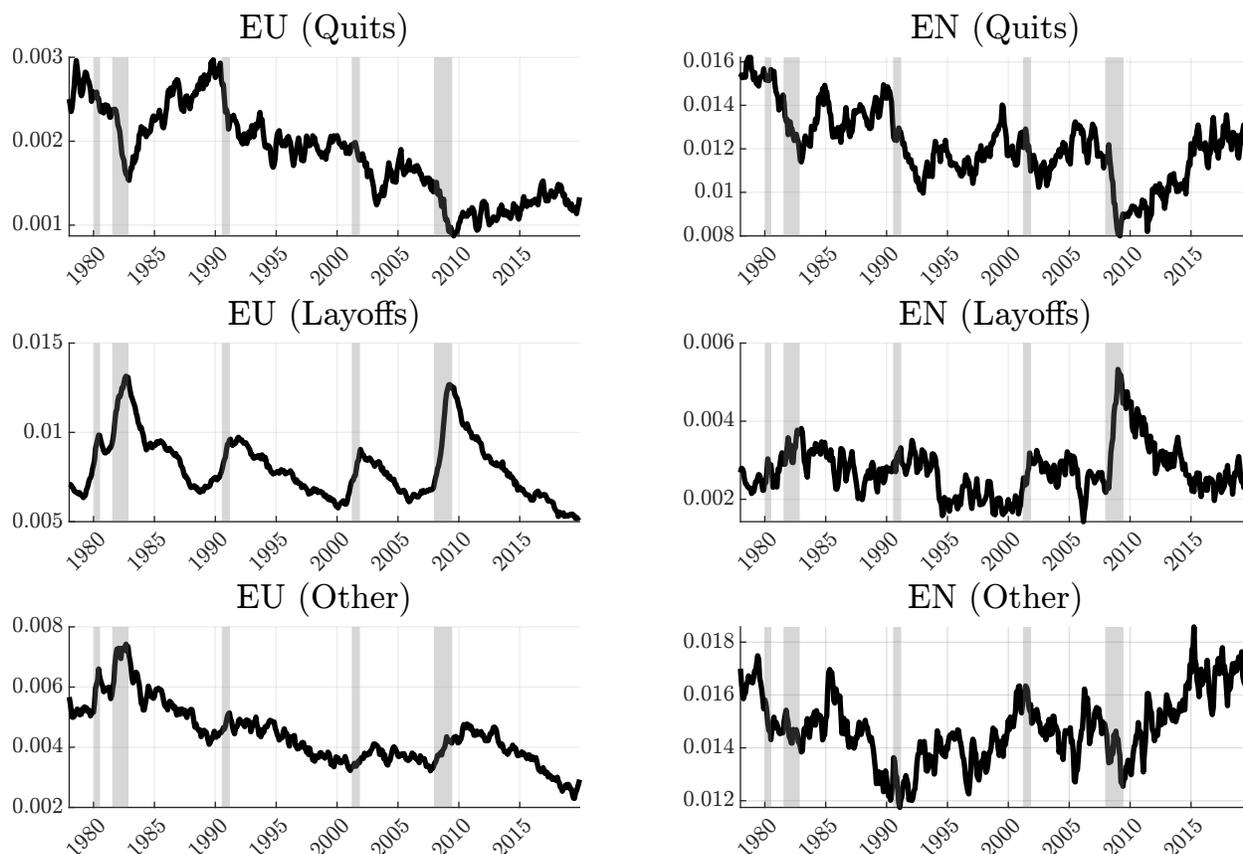
*Note:* Transition rates are calculated using CPS microdata. All series are smoothed using a centered 5-month moving average.

Figures A.1, A.2, and A.3 show the time series of labor market flows, decomposed series of EU and EN flows, and measures of the intensive margin of job search. We discuss our measures of labor market flows in Sections 2.1 and 2.2 of the main text, along with an extended discussion of our decomposition of EU and EN flows into quits and layoffs in Appendix B. Here, we offer a short discussion of how we construct our various measures for the intensive margin of job search.

Following Mukoyama, Patterson and Şahin (2018) and others, we adopt the number of distinct job search methods reported by unemployed job seekers as a measure of the intensive margin of job search for unemployed workers; and the fraction of nonparticipants who report wanting a job as a measure of the intensive margin of job search for nonparticipants.

The redesign of the CPS in 1994 complicates the construction of a consistent series for the former measure, as it increased the number of possible job search methods from 6 to

FIGURE A.2. Time Series Decomposition of EU and EN Flows

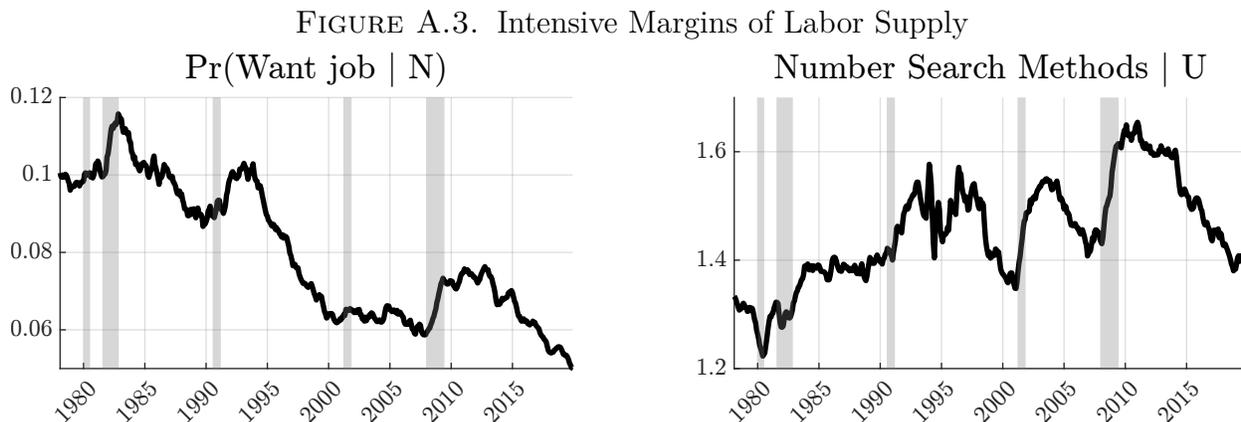


*Note:* Employment-unemployment (EU) and employment-nonparticipation (EN) flows are decomposed into quits, layoffs and other separations as explained in Appendix B.1.1. All series are smoothed using a centered 5-month moving average.

12. Consequently, we allow for 5 possible methods of active search: “contacted public employment agency”, “contacted private employment agency”, “contacted friends or relatives”, “contacted employer directly/interview” and “other active”. We then group the answers from pre- and post-1994 into these 5 categories and calculate the average number of search methods among unemployed individuals.<sup>1</sup> Similar measures have been used elsewhere in the literature to show that search is countercyclical, including Mukoyama, Patterson and Şahin (2018). Relative to these papers, we construct a consistent measure of the number of search methods starting from 1978, rather than 1994, shown in the right panel of Figure A.3.

Measuring the fraction of nonparticipants who report wanting a job is slightly complicated by the CPS redesign. Before 1994, nonparticipants were only asked if they wanted a job in

<sup>1</sup>In principle, “placed or answered ads” is a sixth method that is included both before and after 1994. However, we have found that the number of individuals reporting this method dropped sharply after 1994. This is likely explained by the introduction of “Sent out resumes/filled out applications” as a possible search method at this time.



*Note:* We calculate the fraction of nonparticipants that want a job (left-panel) and the number of search methods of the unemployed (right-panel) using the procedure described in the text. All series are smoothed using a centered 5-month moving average.

the outgoing rotation group. The possible answers were “Yes”, “Maybe, it depends”, “No”, or “Don’t know”. From 1994 this question was asked to all nonparticipants and the possible answers changed to “Yes, or maybe, it depends”, “No”, “Retired”, “Disabled”, or “Unable to work”. Given the change in possible answers, we group “Yes” and “Maybe, it depends” as “Yes” and all other answers as “No”. This gives us a consistent series over time that displays no break at the 1994 redesign (the left panel of Figure A.3).

## APPENDIX B. MEASUREMENT OF EU/EN QUILTS AND LAYOFFS

A distinctive contribution of our paper comes from developing a novel decomposition of EN flows measured from the CPS into quits and layoffs.<sup>2</sup> Here, we describe our methodology for decomposing both EU and EN flows into quits and layoffs, where we denote worker-initiated separations as “quits” and firm-initiated separations as “layoffs”. We use the label “other separations” for situations where either (a) there is no clear distinction of a quit versus a layoff (e.g., fixed-term jobs), or (b) it is not clear which party initiated the separation. After describing how we implement the decomposition, we provide further validation that our measures of quits and layoffs capture economically distinct phenomena (beyond that documented elsewhere in the main paper). Finally, we discuss the robustness of our measures to various issues specific to the CPS data. The time series for our decomposition of EU and EN transition rates are shown in Figure A.2.

<sup>2</sup>Note, since initial drafts of our paper were circulated and posted online, a recent paper by Ellieroth and Michaud (2024) also discusses separating EN flows into quits and layoffs using a methodology that appears to be very similar to our own.

**B.1. Data Construction.** Here, we describe our categorization of EU and EU separations into quits and layoffs, and we provide details on providing a harmonized series for each from the CPS.

*B.1.1. Decomposition of EU Flows: Quits versus Layoffs.* The decomposition of EU flows into quits and layoffs is the more straightforward. We label an EU transition as a quit if the reason for unemployment is “job leaver” and as a layoff if the reason for unemployment is “job loser/on layoff” or “other job loser”. We label as “other separations” transitions where the reason for unemployment is “temporary job ended”, “re-entrant” or “new entrant”.<sup>3</sup>

We label the end of temporary or seasonal jobs as “other separations.” Compared to the ending of an open-term job, there is no clear economic rationale for labeling the ending of fixed-term job as a quit or a layoff. However, while it is simple to separately categorize such EU transitions for the majority of our data, “temporary job ended” was removed as a possible response from the survey from 1989 to 1993. An inspection of the data shows that during this period such transitions were labelled as “job loser/on layoff” or “other job loser”. Thus, we estimate the share of EU transitions due to temporary jobs ending for each month between 1989 and 1993, and then remove this share from that which is initially defined as layoffs during this period.

