THE LABOR DEMAND AND LABOR SUPPLY CHANNELS OF MONETARY POLICY

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Abstract. Monetary policy is conventionally understood to influence labor demand, with little effect on labor supply. We estimate the response of labor market flows to high-frequency changes in interest rates around FOMC announcements and Fed Chair speeches and find evidence that, in contrast to the consensus view, a contractionary monetary policy shock leads to a significant increase in labor supply: workers reduce the rate at which they quit jobs to non-employment, and non-employed individuals increase their job-seeking behavior. These effects are quantitatively important: holding supply-driven labor market flows constant, the decline in employment from a contractionary monetary policy shock would be twice as large. To interpret our findings, we estimate a heterogeneous agent model with frictional labor markets and an active labor supply margin. The model rationalizes existing estimates of small labor supply responses to idiosyncratic transfers with our new evidence of a large labor supply response to an aggregate shock.

1. Introduction

> "*Policies to support labor supply are not the domain of the Fed: Our tools work principally on demand.*" –Federal Reserve Chairman Jerome Powell, November 30, 2022

Monetary policy is traditionally viewed as affecting labor demand and having little effect on labor supply, as reflected in the quote by Fed Chair Powell, above. This conventional wisdom is also embodied in the original Keynesian IS-LM framework, as discussed by Galí (2013); in statements by other monetary policymakers around the world; and in the New Keynesian (NK) literature, where the standard assumption of sticky wages in a neoclassical

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labor market precludes any significant quantitative role for labor supply considerations to affect the response of employment to a monetary policy shock.[1]

In contrast to the consensus view, we offer new empirical evidence consistent with a substantial labor supply response to monetary policy. We begin by identifying labor market flows (and components of flows) that are plausibly driven by labor supply considerations. While the response of all labor market flows can be thought of as being determined in general equilibrium, certain labor market flows are more directly reflective of labor supply insofar as they are initiated by the worker. Thus, we classify flows from unemployment (U) to nonparticipation (N) and vice versa as supply-driven, given that such flows occur when an individual decides to stop or start searching actively for work. Similarly, we classify quits to non-employment as supply-driven, given that these separations are initiated by the worker. One contribution of our paper is to provide a new decomposition of flows between employment (E) and nonparticipation (N) into quits and layoffs, which shows that a large and procyclical component of flows from E to N is due to quits.

We then estimate the response of labor market flows to exogenous changes in monetary policy. There are three main reasons to look at the conditional response of labor market flows to an exogenous demand shock (like a monetary policy shock) as opposed to their unconditional behavior. First, knowing how labor market flows respond to a monetary policy shock improves our understanding of how monetary policy affects the economy. Second, the conditional response of labor market flows to a cleanly identified demand shock can provide insights that would be obscured in the unconditional setting, which combines the responses to many types of shocks (technology shocks, monetary policy shocks, preference shocks, etcetera). For example, it would not be surprising if supply-driven flows varied in response to a preference shock, while it is more surprising if they respond to a monetary policy shock. Third, the conditional responses of labor market flows to different shocks can similarly provide more stringent tests of a given model. Indeed, in the final part of the paper, we use our impulse responses as targets to estimate a heterogeneous agent model with frictional labor markets and an active labor supply margin.

We estimate the response of labor market flows to exogenous monetary policy shocks by extending a standard structural monetary policy vector autoregression (VAR) to include those flows. Following Stock and Watson (2012), Gertler and Karadi (2015), and others, we identify the effects of monetary policy using high-frequency changes in interest rate futures around FOMC announcements as an external instrument. Crucially, we also employ the recent methodology of Bauer and Swanson (2023b) to improve the relevance and exogeneity of our instrument, in part by exploiting additional interest rate variation around Fed Chair

[1]Christiano (2011), Broer et al. (2020) and Wolf (2023) offer detailed discussions of this property of the sticky-wage NK model. See also the discussion below.

speeches. We are thus able to obtain substantially more accurate estimates of the response of labor market flows to monetary policy shocks than are available in the existing literature.

Consistent with the consensus view described above, our VAR analysis shows that flows from E to U increase following a monetary policy tightening, and flows from U to E decrease, in line with the standard interpretation of lower labor demand amidst a weakening economy.[2] However, in contrast to the consensus view, we also show that flows from N to U significantly *increase* following the monetary policy tightening, and flows from U to N *decrease*, consistent with heightened job search from non-employment. We further identify a significant reduction in quits from employment to nonparticipation. Intuitively, this response of supply-driven flows is consistent with an income effect, where households increase their labor supply in a weakening economy to maintain their consumption, as in the classic "added worker effect" literature of Lundberg (1985) and others; as well as a precautionary response to increased income risk.

Importantly, we verify that cyclical changes in the composition of workers within labor market states plays only a limited role in explaining our estimated responses of supply-driven labor market flows to a monetary policy shock. The response of these flows thus seem to be largely driven by variation at the individual level. This finding, however, does not preclude different labor market responses across different subgroups of workers: indeed, we document evidence consistent with larger increases in labor supply among lower-educated workers.

We quantify the importance of the response of supply-driven flows using the methods of Shimer (2012) and Elsby, Hobijn and Şahin (2015). We construct hypothetical impulse responses of employment holding candidate labor market flows constant at their average values, allowing us to quantify the contribution of such flows to the total employment response. Holding the response of supply-driven labor market flows fixed, we find the response of employment to a contractionary monetary policy shock would be roughly twice as large—a quantitatively significant effect.

To formalize our economic interpretation of supply-driven flows in the data and understand the implications of our new empirical findings, we study a model of frictional labor markets with an active extensive margin of labor supply following the seminal contribution of Krusell et al. (2017), where agents vary in their assets holdings, labor productivity, and disutility of searching for work. We consider the effects of a contractionary monetary policy shock in the model by feeding in our VAR estimates for the response of the job-finding rate, layoff rate, real interest rate, and real wages. We then study the labor supply response of agents in the model and estimate the model's key parameters to best match the impulse response functions for the labor market transition rates between employment, unemployment and nonparticipation. The model closely matches our empirical estimates of the responses

[2]We use the terminology "flows" and "transition probabilities" interchangeably throughout.

of these flows to a monetary policy shock, while also being consistent with estimates from the literature of a relatively modest marginal propensity to earn (MPE) out of idiosyncratic transfers. We show that the model matches our estimated impulse responses through a broad-based increase in labor supply: the decline in employment in the model is roughly 70 percent larger if we simultate the model holding labor supply policy functions fixed at steady-state.

Thus, our empirical estimates and model indicate an important role for labor supply in explaining the response of employment to a monetary policy shock. As such, our findings sharply contrast with the typical approach of the sticky-wage NK literature, where "demand-determined" labor precludes any quantitatively meaningful role for labor supply (as discussed in detail by Christiano (2011), Broer et al. (2020), Auclert, Bardóczy and Rognlie (2021), and Wolf (2023)). Insofar as our estimates and model indicate an important role for labor supply in explaining the responses of labor market flows (and thus labor market stocks) to a monetary policy shock, our paper highlights a potentially important shortcoming of the transmission mechanism in such models.

We believe our evidence yields insights beyond improving our general understanding of the monetary transmission mechanism: for example, labor supply appeared to have taken on particular importance for the post-pandemic economy, where large fiscal transfers to households were followed by an increase in quits to nonparticipation, a slow recovery of labor force participation, and an increase in inflation. Our findings offer a window into the possibly important role of labor supply during this episode.

After surveying the literature, the remainder of our paper proceeds as follows. In Section 2, we review the standard empirical measures of labor market stocks and flows, we introduce our decompositions of EU and EN flows, and we describe our empirical VAR analysis. In Section 3, we report our baseline estimates of how the labor market responds to a monetary policy shock. In Section 4, we explore the role of composition and document heterogeneity in responses for different education groups. In Section 5, we compute hypothetical responses of employment when shutting down the response of various labor market flows. In Section 6, we introduce and estimate our model of frictional labor markets with an active labor supply margin. Section 7 concludes and discusses directions for future research.

Related Literature. Our paper is related to a few recent working papers that also study the conditional responses of labor market flows to monetary policy shocks (e.g., White, 2018; Broer, Kramer and Mitman, 2021; Coglianese, Olsson and Patterson, 2023; Faia, Shabalina and Wiczer, 2023). The responses of labor market flows are typically imprecisely estimated for the subset of papers in this literature analyzing U.S. data, likely due to the interaction of the well-known difficulty of identifying suitable measures of monetary policy shocks and the additional sampling noise introduced from the longitudinal linking of individual-level data necessary to construct measures of labor market flows. To mitigate these issues, we follow the approach of Bauer and Swanson (2023a,b) in adopting an instrument that incorporates additional interest rate variation around Fed Chair speeches and is orthogonalized with respect to recent macroeconomic and financial market news. In doing so, not only do we avoid standard critiques of monetary policy SVARs (e.g., Ramey, 2016), we also obtain an instrument that is both more relevant and more exogenous than those used by other authors, giving us more precise and less biased estimates. Thus, our paper offers new benchmark estimates for the response of U.S. labor market flows to a monetary policy shock.

The greater accuracy of our estimated impulse responses also allows us to extend the above literature in several ways, by: 1) studying the quit and layoff components of flows from employment to non-employment; 2) considering the role of composition effects in the responses of labor market flows; 3) studying heterogeneity in impulse responses of disaggregated labor market flows; and 4) analyzing the quantitative importance of the response of supply-driven labor market flows.

Our paper is also related to the broader empirical literature studying labor market flows and their implications for aggregate labor market variables such as employment and unemployment (e.g., Davis, Faberman and Haltiwanger, 2006; Shimer, 2012). In studying flows between unemployment and nonparticipation, we follow Elsby et al. (2015), who assess the importance of these flows for cyclical variation in unemployment and labor force participation. We additionally study the effect of these flows on the employment-population ratio, showing that flows between U and N are quantitatively more important for employment dynamics than unemployment dynamics in response to a monetary policy shock.

A distinctive contribution of our paper to the empirical literature is to introduce a novel measure of quits from employment to nonparticipation in the CPS, which we show constitutes a large component of the total flow of workers from employment to non-employment. Beyond using this new data to document the unconditional cyclical behavior of quits to non-employment, we also estimate that quits to nonparticipation decrease in response to a surprise monetary policy contraction, and we document that this response plays a particularly important role in shaping the response of the employment-population ratio to a monetary policy shock. Although macroeconomic models à la Krusell et al. (2017) (such as ours) offer direct predictions for quits to nonparticipation, these implications typically go unexplored, likely due to a lack of data.

While conditional responses of labor market flows to monetary policy shocks are of independent interest, our estimates highlight some differences from the unconditional cyclical behavior of labor market flows: 1) our estimates show a more important role for EU flows compared to the unconditional literature (Appendix C.7); 2) we find a less prominent role for composition in explaining the response of labor market flows (Section 4.2); and 3) we find no response of job-to-job flows to a monetary policy shock (Appendix C.3.2).

While we estimate a response of labor market flows consistent with an increase in labor supply after a contractionary monetary policy shock, we also estimate a slight (and sluggish) decline in the labor force participation rate, which some authors would interpret as evidence of a decline in labor supply (e.g., Galí, Smets and Wouters, 2012; Christiano, Trabandt and Walentin, 2021). However, we show that our estimated increase in labor supply significantly dampens a decline in labor force participation that would have been *much larger* in the absence of that supply response. We find that labor force participation declines following a contractionary monetary policy shock primarily because unemployment increases, consistent with Hobijn and Şahin (2021), who find similar results based on the unconditional cyclical dynamics of participation. Our quantitative model in Section 6 also exhibits these features.

Our paper also relates to the sticky-wage New Keynesian literature, which typically assumes that workers are assigned hours by a representative union (e.g., Christiano, Eichenbaum and Evans, 2005; Smets and Wouters, 2007; Auclert, Rognlie and Straub, 2020) or includes search and matching frictions but assumes labor to be supplied inelastically (e.g., Gertler, Sala and Trigari, 2008; Christiano, Eichenbaum and Trabandt, 2016; Ravn and Sterk, 2017; Graves, 2023). For standard parameterizations of models in the former case, the combination of sticky wages and a representative union limits the labor supply response of households to such an extent that employment is effectively demand-determined, as discussed by Christiano (2011), Broer et al. (2020), and Wolf (2023); whereas in the latter case, labor supply considerations are ruled out altogether.[3]

The literature typically offers two justifications for the assumptions of a limited household labor supply response: First, the intensive margin of labor (i.e., hours) shows very little conditional or unconditional business cycle variation, which is taken as evidence for the limited importance of labor supply.[4] Second, estimates of the marginal propensity to earn (MPE) from idiosyncratic transfers are small, suggesting that labor supply is relatively inelastic (Auclert et al., 2021). Our analysis tackles both of these justifications. First, even if hours variation is limited, we still document considerable variation along the extensive margin of labor supply (i.e., flows between U and N and quits from E to N). Second, we show that a low MPE from an idiosyncratic transfer does not necessarily imply a small labor supply response to an aggregate shock: in particular, our model matches the substantial response of supply-driven labor market flows to a monetary contraction, but also generates a small MPE consistent with typical estimates in the literature.

[3]Note that analytic sticky-price NK models with fixed real rates, such as Woodford (2011) and Angeletos, Lian and Wolf (2023), also exhibit demand-determined labor.

[4]For an alternative view, see Bilbiie, Primiceri and Tambalotti (2023) and Cantore et al. (2023), who consider TANK models incorporating cross-sectional variation in hours within a representative labor union setting.

Finally, our paper is complementary to the contemporaneous work of Alves and Violante (2023), who extend a framework similar to that in Krusell et al. (2017) into a rich HANK model to study how monetary policy rules influence long-run inequality. Instead, we provide new empirical evidence in support of such models and establish a minimal heterogeneous agent modeling environment (with labor market frictions and an extensive margin of labor supply) necessary to interpret our new estimates. Our paper also relates to Blanco et al. (2024), who study inefficient separations through quits and layoffs in an analytic model. Our estimates of an increase in layoffs and a decrease in quits in response to a contractionary monetary policy shock offers validation for their results.

2. Data and Methodology

We begin by describing the labor market flows data and its relationship to aggregate labor market variables such as employment and unemployment. We then identify labor market flows (and components of flows) that are plausibly driven by labor supply considerations. Finally, we describe how to estimate the responses of labor market flows to exogenous variation in monetary policy by extending a standard structural monetary policy VAR with high-frequency identification.

2.1. **Labor Market Stocks and Flows.**

We study the cyclical behavior of aggregate labor market stocks and flows. Our primary data source for gross worker flows is the longitudinally linked data from the monthly Current Population Survey (CPS) from 1978 to 2019. We organize our discussion of labor market stocks and flows in terms of three distinct labor market states: employment (E), unemployment (U), and nonparticipation (N).