To implement this procedure, we run a regression of the share of EU transitions due to temporary jobs ending on all six labor market transition rates, month dummies and a time trend for the period from January 1978 to December 1988. The  $R^2$  of this regression is 0.58, implying that the share of EU transitions due to temporary jobs ending is largely predictable. We then use this regression to predict the share of EU separations due to temporary jobs ending from January 1989 to December 1993. Finally, we adjust down the share of EU separations due to layoffs in this period accordingly. It should be noted that this adjustment is relatively minor, as “temporary job ended” is only ever the reason for a small fraction of EU transitions: in years where it was an available response, only 13% of EU transitions are classified in this way.

*B.1.2. Decomposition of EN Flows: Quits versus Layoffs.* The decomposition of EN flows is slightly more involved: to our knowledge, our paper is the first to use the CPS to develop a harmonized measure of EN quits and layoffs suitable for time series analysis.

A subset of CPS respondents in an Outgoing Rotation Groups (ORG) identified to be nonparticipants are asked the reason that they left their last job. However, the conditions under which an ORG nonparticipant is included in this subset has changed over time. Since 1994, this question is asked to individuals in the outgoing rotation group that are: (1) not

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<sup>3</sup>In principle an individual who has moved from employment to unemployment should be neither a “re-entrant” nor a “new entrant”. Thus these latter reasons for unemployment appear to be measurement error. They account for a little over 15% of all EU transitions in our sample period.

in the labor force, (2) neither classified as retired nor disabled and (3) who report having worked in the past 12 months. Prior to 1994 this question was asked to individuals in the outgoing rotation group that are: (1) not in the labor force and (2) who reported having worked in the past five years. Moreover, the possible answers to the question also changed slightly starting in 1994, as discussed below.<sup>4</sup>

To create a harmonized series, we restrict our attention to individuals who report having worked in the past 12 months.<sup>5</sup> We label an EN transition as a quit if the reason for leaving the job is “personal, family or school” or “unsatisfactory work arrangements”.<sup>6</sup> We label an EN transition as a layoff if the reason for leaving the job is “slack work or business conditions”. We label all remaining EN transitions as other separations.<sup>7</sup> After 1994 we assume that individuals who make an EN transition and either report being retired or disabled would have given this as their reason for leaving their job had they been asked the question. Consequently, such transitions are defined as neither quits nor layoffs. Finally, as our sample is only ever a fraction of all EN transitions, in all periods we calculate the share of EN transitions in each classification and then multiply this by the overall EN transition rate to complete our decomposition.

At this point we note one main difference between our classification of separations into quits, layoffs and other separations, and that of the Job Openings and Labor Turnover Survey (JOLTS). We categorize the end of temporary or seasonal jobs as other separations, while JOLTS includes such separations in layoffs. While we prefer our classification on economic grounds, it is also worth noting that trying to implement a decomposition of EN transitions using the JOLTS classification also leads to measurement issues.

Prior to the redesign of the CPS in 1994, nonparticipants were given two possible answers relating to the end of temporary jobs: “Seasonal job completed” or “Temporary nonseasonal job completed”. After the redesign, these were reduced to only “Temporary, seasonal, or intermittent job completed”. While in theory this should have no effect on the share of EN transitions occurring due to the end of temporary jobs, in practice it leads to a significant decline in this share, from an average of 17% before 1994 to an average of 9.5% afterwards. After 1994, transitions which previously would have been labelled as the end of temporary jobs appear to be labelled as “other separations”. Thus, when we include the end of temporary jobs in “other separations”, as we do in our preferred measure, our decomposition does not show breaks around the 1994 redesign. If we were to label the end of temporary jobs as layoffs, there would be a notable drop in the layoff rate to nonparticipation in 1994.

<sup>4</sup>For technical background on these changes, see U.S. Census Bureau (2019, pg. 111).

<sup>5</sup>In principle, all individuals that make EN transitions should report having worked in the past 12 months. In practice, a minority do not, as we discuss later.

<sup>6</sup>These are the possible answers from before 1994. After 1994 we define such transitions analogously.

<sup>7</sup>Other EN separations include retirements, individuals reporting disability, and the end of temporary seasonal or non-seasonal jobs.

**B.2. Further Evidence for Economic Relevance of Quit/Layoff Distinction.** In the main paper, we show that both EU and EN quits are procyclical; and that both EU and EN layoffs are countercyclical. Then, we show that EU and EN quits decrease in response to a contractionary monetary policy shock, whereas EU and EN layoffs increase. Finally, we show that our estimated model is largely able to match the response of EU/EN quits and layoffs. Taken as a whole, this evidence suggests an economically relevant distinction between quits and layoffs from our empirical measures.

Here, we provide additional evidence that the distinction between quits and layoffs is economically meaningful at the individual level, by documenting that the subsequent labor market transition probabilities for individuals who quit to either unemployment or nonparticipation are notably different from those of individuals who are laid off.

TABLE B.1. Post-EU Transition Rates: Quits vs Layoffs

<i>From</i>	<i>To</i>		
	E	U	N
E – U(Quit)	0.448	0.399	0.153
E – U(Layoff)	0.426	0.468	0.106

*Note:* Transition rates are shown for individuals that are in their first month of unemployment following an employment spell, split by reason for unemployment, as defined in Appendix B.1.1.

Table B.1 shows transition probabilities of workers who entered unemployment from employment in the previous month either due to a quit (e.g., E–U(Quit)) or a layoff (e.g., E–U(Layoff)). Workers making E–U(Quit) transitions have slightly higher re-employment probabilities *and* significantly higher probabilities of entering nonparticipation than workers making E–U(Layoff) transitions.<sup>8</sup> This suggests that individuals quitting to unemployment likely fall into two groups: The first are individuals who appear to have strong employment prospects when they quit to unemployment, and thus move back to employment at a high rate. The second are individuals with low attachment to the labor market, who thus move to nonparticipation at a higher rate than individuals laid off to unemployment.

The same exercise is not possible for EN quits and layoffs, as nonparticipants are only asked their reason for leaving their last job if they are in the outgoing rotation group, and thus we do not see their employment status the following month.

However, we are able to provide evidence that such individuals likely have very different subsequent labor market transition probabilities. Table B.2 shows that those who are laid off to nonparticipation are more than twice as likely to report that they want a job as those who quit to nonparticipation, and that nonparticipants who want a job are around four

<sup>8</sup>We can reject the null hypothesis that the two rows of transition probabilities given in Table B.1 are equal using a chi-squared goodness-of-fit test with a p-value that is less than 0.01%.

TABLE B.2. Post-EN Report: Quits vs Layoffs

	Average Probability
Want Job   E-N(Quit)	0.210
Want Job   E-N(Layoff)	0.515
NE   Want Job	0.145
NE   Do Not Want Job	0.037
NU   Want Job	0.172
NU   Do Not Want Job	0.012

*Note:* The first and second rows show the probability that individuals want a job if they have just made an EN transition, split by the reason for leaving their job, as defined in Appendix B.1.1. The final four rows show the probabilities of transitioning to employment or unemployment for all nonparticipants, split by whether or not they report wanting a job.

(fourteen) times more likely to move to employment (unemployment) in the next month than nonparticipants who report that they do not want work.

This suggests that people who quit to nonparticipation are less attached to the labor market than individuals laid off to nonparticipation, and thus are more likely to stay there. This is consistent with the description above of many individuals that quit to unemployment.

**B.3. Robustness: EU Flows.** Shimer (2012) points out potential inconsistencies in the measurement of quits and layoffs to unemployment in the CPS, noting that, prior to the 1994 survey redesign, a portion of EU quitters who are newly unemployed in month  $t$  and remain unemployed in month  $t + 1$  then report having being laid off; and a much smaller portion of those laid off to unemployment in month  $t$  that remain unemployed in month  $t + 1$  then report having quit. In this section, we investigate these issues and show that they present only minor concerns for our measures of EU quits and layoffs.

We reproduce evidence akin to Shimer (2012) in Table B.3. For individuals with an E-U-U labor market sequence, around 4% of those who initially report having been laid off subsequently report having quit their job, before the 1994 redesign of the CPS. Switching is higher among those who initially report having quit: around 20% of such individuals subsequently report having been laid off. After the redesign of the survey the likelihood of switching in either direction drops dramatically. Note, the patterns from Table B.3 have two possible interpretations: First, that quits and layoffs are measured inaccurately in the CPS, as suggested by Shimer (2012). Second, the patterns presented in Table B.3 could be explained by the existence of short-term jobs that are not picked up by the monthly CPS survey. Although we cannot easily distinguish between these two explanations, we next provide evidence that such switching is not quantitatively relevant for our measures of EU quits and layoffs.

TABLE B.3. Sequences of Reasons for U among E–U–U Individuals

<i>Sample period</i>	Pr(Quit  Layoff)	Pr(Layoff  Quit)
pre-Redesign	0.039	0.208
post-Redesign	0.007	0.026

*Note:* The first row shows the probability of individuals switching their reason for unemployment from layoff to quit (in the first column), or from quit to layoff (in the second column), prior to the 1994 CPS redesign. The second row shows the same, but for the period following the redesign.

TABLE B.4. Transition Rates Across E–U–U Individuals

	<i>From</i>	<i>To</i>		
		E	U	N
(a)	E – U(Quit) – U(Layoff)	0.339	0.553	0.108
(b)	E – U(Quit) – U(Quit)	0.343	0.536	0.121
(c)	E – U(Layoff) – U(Quit)	0.352	0.557	0.091
(d)	E – U(Layoff) – U(Layoff)	0.264	0.667	0.068

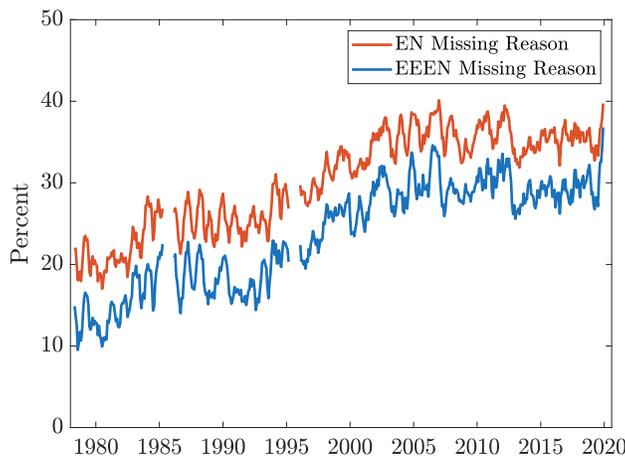
*Note:* Transition rates are shown for individuals that are in their second month of unemployment following an employment spell, split by reason for unemployment, as defined in Appendix B.1.1. The rates are computed for the period prior to the 1994 CPS redesign.

Table B.4 reports subsequent transition rates for workers having previously made an E–U–U transition during the period prior to the 1994 CPS redesign, with four separate rows for each sequence of reasons for unemployment across the two months, with rows as follows: (a) E–U(Quit)–U(Layoff), (b) E–U(Quit)–U(Quit), (c) E–U(Layoff)–U(Quit), and (d) E–U(Layoff)–U(Layoff).

In rows (a) and (b), we compare labor market transitions of workers who quit to unemployment and then report a layoff (i.e., E–U(Quit)–U(Layoff)) to those of workers who quit to unemployment and continue to report a quit (i.e., E–U(Quit)–U(Quit)). Table B.3 showed that around 20% of individuals who initially report having quit and remain in unemployment then report a layoff. However, the subsequent labor market transitions of workers reporting quit-layoff are very similar to those of individuals who continue report quit-quit, as seen by comparing rows (a) and (b). Indeed, using a chi-squared goodness-of-fit test, we cannot reject the null hypothesis that the two rows are the same, with a p-value of 0.72. Hence, for such individuals, we find that only the reason for unemployment reported in the first month is relevant for predicting future employment transitions, offering validation for our measure of EU quits.

In rows (c) and (d), we compare labor market transitions of workers who are laid-off to unemployment and then report a quit to those of workers who are laid-off to unemployment and continue to report a layoff. We find that transition patterns of E–U(Layoff)–U(Quit)

FIGURE B.1. Fraction of EN Transitions With Missing Reason



*Note:* The red line shows the proportion of individuals making an EN transition for which there is missing data on the reason for leaving the last job. The blue line shows the same calculation for individuals that were employed in each of the first three months before moving to nonparticipation. Series are smoothed using a centered 5-month moving average.

workers are notably different from those of E–U(Layoff)–U(Layoff) workers. However, even if such layoff-quit transitions represent measurement error, they are relatively uncommon: only around 4% of E–U–U workers who initially report being laid off then report having quit in the following month (as shown in Table B.3). Thus, this group accounts for a small enough proportion of total E–U layoffs as to be considered quantitatively insignificant.

**B.4. Robustness: EN Flows.** Recall, our measurement of quits and layoffs for EN transitions is based on a variable specific to respondents in outgoing rotation groups that codes the reason why the individual left their previous job. For approximately 30 percent of EN transitions that complete in the month of the outgoing rotation group, the value of this variable is missing. The red line in Figure B.1 shows the time-series for the fraction of transitions where the value of the variable is missing. The proportion of EN transitions where the variable is not assigned a value trended up from about 20 percent in the early 1980s to around a third by the early 2000s and has been relatively stable since. Here, we offer evidence that such patterns are not a concern for our measure of EN transitions.

Since 1994, nonparticipants are only asked their reason for leaving their last job if they report that this job occurred during the past 12 months.<sup>9</sup> For individuals that are coded as working in this required time period, there is no missing data on the reason for leaving their job. Thus, data appears to be missing because some fraction of workers recorded making transitions from employment in month  $t$  to nonparticipation in month  $t + 1$  are coded in month  $t + 1$  as not having worked in the past year. While this could reflect spurious EN transitions—where employment status was mismeasured in month  $t$ , and the individuals

<sup>9</sup>For the pre-1994 period it is asked if they report working in the past 5 years.

truly never were employed in the past 12 months—we describe below that it is far more plausible that potentially spurious EN transitions could only reflect a small minority of the missing data; and instead, that workers are erroneously recorded as not having worked in the prior year.

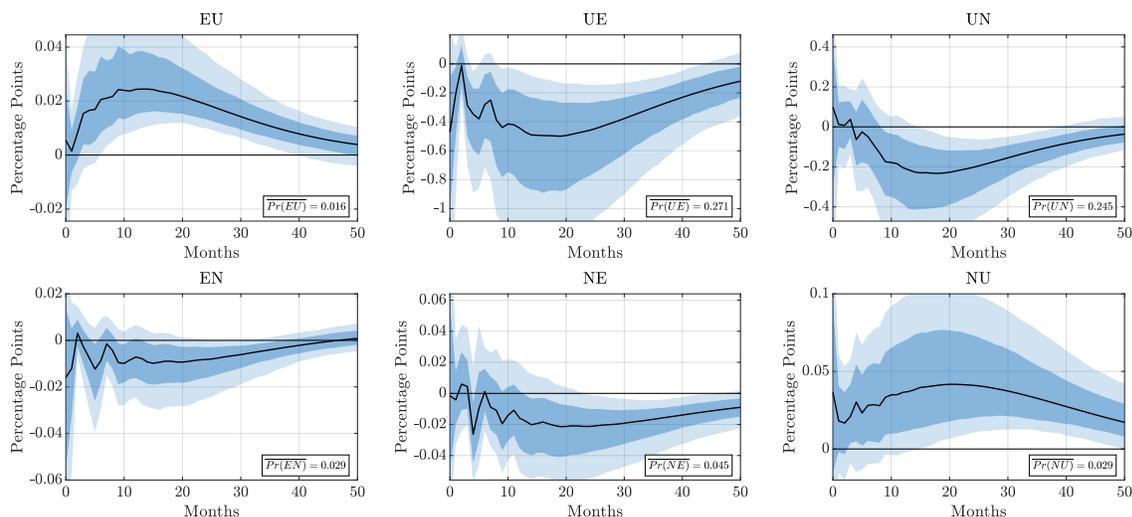
First, we find that the share of EN transitions with missing data on reason for leaving a job does not change significantly across subgroups of workers where one might expect meaningful variation in the fraction of workers who are coded as having not worked in the requisite prior time period (e.g., individuals that are not self-employed, that respond to the survey themselves, and that have worked full-time). Moreover, although workers are asked their reason for leaving their previous job within the last five years (instead of one year) prior to 1994, there is no discernible discontinuity in the fraction of workers with an EN transition who are missing a reason for leaving their previous job. If the discrepancy were due to mismeasurement of employment status in month  $t$ , one would expect a discontinuous jump in the fraction of workers with missing data after the change from a five-year window to a one-year window (given that fewer workers from non-employment could report not having worked in the previous five years versus the previous one year).

Then, we compare the incidence of missing data for all EN transitions to the subset of individuals who report three months of employment prior to their transition to nonparticipation (i.e., EEEN workers). The latter is plotted in the blue line in Figure B.1. EEEN workers are presumably more likely to have truly been employed before their transition to nonparticipation (as otherwise, they would have had three months of incorrectly recorded employment statuses). While the incidence of missing data is slightly smaller for these individuals, still around 25% of observations are missing. We interpret this as further evidence that the missing data are unlikely to be due to misreported EN transitions.

Finally, we develop further evidence that a missing value for this variable does not reflect erroneously reported transitions by examining the subsample of individuals included in the Job Tenure Supplement in the month before they moved to nonparticipation. If we restrict the sample to such individuals who report having worked at their current job for at least one year when answering the Job Tenure Supplement, we still find that, one month later, around 30% of such individuals are classified as having not worked in the past 12 months.

Thus, while it is possible that some individuals are misclassified as employed in the month before they are interviewed as nonparticipants, the evidence indicates it to be more plausible that the dominant source of measurement error stems from workers being incorrectly coded as not having worked in the previous 12 months after 1994 (and previous five years prior to 1994). Moreover, we find no evidence that the miscoding of this variable varies systematically with observable characteristics, including those that might be important in decomposing EN transitions into quits and layoffs.

FIGURE C.1. Response of Time-Aggregation Corrected Labor Market Flows



*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given labor market flow variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals.

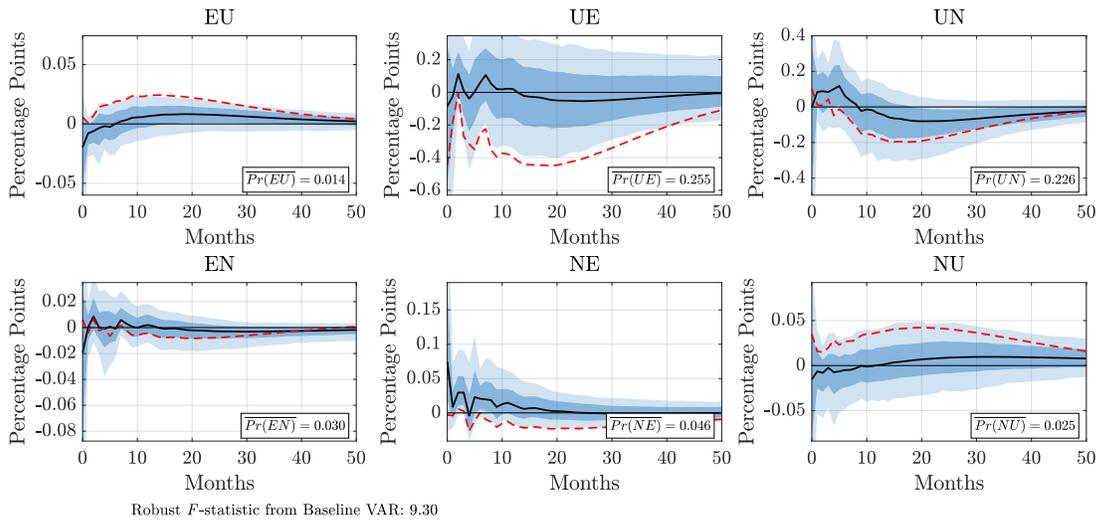
## APPENDIX C. ADDITIONAL VAR RESULTS

**C.1. Time-Aggregation.** Figure C.1 shows the impulse response for the labor market flows corrected for time aggregation, as in Shimer (2012) and Elsby et al. (2015). There are no notable differences between the impulse responses shown in Figures 2 and C.1.

**C.2. Alternative Measures of HFI Monetary Surprises.** In this section, we show the importance that the monetary policy shocks that we use in our primary specifications (a) include Fed Chair speeches and (b) are orthogonalized with respect to recent macroeconomic news.