Table 1 presents summary statistics for three standard labor market stock measures: the employment-to-population ratio, E/(E+U+N), the unemployment rate, U/(E+U), and the labor force participation rate, (E+U)/(E+U+N). The cyclical properties of these labor market aggregates have been widely documented: the employment-population ratio is procyclical but not very volatile, the unemployment rate is countercyclical and highly volatile, and the labor force participation rate is only modestly procyclical and has very low volatility.

The dynamic behavior of the labor market stocks E, U, and N can be understood by the flows of workers between these three states. Labor markets exhibit considerable churn, with positive gross flows in both directions between any two states. Let p_{XY} denote the fraction of workers in labor market state X moving to state Y. Labor market stocks and flows are then related by the Markov process

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t+1} = \begin{bmatrix} 1-p_{EU}-p_{EN} & p_{UE} & p_{NE} \\ p_{EU} & 1-p_{UE}-p_{UN} & p_{NU} \\ p_{EN} & p_{UN} & 1-p_{NE}-p_{NU} \end{bmatrix}_{t+1} \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t}. \tag{1}$$

TABLE 1. Cyclicality of Labor Market Stocks

	Employment-Population Ratio	Unemployment Rate	Participation Rate
mean(x)	61.14	6.19	65.16
std(x)/std(Y)	0.72	8.25	0.23
corr(x, Y)	0.83	−0.85	0.35

Note: x denotes the variable in each column, Y denotes HP-filtered log real GDP. Standard deviations and correlations are computed for HP-filtered quarterly averages. The sample is 1978-2019.

TABLE 2. Cyclicality of Labor Market Flows

	EU	EN	UE	UN	NE	NU
mean(x)	0.014	0.030	0.255	0.226	0.046	0.025
std(x)/std(Y)	5.20	2.46	5.69	4.14	3.00	5.22
corr(x, Y)	−0.83	0.49	0.78	0.71	0.65	−0.68

Note: x denotes the variable in each column, Y denotes HP-filtered log real GDP. Standard deviations and correlations are computed for HP-filtered quarterly averages. The sample is 1978-2019.

Equation (1) can be extended to study the dynamics of labor market stocks across longer time periods. Let P_{t+1} denote the transition matrix in equation (1). Given the vector $[E, U, N]'_t$ and a time series of transition matrices $\{P_{t+j}\}_{j=1}^{k}$, we can express labor market stocks at $t+k$ as

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t+k} = \left(\prod_{j=1}^{k} P_{t+j} \right) \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t} . \tag{2}$$

Thus, given an initial condition, we can understand the dynamic properties of labor market stocks through the time series of labor market flows. In Section 5, we use this relationship to help understand how shifts in supply-driven labor market flows account for the response of labor market stocks to monetary policy surprises.

Table 2 summarizes the average level and cyclical properties of each of the off-diagonal transition probabilities of P_t over the period 1978–2019.[5] The properties of these transition probabilities have been well documented in the literature (e.g., Shimer, 2012; Elsby et al.,

[5]We seasonally adjust each flow using the X-13ARIMA-SEATS software provided by the Census Bureau. Given our subsequent focus on quits and layoffs from non-employment, we do not adjust for time aggregation bias. Our results are robust to corrections for time aggregation, where such corrections are possible (e.g. see Appendix Figure C.1). See Figure A.1 for plots of each transition probability for our sample.

Table 3. Components of EU and EN Flows

	EU Flows				EN Flows			
	Total	Quits	Layoffs	Other	Total	Quits	Layoffs	Other
mean(x)	0.014	0.002	0.008	0.004	0.030	0.012	0.003	0.015
std(x)/std(Y)	5.20	8.11	8.03	5.43	2.46	5.88	14.42	4.80
corr(x, Y)	−0.83	0.60	−0.83	−0.54	0.49	0.53	−0.44	0.25

Note: The process for decomposing EU and EN flows into quits, layoffs and other separations is described in Appendix B.1.1. x denotes the variable in each column, Y denotes HP-filtered log real GDP. Standard deviations and correlations are computed for HP-filtered quarterly averages. The sample is 1978-2019.

2015; Krusell et al., 2017). Here we simply note that we consider flows between nonparticipation and unemployment as being driven by supply considerations, given that such flows are initiated by workers. The procyclicality of UN flows and countercyclicality of NU flows can be interpreted as evidence of greater job-seeking behavior among the non-employed during downturns and account for around one-third of cyclical variation in the unemployment rate (Elsby et al., 2015). Finally, note that the average UE probability is more than five times greater than the average NE probability, consistent with a higher job-finding probability from unemployment compared to nonparticipation.

2.2. **Decomposing Separations into Quits and Layoffs.** To investigate the extent to which EU and EN transitions are driven by labor supply choices, we decompose EU and EN flows into "quits", "layoffs", and "other separations" using additional detail from the CPS.[6] Given that quits (by definition) are initiated by the worker, we classify quits from employment to non-employment as supply-driven.

Although many authors have studied the cyclicality and composition of EU flows, far less attention has been paid to EN flows, despite the fact that they are roughly twice as large. To the best of our knowledge, we are the first to provide a decomposition of EN flows into quits and layoffs. This decomposition is more complicated to construct than that for EU flows, as nonparticipants are only asked their reason for leaving their previous job if they are in the outgoing rotation group of the CPS. Additionally, the possible answers to this question have changed over time. In Appendix B, we offer a detailed discussion of our new methodology for classifying EN transitions into quits and layoffs, including evidence showing that the subsequent labor market transition probabilities of individuals who quit to non-employment differ significantly from those of individuals who are laid off.

[6]For example, if a worker transitioning from E to U lists the reason for unemployment in the CPS as being a "job leaver", then we classify that transition as a quit, while if they report being a "job loser/on layoff", we classify that transition as a layoff. See Appendix B for additional details.

The left panel of Table 3 summarizes the size and cyclical properties of the subcomponents of EU flows. About 60% of EU flows are due to layoffs, and these flows are highly countercyclical and volatile. Another 10–15% are due to quits, and although these flows are similarly volatile, they are procyclical. The remaining 25–30% of EU flows that cannot be categorized as either layoffs or quits are less volatile and countercyclical.

The right panel of Table 3 reports the size and cyclical properties of the various components of EN flows. EN layoffs are countercyclical and EN quits are procyclical, as is the case for EU flows. However, in contrast to EU flows, quits represent a much larger share of EN flows than layoffs, implying a much more important role for both the magnitude and cyclicality of quits to non-employment than has been previously recognized. Indeed, the portion of EN flows that can be identified as quits is of similar magnitude to the entirety of EU flows. Our finding of a quantitatively significant role for quits to nonparticipation stands in sharp contrast to much of the literature (e.g., Faberman and Justiniano, 2015), which often equates quits with job-to-job transitions.[7]

2.3. **Monetary Policy VARs and High-Frequency Identification.** Several recent papers have used high-frequency interest rate changes around the Federal Reserve's Federal Open Market Committee (FOMC) announcements, or *monetary policy surprises*, to estimate the effects of monetary policy in a VAR (e.g., Cochrane and Piazzesi, 2002; Faust et al., 2003, 2004; Stock and Watson, 2012, 2018; Gertler and Karadi, 2015; Ramey, 2016; Bauer and Swanson, 2023b). Monetary policy surprises are appealing in these applications because their focus on interest rate changes in a narrow window of time around FOMC announcements plausibly rules out reverse causality and other endogeneity problems, as we discuss below.

The core of our VAR includes six monthly macroeconomic variables: the log of industrial production, the unemployment rate, the labor force participation rate, the log of the consumer price index, the Gilchrist and Zakrajšek (2012) excess bond premium, and the two-year Treasury yield.[8] This specification is very similar to Bauer and Swanson (2023b), except that we include labor force participation as an additional variable, given our focus on the labor market (and we will also extend this core VAR to include labor market flow variables,

[7]Faberman and Justiniano (2015) explain their use of the JOLTS quit rate as a proxy for the job-to-job transition rate from the finding of Elsby, Hobijn and Sahin (2010) that only 16% of quits lead to unemployment. Our findings suggest that a non-trivial fraction of JOLTS quits may reflect quits to nonparticipation rather than job-to-job transitions.

[8]Industrial production, the unemployment rate, the labor force participation rate, the CPI, and the two-year Treasury yield are from the Federal Reserve Bank of St. Louis FRED database. We include the GZ excess bond premium for consistency with Bauer and Swanson (2023b) and because Caldara and Herbst (2019) found including a credit spread is important for the estimation of monetary policy VARs. As discussed in Swanson and Williams (2014) and Gertler and Karadi (2015), the two-year Treasury yield was largely unconstrained during the 2009–15 zero lower bound period, making it a better measure of the overall stance of monetary policy than a shorter-term interest rate like the federal funds rate.

below). We stack these six core variables into a vector Y_t and estimate the reduced-form VAR,

$$Y_t = \alpha + B(L)Y_{t-1} + u_t, \tag{3}$$

where α is a constant, $B(L)$ a matrix polynomial in the lag operator, and u_t is a 6×1 vector of serially uncorrelated regression residuals, with $\text{Var}(u_t) = \Omega$. We estimate regression (3) from January 1978 to December 2019 via ordinary least squares with 6 monthly lags.

We follow standard practice and assume that the economy is driven by a set of serially uncorrelated structural shocks, ε_t, with $\text{Var}(\varepsilon_t) = I$ (see, e.g., Ramey, 2016). Since the dynamics of the economy are determined by $B(L)$, the effects of different structural shocks ε_t on Y_t are completely determined by differences in their impact effects on Y_t in period t, given by

$$u_t = S\varepsilon_t, \tag{4}$$

which we assume are linear, with S a matrix of appropriate dimensions. We assume that one of the structural shocks is a "monetary policy shock", and we order that shock first in ε_t and denote it by ε_t^{mp}.[9] The first column of S, denoted s_1, then describes the impact effect of the structural monetary policy shock ε_t^{mp} on u_t and Y_t.

To identify the impact effect s_1 of the monetary policy shock ε_t^{mp}, we use high-frequency identification: Let z_t denote our set of high-frequency interest rate changes (surprises) around FOMC announcements and Fed Chair speeches, converted to a monthly series by summing over all the high-frequency surprises within each month.[10] In order for z_t to be a valid instrument for ε_t^{mp}, it must satisfy an instrument *relevance* condition,

$$E[z_t \varepsilon_t^{mp}] \neq 0, \tag{5}$$

and an instrument *exogeneity* condition,

$$E[z_t \varepsilon_t^{-mp}] = 0, \tag{6}$$

where ε_t^{-mp} denotes any element of ε_t other than the first (Stock and Watson, 2012, 2018).

[9]If the number of structural shocks in ε_t equals the number of variables in the VAR, and S is nonsingular, then equation (4) implies that the VAR is invertible. However, we do not require invertibility for our analysis and the number of shocks in ε_t is unrestricted. See Bauer and Swanson (2023b) for additional discussion.

[10]High-frequency interest rate changes around FOMC announcements and Fed Chair speeches are from Swanson and Jayawickrema (2023) and include all 323 FOMC announcements from 1988–2019 and all 404 press conferences, speeches, and Congressional testimony by the Fed Chair ("speeches" for brevity) over the same period that had potential implications for monetary policy, according to financial market commentary in the *Wall Street Journal* or *New York Times*. This is somewhat larger than the set of speeches in Bauer and Swanson (2023b), who used an earlier version of the data that contained only the 295 most influential Fed Chair speeches. We compute z_t in the same way as Bauer and Swanson, taking the first principal component of the change in the current-quarter and 1-, 2-, and 3-quarter-ahead Eurodollar future rates in a narrow window of time around each announcement, which helps capture changes in forward guidance as well as the federal funds rate.

The appeal of high-frequency monetary policy surprises is that they very plausibly satisfy conditions (5)–(6). First, FOMC announcements and Fed Chair speeches are an important part of the news about monetary policy each month, so the correlation between z_t and ε_t^{mp} in (5) should be positive and large. Importantly, including Fed Chair speeches provides us with a much more relevant instrument than using FOMC announcements alone, as shown by Bauer and Swanson (2023b). Second, high-frequency monetary policy surprises capture interest rate changes in narrow windows of time around policy announcements. It's therefore unlikely that other structural shocks in ε_t^{-mp} are significantly affecting financial markets at the same time, so that these other shocks should be uncorrelated with z_t, implying (6).[11]

Given our external instrument z_t, we estimate the impact effects s_1 in the SVAR as described in Stock and Watson (2012, 2018), Gertler and Karadi (2015), and Bauer and Swanson (2023b). For concreteness, order the two-year Treasury yield first in Y_t, and denote it by Y_t^{2y}. We then estimate the regression

$$Y_t \;=\; \tilde{\alpha} + \tilde{B}(L)Y_{t-1} + s_1 Y_t^{2y} + \tilde{u}_t \tag{7}$$

via two-stage least squares, using z_t as the instrument for Y_t^{2y}.[12] It's straightforward to show that (5)–(6) imply that (7) produces an unbiased and consistent estimate of s_1, with the first element normalized to unity. (In our empirical results below, we rescale s_1 so that the first element has an impact effect of 25 basis points, rather than 1 percentage point.) Once we have estimated s_1, the impulse response functions for each variable follow from the estimated matrix lag polynomial $B(L)$ in (3).[13]

Finally, we follow the prescriptions of Bauer and Swanson (2023a,b) and adjust our high-frequency instrument z_t by projecting out any correlation with recent macroeconomic and financial news. As Bauer and Swanson (2023b) show, this purges our estimates of a significant "Fed Response to News" endogeneity bias.

3. Estimates

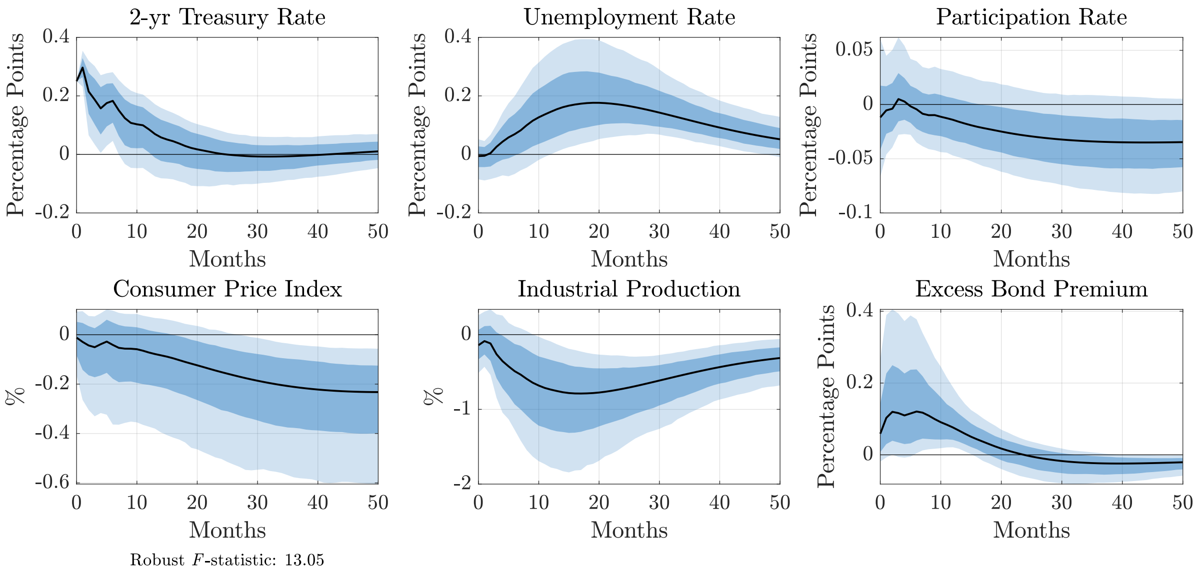
We present several sets of results. First, we report baseline impulse response functions (IRFs) for the core six-variable VAR described above. Second, we extend this core VAR to include labor market flow variables and report IRFs for labor market flows. Third, we augment the core VAR to include the quit and layoff subcomponents of EU and EN flows to provide