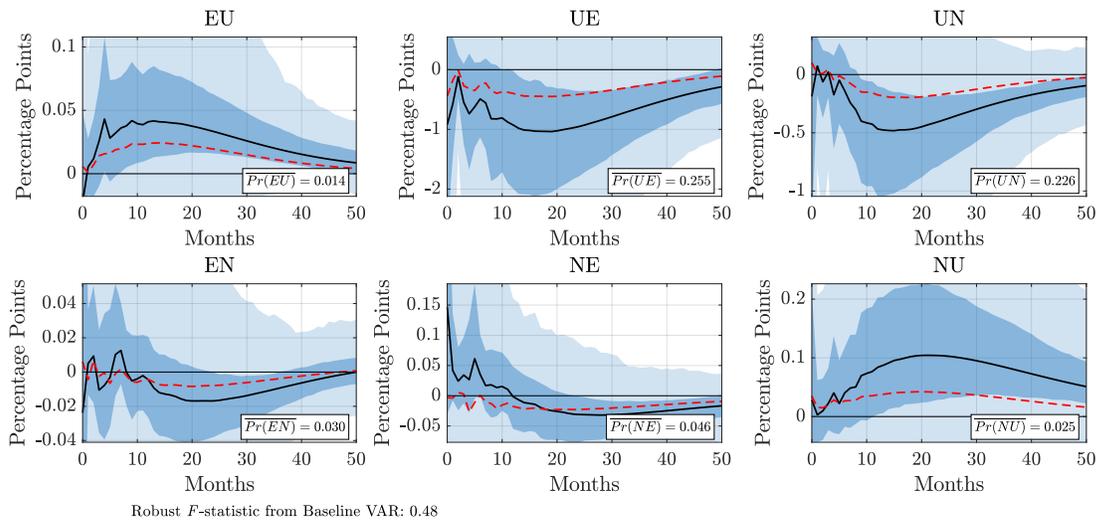
Figure C.2 shows the response of flows if we use high-frequency shocks that are only from FOMC announcement and are not orthogonalized. The results are much attenuated relative to those in Figure 2. This is consistent with the results in Bauer and Swanson (2023): the fact that unadjusted high frequency shocks are correlated with positive macroeconomic news biases the estimated effects of a monetary tightening towards zero. Figure C.3 shows the response of flows if we use this same sample of shocks but orthogonalize with respect to recent macroeconomic news. The attenuation bias is removed from the estimates, but the standard errors increase significantly. There is clear evidence of a weak-instrument problem, with a first-stage F-statistic that is less than 1.

FIGURE C.2. Labor Market Flows: Non-Orthogonalized Shocks, No Chair Speeches



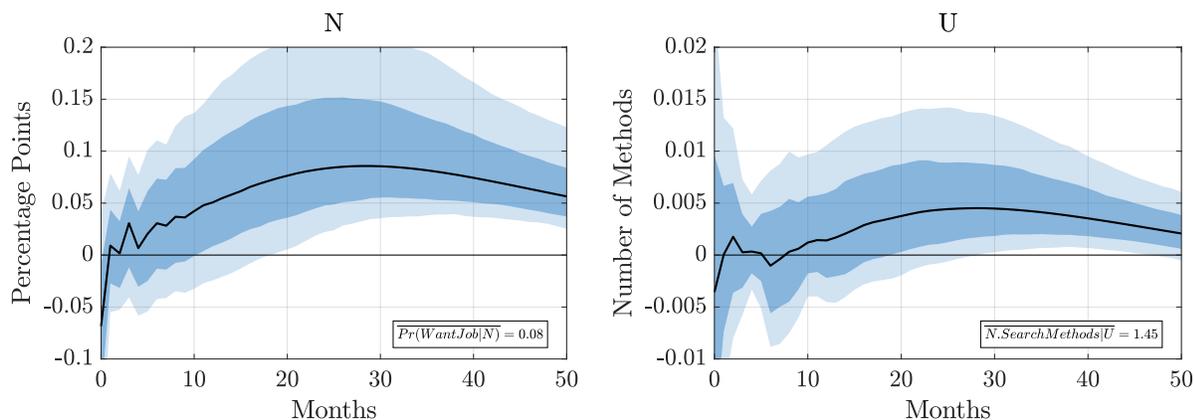
*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1, using only FOMC announcements for our monetary policy shocks, without orthogonalizing as in Bauer and Swanson (2023). Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Red dashed lines report the results from Figure 2. Robust F-statistic reported for baseline VAR using non-orthogonalized shocks w/o Chair speeches.

FIGURE C.3. Labor Market Flows: Orthogonalized Shocks, No Chair Speeches



*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1, using only FOMC announcements for our monetary policy shocks, orthogonalized as in Bauer and Swanson (2023). Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Red dashed lines report the results from Figure 2. Robust F-statistic reported for baseline VAR using orthogonalized shocks without Chair speeches.

FIGURE C.4. Response of Intensive Margins of Job Search



*Note:* Our measurement of the fraction of nonparticipants that want a job and the number of search methods used by unemployed individuals is described in Section A. Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Inset boxes report average values.

### C.3. Impulse Responses of Other Variables.

C.3.1. *Responses of Intensive Margins of Job Search.* For additional evidence on the response of labor supply to a monetary policy shock, we examine the response of the intensive margins of job search for the non-employed. Such responses reflect an increased desire to work and may influence the rate at which workers move to employment.

We first look at the fraction of nonparticipants who report wanting a job despite not being engaged in active search. As shown in Table B.2, such workers are almost four times more likely to move to employment in the following month than nonparticipants who do not want a job, indicating that the stated preference of “wanting a job” is an informative indicator that a worker will accept a job offer (and perhaps is more likely to receive one). Thus, this is an important “intensive margin” of job search. The left panel of Figure C.4 shows the response of this fraction to a contractionary monetary policy shock. There is a robust and persistent increase in the desire to work among workers in nonparticipation. Hence, the movement of workers from nonparticipation to unemployment in response to a monetary policy surprise may be considered part of a broader labor supply response within non-employment.

Next, we look at the number of job search methods used by workers in unemployment. This metric has been adopted elsewhere in the literature and has been shown to be highly correlated with time spent looking for a job, e.g., Mukoyama, Patterson and Şahin (2018). Moreover, unemployed workers who use two or more search methods are around 15% more likely to transition to employment than those that only use one search method. The right

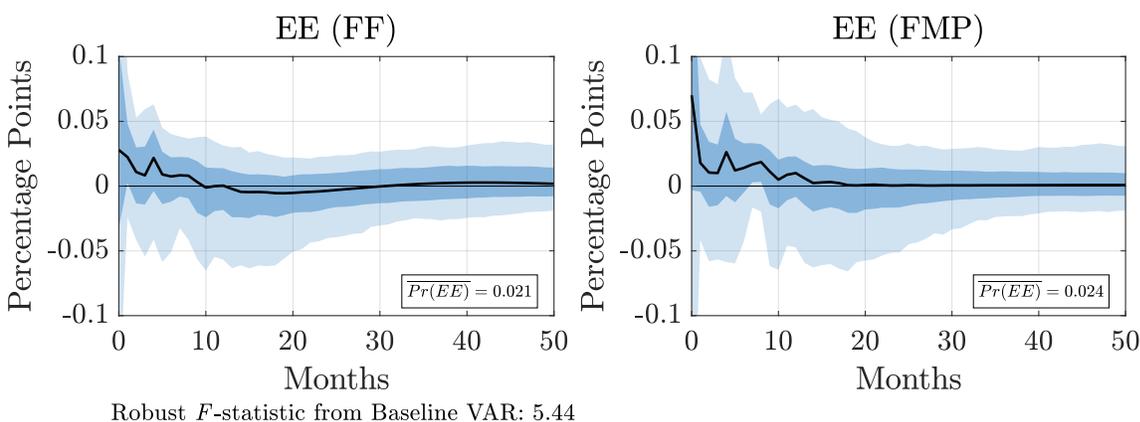
panel of Figure C.4 shows the response of the number of search methods for unemployed workers. After a contractionary monetary policy surprise, the average number of search methods used by unemployed workers gradually increases, peaking at around 24 months.

These findings show that, even within distinct labor market states, workers exhibit behavioral responses to a contractionary monetary policy surprise consistent with an increase in labor supply.

*C.3.2. Job-to-Job Transitions.* Beginning with Faberman and Justiniano (2015), an empirical literature has documented a high unconditional correlation between quits and wage growth. While Faberman and Justiniano interpret quits to be job-to-job transitions, subsequent papers directly measure job-to-job transitions and document a robust unconditional correlation between job-to-job transitions with various measures of wage growth, e.g., Moscarini and Postel-Vinay (2016) and Karahan et al. (2017).

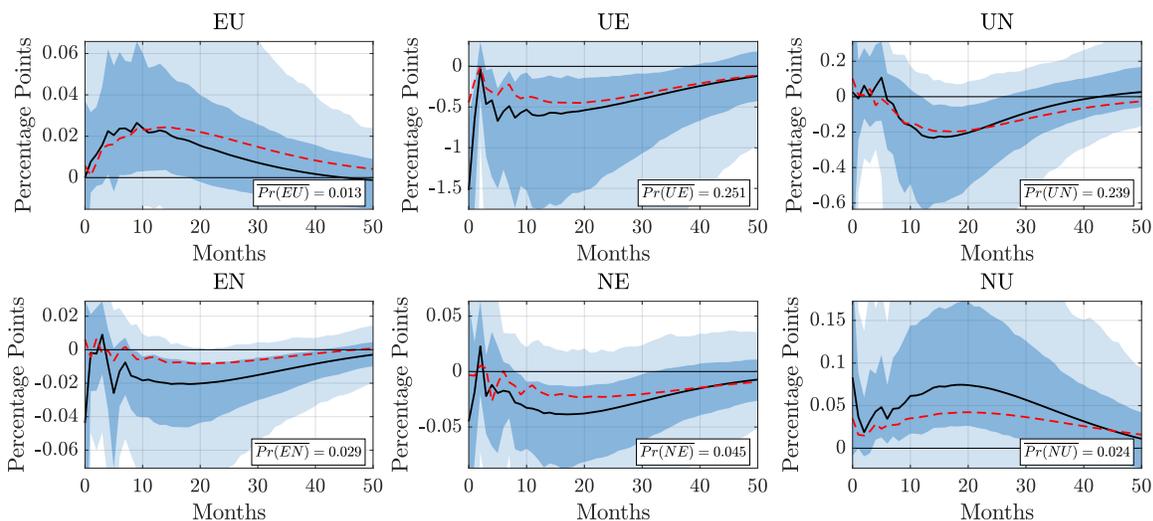
Motivated by this, a recent literature has developed New Keynesian models with on-the-job search, e.g., Birinci et al. (2022), Moscarini and Postel-Vinay (2023), and Faccini and Melosi (2023). Such models consider an “offer-matching” theory of inflation, whereby competition between firms over workers bids up wages and increases marginal costs. This implies the rate of job-to-job changes to be an important measure of labor market slack: a contractionary monetary policy shock may decrease inflation in part by reducing the rate of job-to-job transitions, and thus the rate at which workers meet potential employers.

FIGURE C.5. Response of Job-to-Job Transitions



*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given labor market flow variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. The left panel uses the job-to-job transition rate of Fallick and Fleischman (2004) while the right panel uses that of Fujita et al. (2020). Inset boxes report average transition rates. Robust F-statistic reported for baseline VAR, estimated since 1995 when the job-to-job change series first becomes available.

FIGURE C.6. Response of Labor Market Flows: 1995-2019 Sample

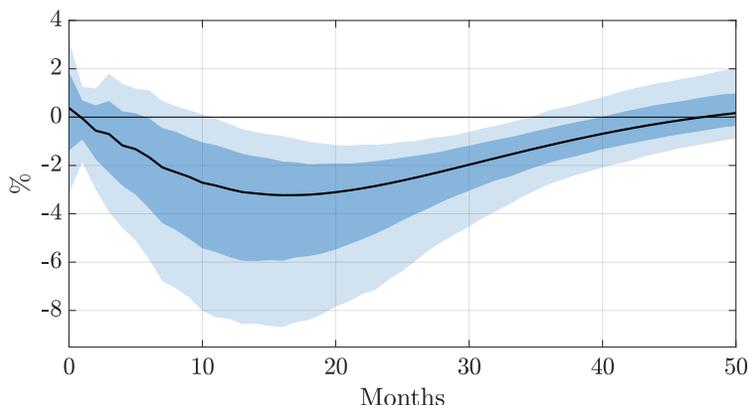


*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given labor market flow variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Dashed red lines report impulse responses for the full sample, as in Figure 2. Inset boxes report average transition rates. Robust  $F$ -statistic reported for baseline VAR, estimated since 1995 when the job-to-job change series first becomes available.

To consider this channel, we estimate the IRF for the rate of job-to-job transitions in response to a contractionary monetary policy surprise. We consider two measures of job-to-job transitions: one due to Fallick and Fleischman (2004), and another due to Fujita, Moscarini and Postel-Vinay (2020). The estimated IRFs are plotted in Figure C.5. Note, both measures are only available since 1995. Neither measure of job-to-job transitions shows any significant response to a contractionary monetary policy shock. In Figure C.6 we show that this is not true for the other labor market flows when estimated over the same sample.

Taken at face value, the estimated IRFs might appear inconsistent with the offer-matching theory of inflation, as we cannot reject a null response of job-to-job transitions to a contractionary monetary policy shock. We speculate that the flat IRFs of job-to-job transitions might in part reflect a problem of measurement: neither the Fallick and Fleischman (2004) nor the Fujita, Moscarini and Postel-Vinay (2020) measures of job-to-job transitions condition on whether or not workers making job-to-job transitions are moving to better-paying jobs. Tjaden and Wellschmied (2014) document that a considerable portion of workers making job-to-job transitions move to lower-paying jobs, perhaps to avoid an involuntary layoff to unemployment. Gertler, Huckfeldt and Trigari (2020) document that the fraction of workers making job-to-job transitions associated with an improvement in wages is highly procyclical.

FIGURE C.7. Response of Vacancies



*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the log of the number of vacancies to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. We measure vacancies using the extended help-wanted index of Barnichon (2010).

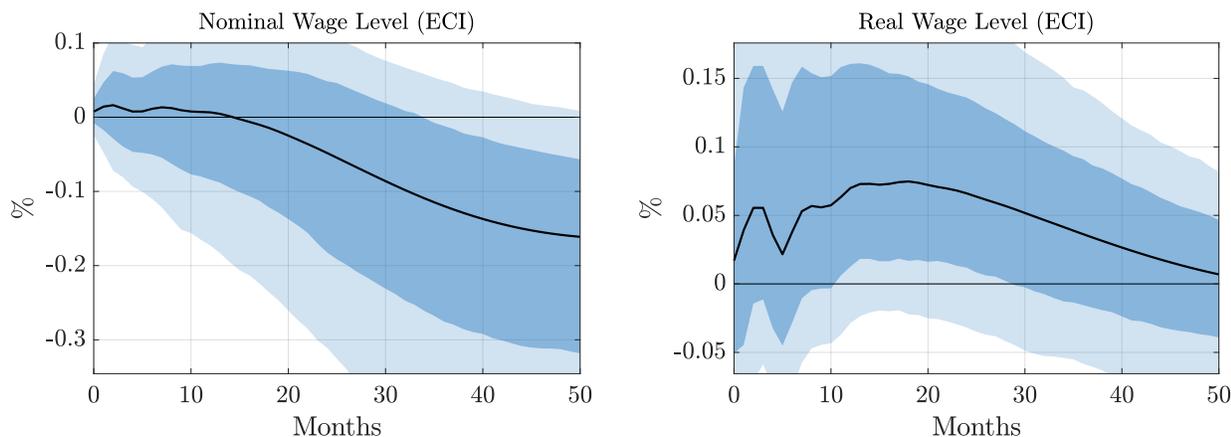
Thus, it is possible that a series measuring job-to-job changes to higher-paying jobs might offer a more robust series by which to assess the offer-matching theory of inflation.

C.3.3. *Vacancies.* Figure C.7 shows the IRF of vacancies  $v$  in response to a contractionary monetary policy surprise. Vacancies show a gradual decline, reaching a trough at around 15 months. To the extent that the process by which workers and vacancies match to create jobs can be understood through a matching function, a decline in vacancies leads to a decline in the probability that a worker finds a job from unemployment. Hence, the decline in vacancies shown here is useful for understanding the simultaneous drop in UE and NE rates.

C.3.4. *Wages.* Here we estimate the response of wage growth to monetary policy shocks. Figure C.8 plots the response of the Employment Cost Index (ECI) produced by the BLS, in both nominal and real terms, where the latter is deflated using the CPI.

We find that nominal wages do not respond to a contractionary monetary policy shock for the first 15 months, after which they begin to decline. As this response is slower than that of the consumer price index, shown in Figure 1, we find that real wages rise very modestly in the first few years following the shock, before declining back to their steady-state after around four years.

FIGURE C.8. Responses of Nominal and Real Wages



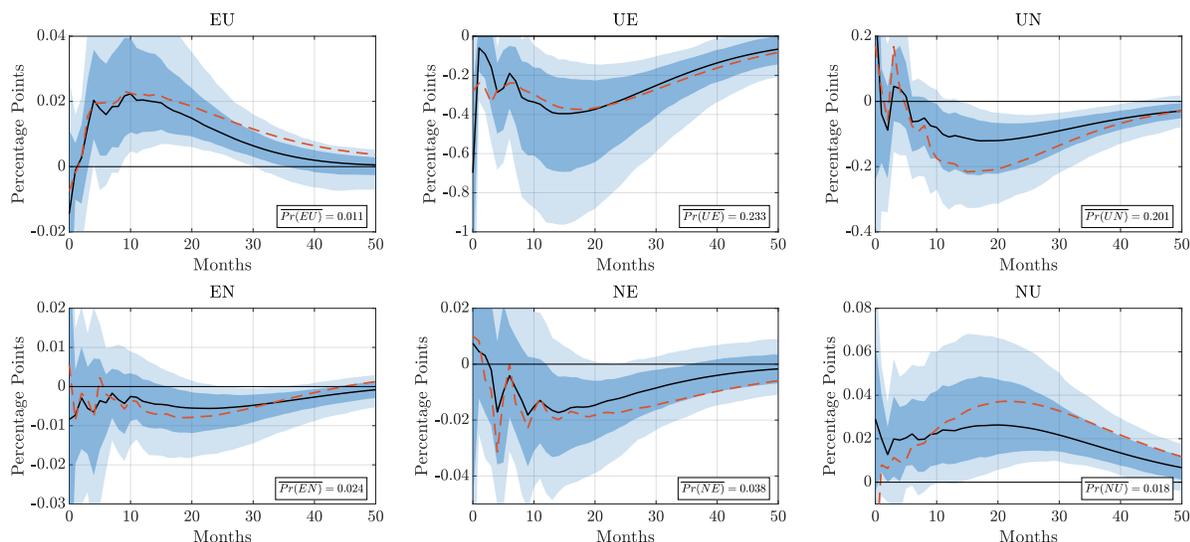
*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Real wages are calculated by deflating the ECI using the CPI.

**C.4. Composition.** In this section, we discuss further results when using compositionally-adjusted labor market flows. First, we show the response when using flows that are compositionally-adjusted using the full set of controls considered in Elsby, Hobijn and Şahin (2015). That is, in addition to grouping individuals by combinations of age, gender, educational attainment and (if unemployed) by their reason for unemployment, we now also include their labor market status one year prior.

We relegate the results using this full set of controls to the Appendix as it is more difficult to compare results using this sample to the baseline results. This is because conditioning on employment status one year prior automatically restricts our attention to individuals in the fifth to eighth CPS interviews. These individuals are not representative of the overall CPS sample, as highlighted by Ahn and Hamilton (2022) among others.

Figure C.9 shows the response of compositionally-adjusted flows using the full set of controls in Elsby, Hobijn and Şahin (2015). Qualitatively, the responses look similar to those in Figure 5: the largest effect of composition-adjustment is to dampen the response of the UN rate by around half. However, the quantitative similarity is hard to gauge, given the different samples. One way to see this is in the unconditional transition probabilities. For example, employed individuals in the Figure C.9 sample are less likely to transition to either unemployment or nonparticipation than those in the full sample (seen by comparing inset boxes across Figures 2 and C.9).