[11]Swanson and Jayawickrema (2023) use narrow intradaily windows around these announcements and are careful to avoid overlapping with any other macroeconomic data releases.

[12]One can obtain the same point estimates for s_1 by regressing the reduced-form residuals u_t from (3) on u_t^{2y} using z_t as the instrument. Stock and Watson (2018) recommend using (7) to avoid a generated regressor and correctly estimate the first-stage F-statistic of the instrument.

[13]Note that the sample for (7) used to estimate s_1 does not have to be the same as for the reduced-form VAR in (3) used to estimate $B(L)$. Our high-frequency monetary policy surprises are only available from 1988:2–2019:12, while we estimate $B(L)$ over the longer sample 1978:1–2019:12.

FIGURE 1. Response of Aggregate Variables to a Monetary Policy Shock



Note: Estimated impulse responses to a 25bp monetary policy tightening shock in the baseline VAR. Solid black lines report impulse response functions, while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. See text for details.

additional evidence of the response of supply-driven flows. Finally, we augment our core VAR with additional variables to further understand the response of the participation rate.

3.1. **Baseline VAR Impulse Responses to a Monetary Policy Shock.** Estimated IRFs from the core six-variable monetary policy VAR described above are presented in Figure 1. The solid black line in each panel reports the IRF, while dark and light shaded regions report 68% and 90% confidence intervals, computed using a moving block bootstrap as in Jentsch and Lunsford (2019). We calculate a first-stage F-statistic of 13.05, comfortably above the rule-of-thumb value of 10 for weak instruments described by Stock and Yogo (2005).

The impact effect of a monetary policy shock on the 2-year Treasury yield is normalized to a 25bp tightening. After impact, the 2-year Treasury yield increases slightly and then gradually returns to steady state over the next two years. The Gilchrist and Zakrajšek (2012) excess bond premium, in the bottom right panel, increases by 5bp on impact and rises for several months before gradually returning to steady state. The three other variables typically considered in a monetary policy VAR—unemployment, industrial production, and the CPI—respond more sluggishly, with essentially no effect on impact. After a few months, industrial production begins to decline and the unemployment rate starts to rise, followed by a decrease in the CPI. The peak effect is a little under 0.2 percentage points for the unemployment rate, -1 percent for industrial production, and -0.2 percent for the CPI. These responses are similar to those from monetary policy VARs estimated by other authors, such as Bauer and Swanson (2023b), and are consistent with the aggregate economy weakening moderately and inflation falling slightly after a monetary policy tightening.

Given our focus on the effect of monetary policy on the labor market, we also estimate the response of the labor force participation rate. Although speeches by monetary policymakers increasingly include references to labor force participation to convey the economy's proximity to "maximum employment," the response of labor force participation to a monetary policy shock has received less study than that of other labor market variables. Our estimates suggest that a contractionary monetary policy shock generates a slow-moving decline in labor force participation, which begins to fall around six months after impact, reaching a peak effect of around -0.04 percentage points after three years. Note that, while a negative response of participation would often be interpreted as reflecting a fall in labor supply, we show in Section 3.4, below, that it represents the net effect of two forces: an increase due to higher labor supply, but an even larger decrease due to higher unemployment interacting with the high average level of UN relative to EN transitions (22.6 percent vs. 3 percent).

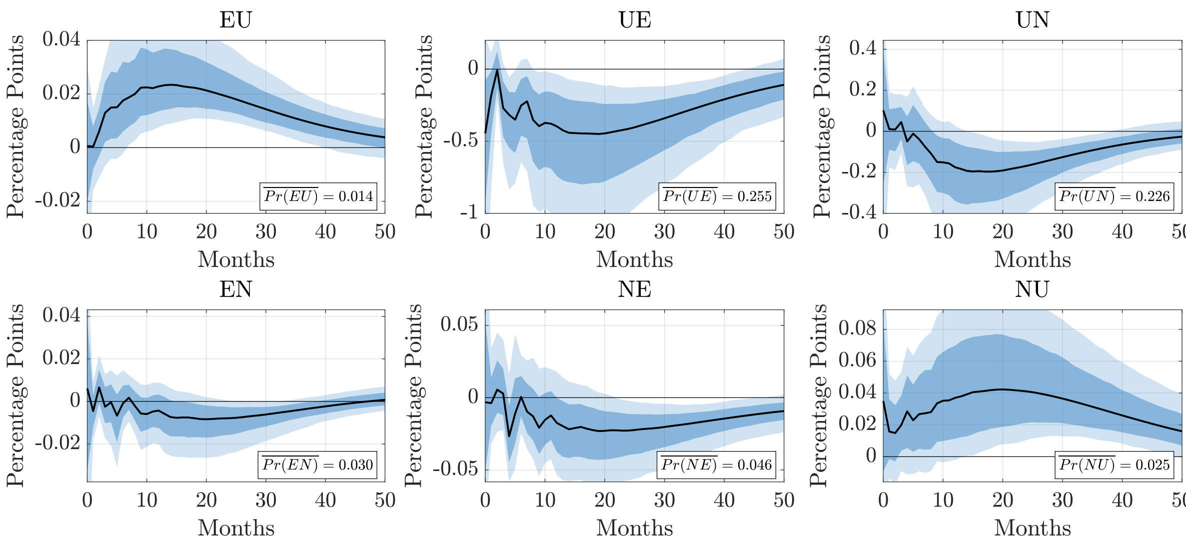
3.2. **Responses of Labor Market Flows to a Monetary Policy Shock.** We next extend our core six-variable VAR to include labor market flows. Extending the VAR to include all six labor market flows (EN, EU, NE, NU, UE, and UN) at once would introduce too many parameters into the VAR, resulting in poor estimates and overfitting, so we extend the baseline VAR with one labor market flow variable at a time, following the approach used by Gertler and Karadi (2015) to analyze financial market responses to monetary policy shocks.

The results for each labor market flow are reported in Figure 2, where each panel corresponds to a separate seven-variable VAR—the six variables in the baseline VAR, above, plus the labor market flow variable listed at the top of the panel.[14] Within each panel, we also report the average rate for that flow in the inset box—for example, 1.4 percent of employed workers move to unemployment each month, on average, while 25.5 percent of unemployed individuals move to employment.

In response to a 25bp monetary policy tightening, the labor market flows in Figure 2 respond gradually, with either a small or statistically insignificant effect on impact and a peak effect after about 1.5 years. The response of UE and EU flows is consistent with the conventional narrative of a reduction in labor demand due to a weakening economy: the transition rate from unemployment to employment (UE) in the top middle panel of Figure 2 falls significantly in response to the monetary tightening, consistent with a fall in hiring, while the transition rate from employment to unemployment (EU) in the top left panel

[14]IRFs for the six flow variables are not reported in Figure 2 in the interest of space, and because they are very similar to those from the baseline VAR in Figure 1. For each VAR in Figure 2, the first-stage F-statistic for the instrument is above the Stock and Yogo (2005) rule-of-thumb value of 10.

FIGURE 2. Response of Labor Market Flows to a Monetary Policy Shock



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, where "E" denotes employment, "U" denotes unemployment, and "N" denotes nonparticipation. 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.

increases significantly, consistent with an increase in layoffs. This latter increase may seem small at first glance—about 0.025 percentage points at its peak—but it is sizeable relative to the steady-state flow of about 1.4 percent each month.[15] Moreover, the increase in EU flows is highly persistent, especially compared to the more transitory increase in EU flows typically seen at the start of a recession (e.g., Elsby, Michaels and Solon, 2009).

Given the conventional wisdom that monetary policy has little effect on labor supply, the response of the flow from nonparticipation to unemployment (NU) in the lower right panel of Figure 2 is more surprising. Following a monetary policy tightening, the rate at which workers enter the labor force from non-employment to look for a job *increases* significantly. Simultaneously, the symmetric flow from unemployment to nonparticipation (UN) in the top right panel *declines*. The increase in NU and decrease in UN flows tilts the composition of non-employment (unemployment + nonparticipation) towards the unemployed, increasing the fraction of active searchers, who accordingly find a job at a higher rate. Such a pattern is consistent with individuals increasing their labor supply in response to a weaker economy (as we formalize with our model, in Section 6). In Appendix C.3.1, we present additional

[15]Because of the differences in average flows, it can be difficult to compare the relative magnitude in the responses across labor market flows. In Appendix C.7, we apply the procedure of Shimer (2012) and Elsby et al. (2015) to quantify the importance of each flow towards shaping the responses of employment, unemployment, and labor force participation.

evidence from two "intensive margins" of job search—the number of search methods used by the unemployed and the fraction of nonparticipants that report wanting a job—that are also consistent with an increase in labor supply.

The flow from employment to nonparticipation (EN) in the bottom left panel of Figure 2 declines modestly. We show in the next section that a labor supply response is crucial for explaining why the EN rate declines in response to a contractionary shock, while the EU rate rises significantly. Finally, the flow from nonparticipation to employment (NE) in the bottom middle panel responds similarly to the UE flow, but by a smaller amount.

Overall, the labor market flow responses in Figure 2 suggest that monetary policy operates through both labor demand and labor supply channels. Although the EU, UE, and NE flow responses are all consistent with the conventional wisdom that contractionary monetary policy leads to lower labor demand, the responses of NU and UN flows—and as we will show in Section 3.3, EN flows as well—provide novel evidence of a labor supply channel.[16] We formalize this interpretation of our estimates in Section 6, where we present a quantitative model that matches our estimates through a broad-based increase in household labor supply.

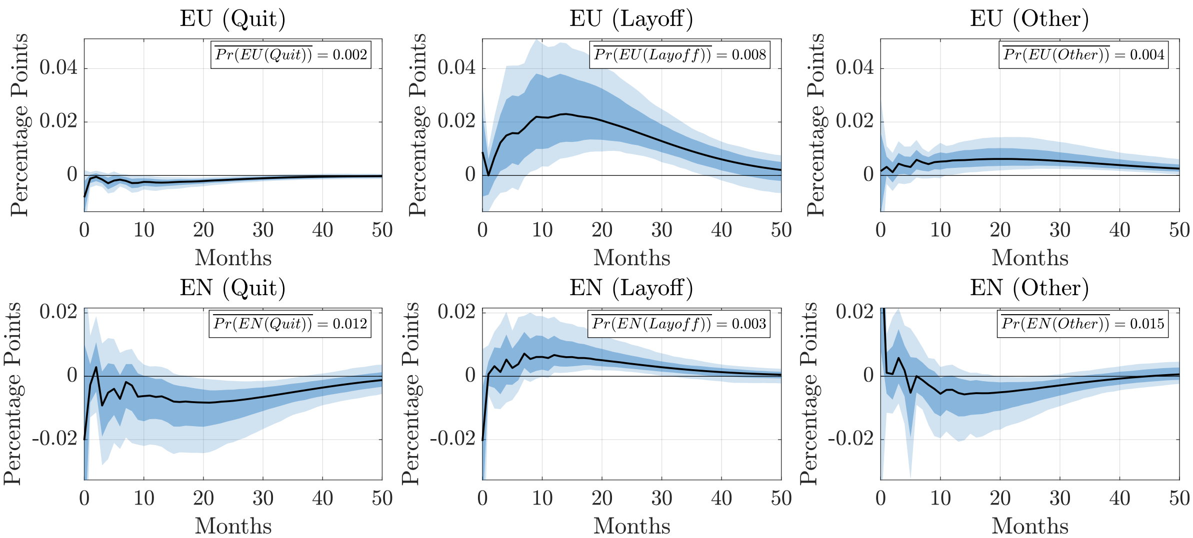
Note that the few other papers that study the responses of labor market flows to monetary policy shocks in the U.S. show far less conclusive estimates. For example, White's (2018) estimated responses of UN and NU flows using Romer and Romer (2004) shocks are not significant from zero at the 68% level for most horizons; and Faia, Shabalina and Wiczer (2023) find ambiguous evidence for the response of UE flows to high-frequency monetary surprises around FOMC announcements, contrasting not only with our estimates of a significant decline following a monetary contraction, but also with the literature documenting substantially procyclical unconditional variation in UE flows (e.g., Shimer, 2012).

We speculate that the problem of imprecise (and possibly biased) estimates in the other papers stems from well-documented issues associated with identifying exogenous and relevant measures of monetary policy surprises, compounded by the presence of additional sampling noise from the longitudinal linking of individual-level data necessary to construct measures of labor market flows. By following the approach of Bauer and Swanson (2023a,b), our instrument is both more relevant and more exogenous than those used by these other authors, giving us more precise and less biased estimates of the response of labor market flows.[17]

[16] In Section 4, we show that these results are robust to controlling for cyclical changes in the composition of each employment state. In the Appendix, we quantify the importance of each flow in explaining the response of labor market stocks to a contractionary monetary policy shock, and we show that our estimates are robust to a correction for time-aggregation of labor market flows.

[17] We offer an example of how our estimates are more relevant and exogenous in Appendix C.2. In particular, when we estimate the response of UE flows to a contractionary monetary policy shock using non-orthogonalized monetary policy surprises around FOMC announcements à la Gertler and Karadi (2015), we get point estimates close to zero and large standard errors, consistent with Faia, Shabalina and Wiczer (2023). As in Bauer and Swanson (2023b), we interpret these results as reflecting problems with exogeneity (due to non-orthogonalization) and relevance (due to looking only at FOMC announcements).