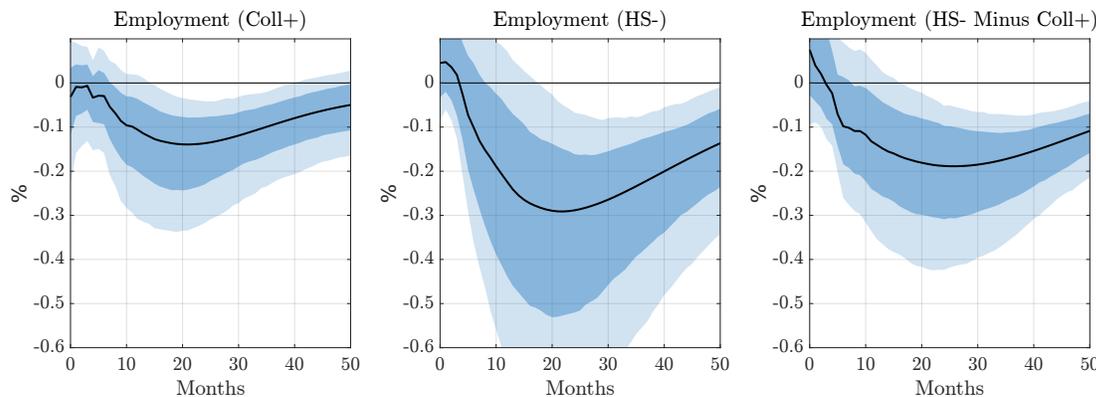
FIGURE C.9. Response of Composition-Adjusted Flows: Full EHS Controls



*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given labor market flow variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions for composition-adjusted flows, while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals for composition-adjusted flows. Dashed red lines report impulse responses for unadjusted flows with the same sample of individuals.

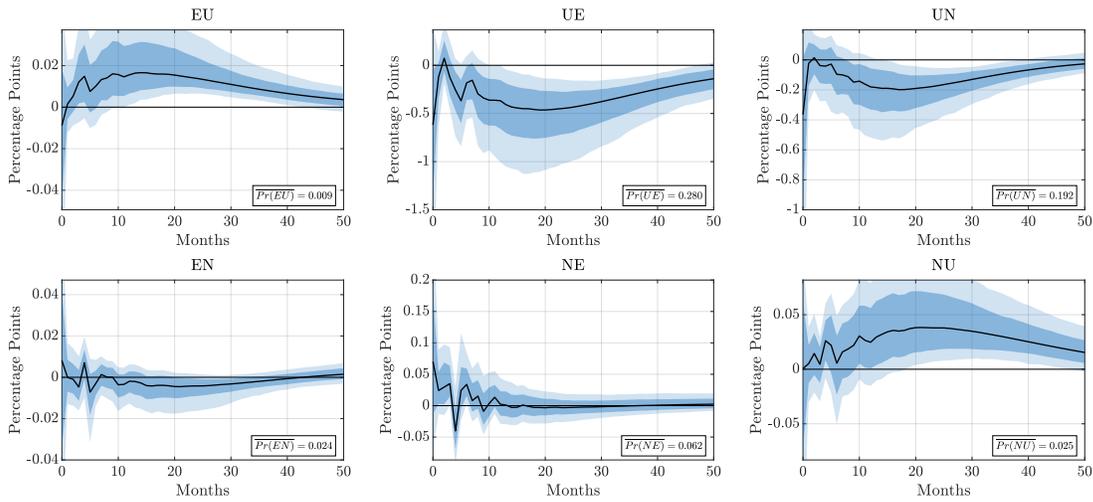
C.5. **Heterogeneity.** Here, we show additional results from Section 4.2. In Figure C.10, we again show the impulse response of employment for higher- and lower-educated workers, but we also show that the greater percentage decline in employment for lower-educated workers is significantly significant. Figures C.11 and C.12 show the full set of impulse responses of labor market flows for higher- and lower-educated workers.

FIGURE C.10. Response of Employment by Education Level



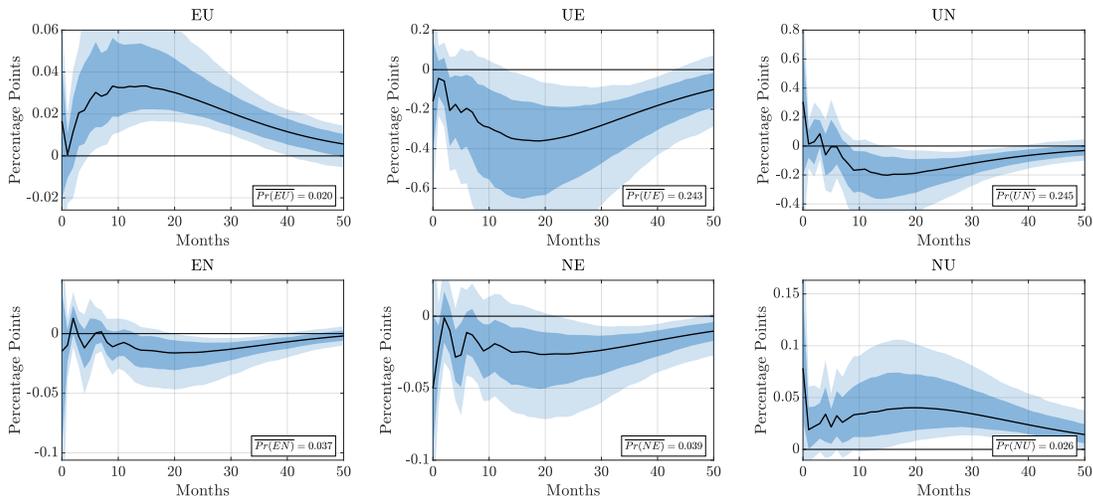
*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals.

FIGURE C.11. Labor Market Flows: Higher-Educated



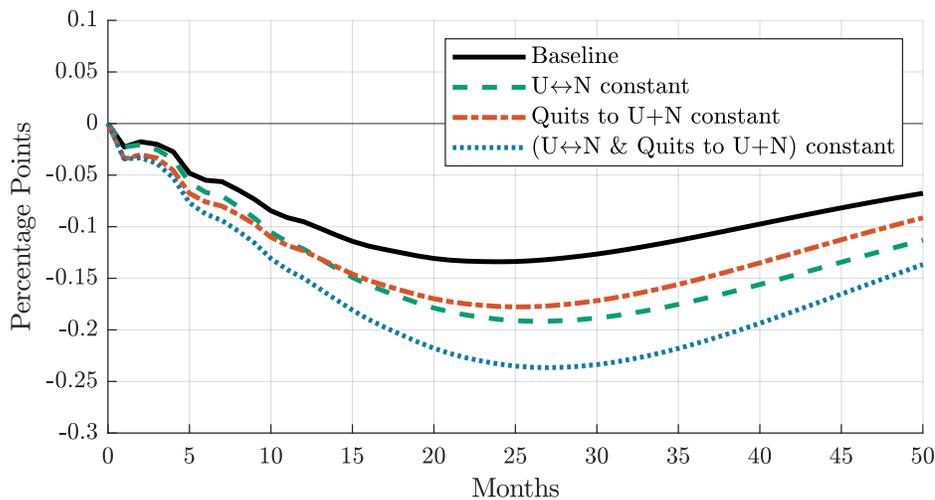
*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Inset boxes report average transition rates.

FIGURE C.12. Labor Market Flows: Lower-Educated



*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Inset boxes report average transition rates.

FIGURE C.13. Flow-Based Accounting for Employment: Fixed Composition



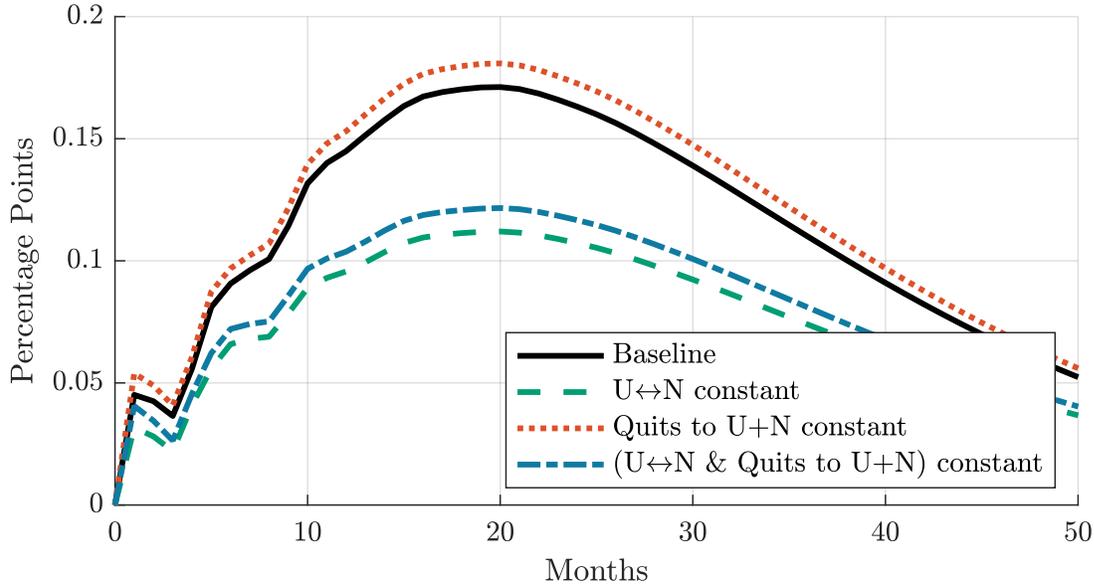
*Note:* The black solid line shows the overall response of the employment-population ratio to a contractionary monetary policy shock. The green dashed line shows the response if both UN and NU rates are held constant. The red dot-dashed line shows the response if quits to U or N are held constant. The blue dotted line shows the response if all supply-driven flows are held constant.

**C.6. Additional Results from Flow-Based Accounting.** Here, we show that our results on the importance of supply-driven labor market flows are robust to compositional adjustment. We also apply the accounting procedure of Section 5 to unemployment and labor force participation.

*C.6.1. Composition.* Figure C.13 repeats our flow-based accounting exercise for the response of employment for our baseline compositional adjustment. This shows that, when using our baseline compositional adjustment, the results are similar to those in Figure 7: we find that, when supply-driven flows are held fixed, employment declines by around 80 percent more than when all flows respond.