FIGURE 3. Decomposition of EU and EN Responses



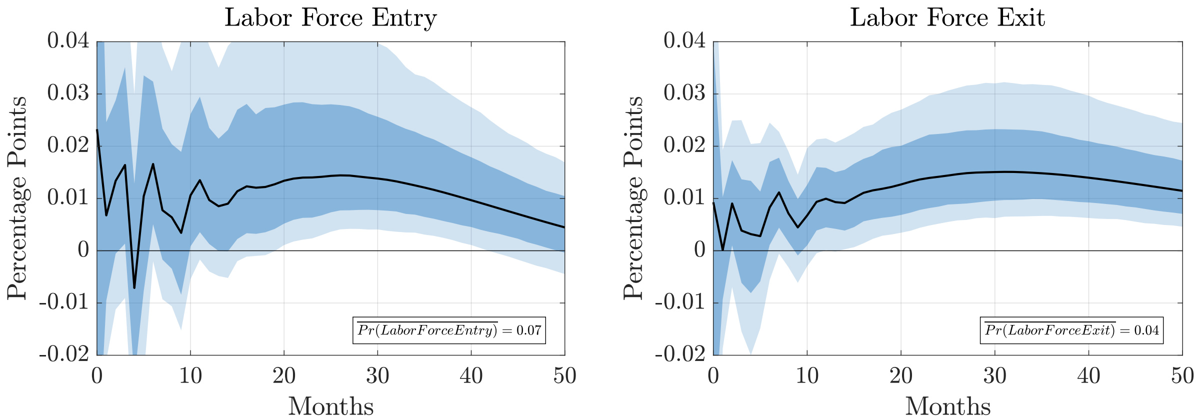
Note: Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given labor market flow variable to the baseline VAR from Figure 1, where "E" denotes employment, "U" denotes unemployment, and "N" denotes nonparticipation. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Inset boxes report average transition rates.

3.3. **Responses of Quits and Layoffs to a Monetary Policy Shock.** We provide further evidence of the response of supply-driven flows by looking at the differential responses of quits and layoffs to a monetary policy shock. Figure 3 reports responses for the quit, layoff and other separation components of both EU and EN flows (defined in Section 2.2) to a 25bp monetary policy tightening. Each of these variables is appended to our core six-variable VAR one at a time, as in Section 3.2.

We find that layoffs to both unemployment and nonparticipation rise significantly after a monetary policy tightening. Again, this is consistent with the standard narrative of lower labor demand amidst a weakening economy. In contrast, the quit rate to both unemployment and nonparticipation *decreases* after a tightening, reinforcing the evidence of an increase in labor supply found in the response of UN and NU flows (as we formalize in the discussion of our model in Section 6). The portion of EU flows that cannot be definitively attributed to layoffs or quits increases modestly, while the unattributed EN flow rate declines slightly.[18] As layoffs represent a much larger fraction of EU flows than quits, the overall response of EU flows tracks that of the layoffs component. The opposite is true for EN flows: the modest decline in the overall EN rate in response to a contractionary monetary policy shock

[18]While we do not categorize it as such, this is also consistent with an increase in labor supply. For example, a tightening of monetary policy may lead to a delay in retirement (which constitutes a significant fraction of other separations to nonparticipation).

FIGURE 4. Response of Labor Force Entry and Exit to a Monetary Policy Shock



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.

occurs as the decline in the quit rate to nonparticipation outweighs the rise in layoffs to nonparticipation.

Note that a worker who is laid off has a choice of whether to immediately begin searching (as an EU transition) or enter nonparticipation (as an EN transition). The impulse responses in Figure 3 show a proportionally larger increase in EU layoffs than EN layoffs, indicating that the share of laid-off workers immediately searching for work rises following a contractionary monetary policy shock. This finding is also consistent with an increase in labor supply.

3.4. **Labor Force Entry and Exit.** Sections 3.2 and 3.3 document that supply-driven labor market flows respond in a manner consistent with an increase in labor supply. However, we also showed in Section 3.1 that a contractionary monetary policy shock leads to a sluggish and modest decline in labor force participation, a response that is sometimes interpreted as consistent with a decline in labor supply (e.g., Galí et al., 2012). Here, we study how labor force entry and exit (and their constituent flows) generate the estimated decline in participation from a monetary contraction. Note first that labor force entry and exit rates satisfy:

$$\Big(\text{Labor Force Entry Rate}\Big)_t = NU_t + NE_t, \tag{8}$$

$$\Big(\text{Labor Force Exit Rate}\Big)_t = u_{t-1} \cdot UN_t + (1 - u_{t-1}) \cdot EN_t, \tag{9}$$

where u_{t-1} denotes the unemployment rate. The labor force entry rate is the sum of the flows from nonparticipation to either unemployment or employment. The labor force exit rate is the weighted average of UN and EN flows, with weights u_{t-1} and $(1 - u_{t-1})$ corresponding to the fractions of the labor force that are unemployed and employed, respectively.

Figure 4 plots the estimated impulse response functions of the labor force entry and exit rates, again each computed by appending the given variable to the baseline VAR from Section 3.1. Labor force entry and exit both increase in response to a contractionary monetary policy shock, with the increase in entry putting upward pressure on participation and the increase in exit doing the opposite. Thus, the overall decline in participation in response to a contractionary monetary policy shock is driven by the increase in labor force exit and mitigated by the increase in labor force entry.

Equation (8) shows that the dynamics of labor force entry reflect those of NU and NE flows. Recall from Section 3.2 that NU flows increase in response to a contractionary monetary policy shock, while NE flows decrease. Thus, from equation (8), the increase in workers moving from nonparticipation to unemployment (NU) more than offsets the decline in job-finding from nonparticipation (NE), generating an overall increase in labor force entry. We have argued that NU flows are driven primarily by labor supply considerations, so the increase in labor force entry in Figure 4 is consistent with an increase in labor supply.

Equation (9) shows that the dynamics of labor force exit reflect not just those of UN and EN flows, but also those of the unemployment rate u_t itself. Intuitively, an increase in unemployment after a contractionary monetary policy shock tilts the distribution of the labor force towards unemployment, and UN transitions are much more common than EN transitions—about 22.6 percent per month vs. 3 percent. This places substantial upward pressure on labor force exits. In fact, recall from Section 3.2 that both UN and EN flows decrease in response to a monetary contraction, which puts downward pressure on labor force exit. Thus, the increase in labor force exit in Figure 4 in response to a monetary contraction—and therefore, the decline in participation—is entirely driven by the increase in unemployment.

Thus, our findings accord with Hobijn and Şahin (2021), who show that the unconditional dynamics of participation are driven by unemployment. In Section 6, we use our model to further illustrate the disconnect between the participation rate and household labor supply: the estimated model matches the responses of labor market stocks and flows through a broad-based increase in labor supply.

3.5. **Additional Results.** Appendix C.3 presents additional results on the response of other labor market variables. We show that a contractionary monetary policy shock leads to increases in two "intensive margins" of job search: the number of search methods used by the unemployed and the fraction of nonparticipants that report wanting a job. We also show that the job-to-job transition rate does not respond significantly. Finally, we show that a monetary contraction leads to a decline in vacancies and a modest rise in real wages.

4. Composition and Heterogeneity

The impulse response functions for supply-driven labor market flows in Figures 2 and 3 are consistent with a quantitatively important increase in labor supply in response to a contractionary monetary policy shock. Here, we establish that these findings are not explained by cyclical changes in the composition of each labor market state, suggesting that our estimated impulse responses reflect true behavioral responses at the individual level. We then explore heterogeneity in the response of supply-driven labor market flows across lower- and higher-educated workers.