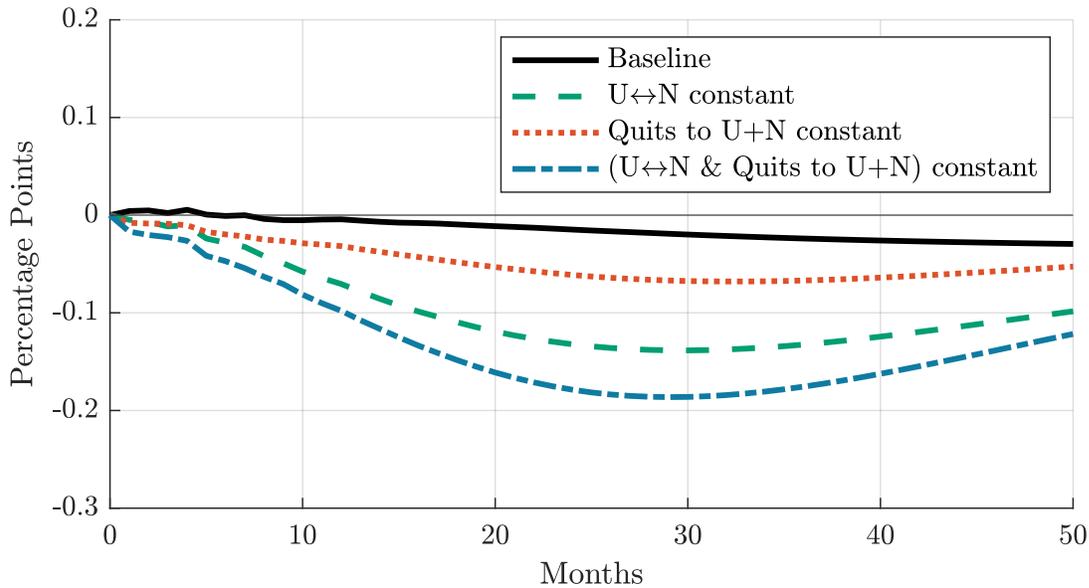
*C.6.2. Unemployment and Participation.* Here, we show the results of applying the accounting methodology discussed in Section 5 to unemployment and participation. We see two broad takeaways: first, quits are more important for shaping the response of employment than of unemployment or participation. Second, flows between U and N are more important for shaping the response of employment and participation than for unemployment.

FIGURE C.14. Flow-Based Accounting for Unemployment



*Note:* The black solid line shows the overall response of the unemployment rate to a contractionary monetary policy shock. The green dashed line shows the response if both UN and NU rates are held constant. The red dot-dashed line shows the response if quits to U or N are held constant. The blue dotted line shows the response if all supply-driven flows are held constant.

FIGURE C.15. Flow-Based Accounting for Participation

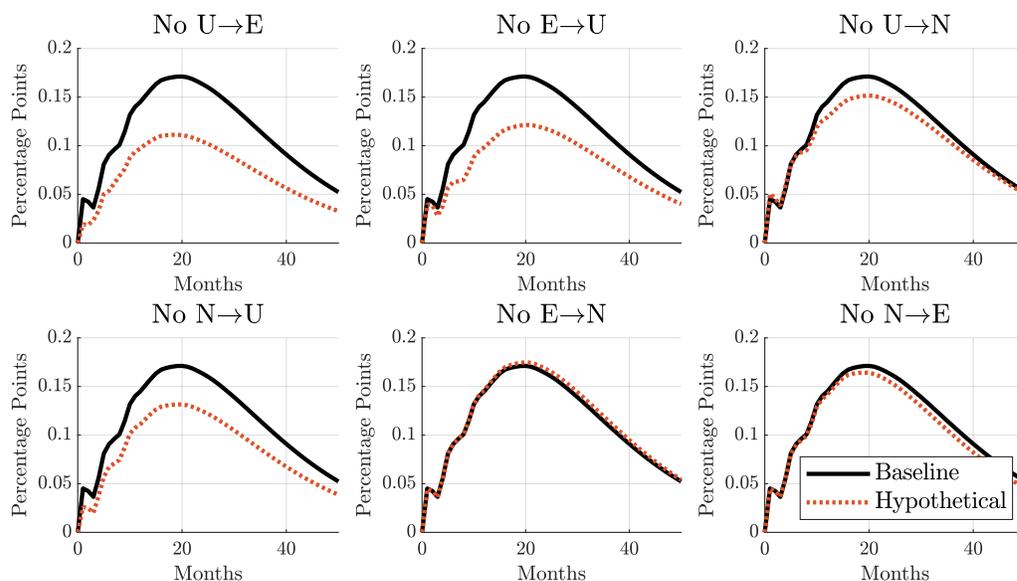


*Note:* The black solid line shows the overall response of the participation rate to a contractionary monetary policy shock. The green dashed line shows the response if both UN and NU rates are held constant. The red dot-dashed line shows the response if quits to U or N are held constant. The blue dotted line shows the response if all supply-driven flows are held constant.

**C.7. The Ins and Outs of Unemployment, Employment and Participation.** The impulse responses reported in Figure 2 show statistically significant responses for all flows. In order to provide evidence on the importance of the response of each flow for determining the response of labor market stocks, here we apply the methodology for constructing hypothetical responses of stocks discussed in Section 5 on a “flow-by-flow” basis.

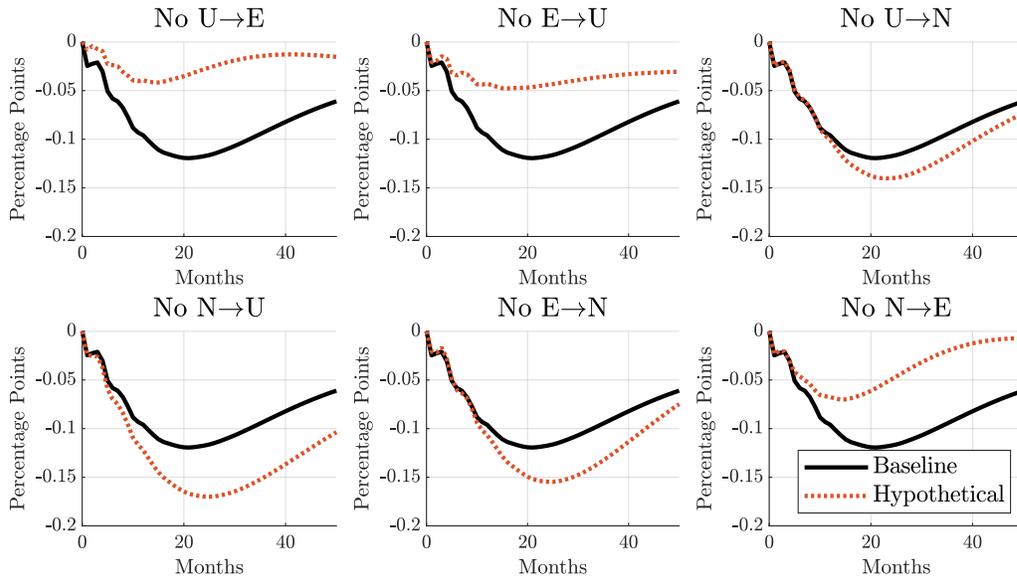
The hypothetical impulse response functions for the unemployment rate are plotted in Figure C.16. The solid black lines show the IRF for the unemployment rate estimated from our baseline VAR, while the dotted red line in each panel shows the hypothetical IRFs generated when we “turn off” the response of a given transition probability. The greater the distance between the counterfactual and baseline IRF, the more important is that transition probability for generating the total response of unemployment. The subplots of Figure C.16 show that the counterfactual IRFs holding the EU and UE rates constant reach roughly similar levels of peak unemployment: the IRF with constant UE flows reaches 65% of the baseline, while the IRF with constant EU flows reaches 70%. The roughly equal contributions of UE and EU flows in shaping the response of unemployment from a monetary contraction contrasts with similar exercises looking at unconditional variation in unemployment: for example, Shimer (2012) concludes that UE flows account for three quarters of the unconditional variation in unemployment rates. We repeat this exercise for employment and the labor force participation rate in Figures C.17 and C.18.

FIGURE C.16. The Ins and Outs of Unemployment



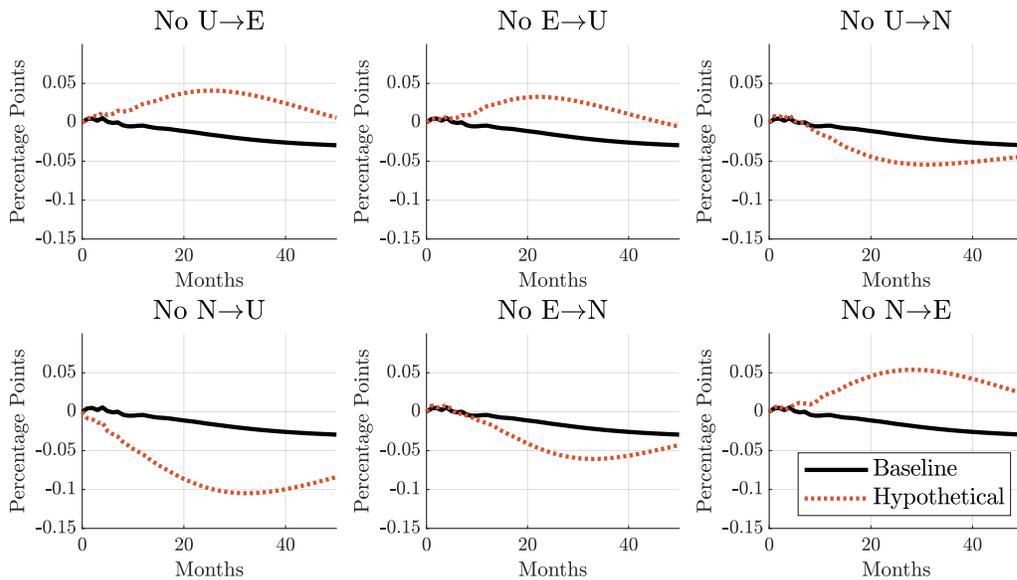
*Note:* The black solid line shows the overall response of the unemployment rate to a contractionary monetary policy shock. The red dotted lines show the response if the specified flow rate is held constant at its average level.

FIGURE C.17. The Ins and Outs of Employment



*Note:* The black solid line shows the response of the employment-population ratio to a contractionary monetary policy shock. The red dotted lines show the response if the specified flow rate is held constant at its average level.

FIGURE C.18. The Ins and Outs of Participation



*Note:* The black solid line shows the response of the participation rate to a contractionary monetary policy shock. The red dotted lines show the response if the specified flow rate is held constant at its average level.

## APPENDIX D. MODEL APPENDIX

D.1. **Timing.** The timing of the model within each period is summarized as follows:

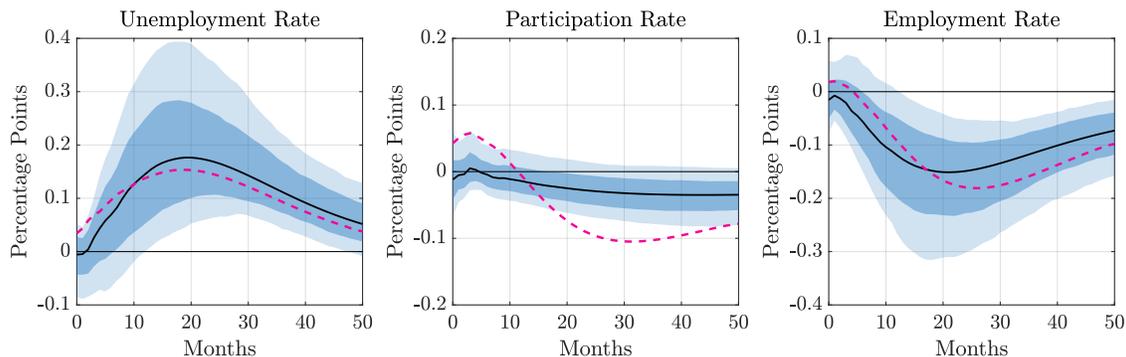
- (1) All individuals draw a new value of productivity,  $z$ . Non-employed individuals draw an i.i.d. search cost,  $\kappa$ .
- (2) Employed individuals make consumption/saving decisions and choose whether or not to quit their job. Non-employed individuals make consumption/saving decisions and choose whether or not to search for a job.
- (3) Employed individuals who do not quit are exogenously laid off with probability  $\delta$ . Non-employed individuals receive job offers with probabilities  $f_s$  or  $f_{ns}$ , depending on whether or not they actively search.
- (4) Non-employed individuals who receive job offers decide whether or not to accept such offers.
- (5) UI-eligible non-employed individuals who search and either do not receive a job offer or do not accept an offer are subject to UI expiry with probability  $\delta_{UI}$ .

D.2. **Additional Computational Details.** Our solution method is as follows:

- We discretize the productivity process using the method of Rouwenhorst (1995) using 25 gridpoints. We discretize the asset grid using 200 gridpoints.
- We solve the consumption/saving problem at each gridpoint using golden-section search, linearly interpolating value functions where required.
- Given the distribution of the search cost, we can calculate the probability that an individual at a given  $(a, z)$  point will search.
- With the policy functions in hand, we simulate the model on the same discrete grid using non-stochastic simulation as in Young (2010) and iterate to the stationary distribution.
- When solving for the response to an aggregate shock, we apply standard methods for dealing with an unexpected “MIT” shock, although we do not impose any market-clearing conditions:
  - Thus we assume that the economy will have returned to steady-state at some  $T$ . We then solve for value and policy functions from  $T - 1$  to  $t$ , using the paths of aggregate variables.
  - Given these policy functions, we then simulate the distribution of agents forward from the original stationary distribution.

In order to generate smooth responses of labor market transition rates, while simulating the model on a discrete grid, we introduce very small “taste shocks” which perturb the quit and job acceptance decisions that agents face.

FIGURE D.1. Response of Labor Market Stocks: Model and Data



*Note:* Estimated impulse responses to a 25bp monetary policy tightening shock. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. The unemployment and participation rate responses are those shown in Figure 1. The employment rate response is from an equivalent VAR where the participation rate is replaced by the employment rate. Dashed magenta lines are the labor market stocks from the estimated model.

In particular, each period employed agents make their quit decision after drawing a taste shock,  $\epsilon_Q$  from a logistic distribution. They then make their quit decision taking into account this taste shifter in their binary choice:

$$V_E(a, z, \epsilon_Q) = \max_{c, a'} \left\{ u(c) + \beta \max \left\{ \mathbb{E} V_N(a', z', \kappa') + \epsilon_Q, \mathbb{E} \left[ \delta_L V_U(a', z', \kappa') + (1 - \delta_L) V_E(a', z') \right] \right\} \right\} \quad (\text{D.1})$$

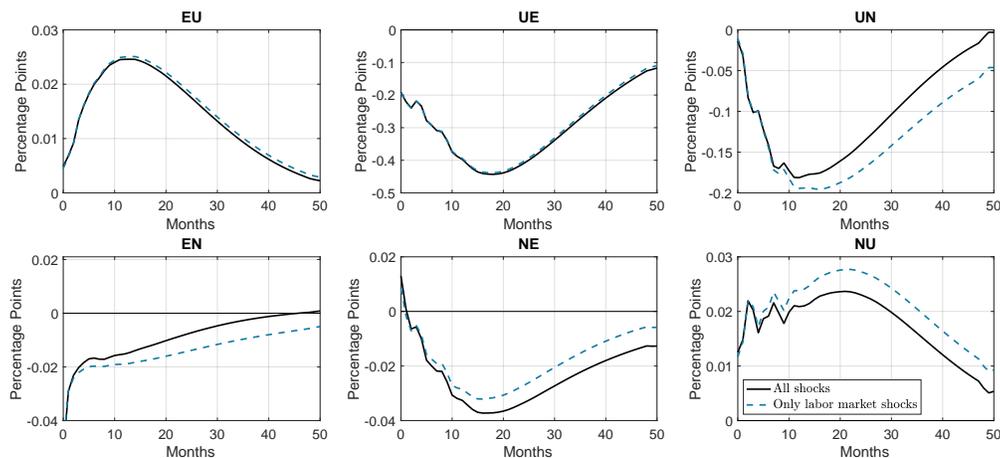
The scale of these shocks is calibrated to be as small as possible. We assume that these taste shocks are drawn from a logistic distribution with mean 0 and scale 0.005. (This scale parameter is nearly two orders of magnitude smaller than that which we estimate for the stochastic search cost,  $\kappa$ .) The economic significance of these shocks is very small: In the stationary distribution of our model, only 1.4% of employed individuals have a quit probability (before the realization of their quit taste shock) that is between 0.01% and 99.99%. We introduce taste shocks of the same size when non-employed workers have a decision on whether to accept a job.

### D.3. Model Dynamics: Additional Results.

D.3.1. *The Response of Labor Market Stocks.* A byproduct of the close fit for the model’s transition rates is that the response of the labor market stocks in the model is also close to that estimated in the data, as shown in Figure D.1. This close fit allows us to construct counterfactuals using the model in Section 6.6, to understand how shifts in labor supply shape the response of labor market aggregates.

D.3.2. *Understanding the Role of Job-Finding and Layoff Rates.* In the main paper, we study the model implications for the labor supply response to a monetary policy shock by feeding

FIGURE D.2. Response of Labor Market Flows: Only Labor Market Shocks

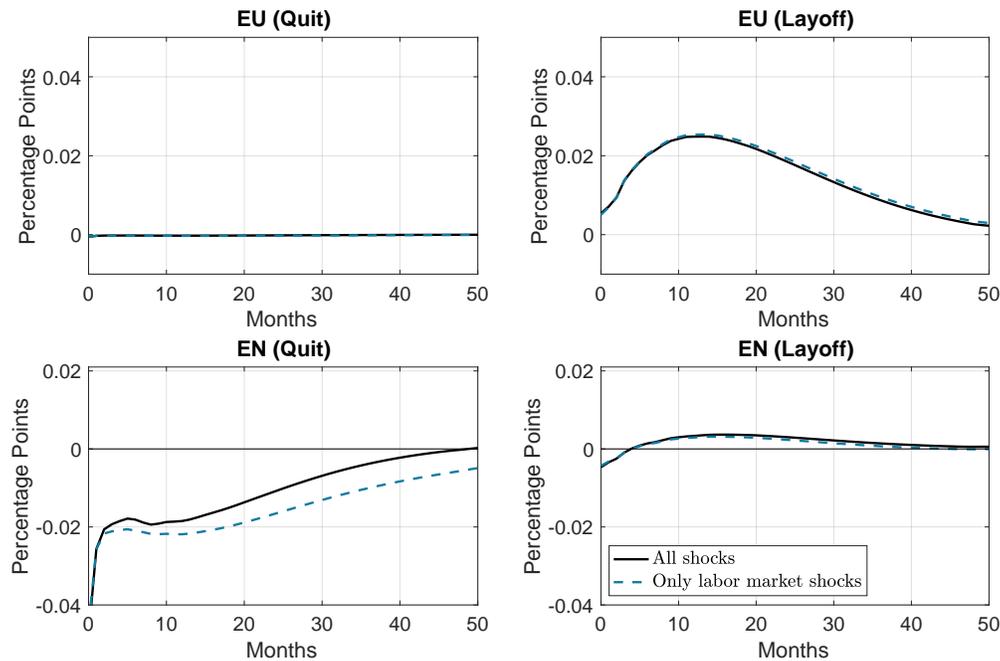


*Note:* The black solid line shows the response of each flow feeding in the responses of job-finding and layoff rates, real interest rates, and real wages following a contractionary monetary policy shock in the estimated model. The blue dotted line shows the responses of each flow feeding in only the responses of job-finding rates and layoffs.

in the estimated responses of job-finding rates, layoffs, real interest rates, and real wages into the model, as described in Section 6.5 (and shown in Figures 9 and 10). Here, we consider the response of labor market flows when we only feed in the response of job-finding rates layoffs, holding real interest rates and real wages fixed at their steady state values.

Figure D.2 shows the response of labor market flows when we only feed in the responses of job-finding and layoff rates to a contractionary monetary policy shock compared to the baseline (from Figure 9). As can be seen, UN, NU, and EN flows show are slightly more responsive under the restricted set of shocks; whereas the response of NE is slightly attenuated. Figure D.3 shows that the greater response of EN flows comes from a more persistent decline in quits. Nonetheless, the response of labor market flows to layoffs and job-finding is largely similar to the response of labor market flows under the baseline, indicating that the labor supply response to a contractionary monetary policy shock is driven by the increase in layoffs and decline in job-finding.

FIGURE D.3. Decomposition of EU and EN responses: Only Labor Market Shocks



*Note:* The black solid line shows the response of each flow feeding in the responses of job-finding and layoff rates, real interest rates, and real wages following a contractionary monetary policy shock in the estimated model. The blue dotted line shows the responses of each flow feeding in only the responses of job-finding rates and layoffs.

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