4.1. **Composition.** Let y_t be an aggregate time series of interest, and $y_{i,t}$ the same time series for a subgroup i with population share $\omega_{i,t}$. Furthermore, denote the time series means of $y_{i,t}$ and $\omega_{i,t}$ as $\bar{y}_i$ and $\bar{\omega}_i$. We can then write

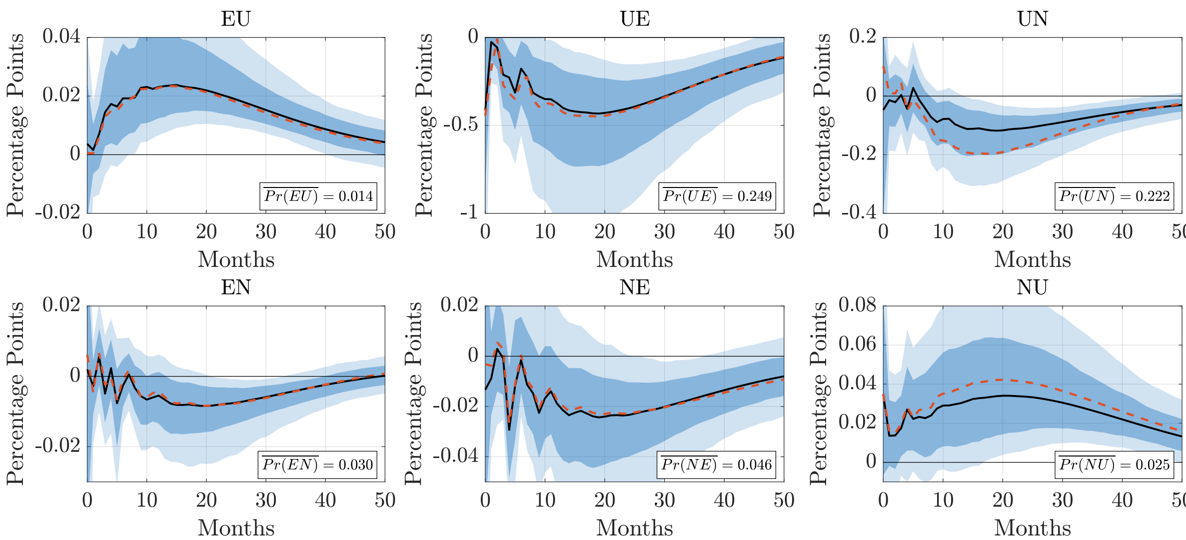
$$y_t = \underbrace{\sum_i y_{i,t} \cdot \bar{\omega}_i}_{\text{variation from } y_{i,t}} + \underbrace{\sum_i \bar{y}_i \cdot \left(\omega_{i,t} - \bar{\omega}_i\right)}_{\text{variation from } \omega_{i,t}} + \underbrace{\sum_i (y_{it} - \bar{y}_i)(\omega_{i,t} - \bar{\omega}_i)}_{\text{covariance}}. \tag{10}$$

The decomposition given by (10) expresses y_t as the sum of three components: a component holding composition fixed, a component allowing composition to vary but holding the variable constant at the group-level, and a final covariance term. Thus, the time series behavior of a variable y_t can be thought of as lying between two extremes: one in which its variation is driven entirely by changes in individual behavior, so that the composition of subgroups remains constant (and only the first term on the right-hand side of (10) is nonzero); and another in which the time-series variation in y_t is driven entirely by changes in the composition, with individual behavior remaining constant (so that only the second term on the right-hand side of (10) varies over time).

We use this decomposition to estimate the effects of changes in labor force composition on our impulse response functions in Section 3. We follow Elsby et al. (2015) and group individuals according to age (16–24, 25–54, or 55+), gender (male or female), educational attainment (less than high school, high school, some college, or BA+), and reason for unemployment if unemployed (quit, layoff, or other). Thus, we consider 24 subgroups of employed workers, 24 subgroups of nonparticipants, and 72 subgroups of unemployed workers.[19] We

[19]We differ from Elsby et al. (2015) only in that we do not further classify workers according to their labor market status one year prior (e.g., employment, unemployment, or nonparticipation). Such further classification requires studying CPS respondents in rotation groups five through eight and, as shown by Ahn and Hamilton (2022), workers in later rotation groups are a non-representative sample, displaying lower unemployment rates. Thus, we cannot compare the response of flows from such a sample with those in Figure 2. In Appendix C.4, we show that our conclusions regarding the importance of composition are unchanged when considering the full set of compositional characteristics from Elsby et al. (2015), but that the IRFs of labor market flows are slightly different, consistent with Ahn and Hamilton's findings.

Figure 5. Response of Composition-Adjusted Flows to a Monetary Policy Shock



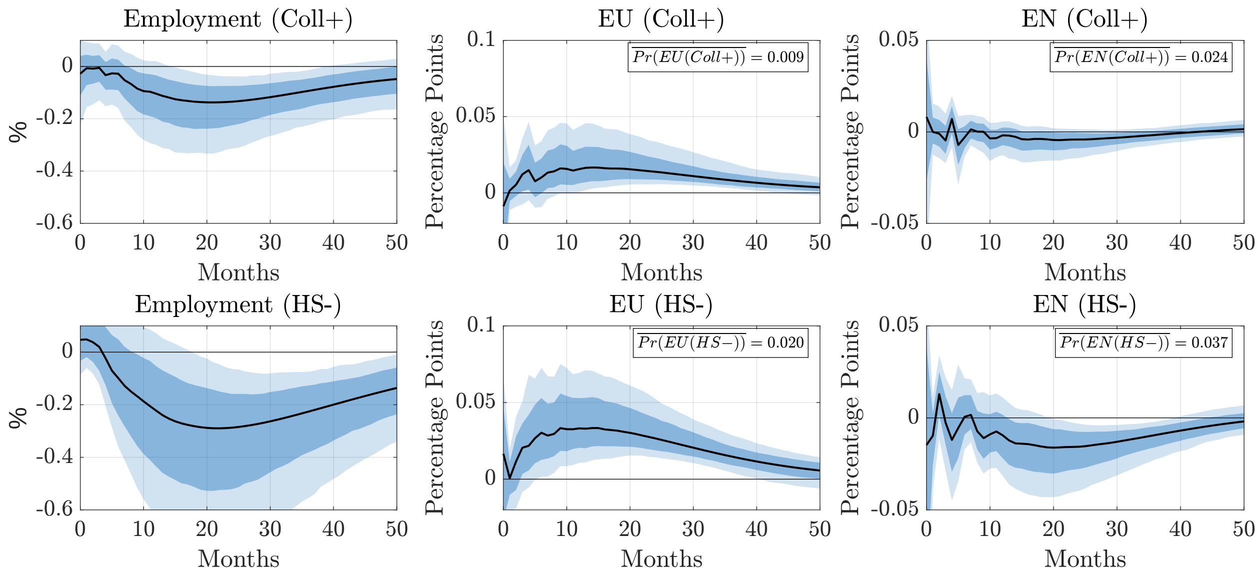
Note: Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given labor market flow variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions for composition-adjusted flows, while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals for composition-adjusted flows. Dashed red lines report impulse responses for unadjusted flows, as in Figure 2.

construct composition-adjusted labor market flow as the first term on the right-hand side of equation (10), as in Elsby et al. (2015).

As in Section 3.2, we extend our core six-variable monetary policy VAR to include labor market flows, but now we use the composition-adjusted flows and report the results in Figure 5. Compared to the IRFs for the unadjusted flows (given by the dashed red lines), the impulse responses in Figure 5 are largely unchanged. An exception is the IRF for UN flows, which decreases by roughly half as much when holding composition fixed. This suggests that part of the decline in UN flows in response to a monetary contraction does reflect a change in the composition of the unemployed towards workers with greater labor force attachment. While our estimates of the role of composition are somewhat smaller, our findings here echo those of Elsby et al. (2015), who calculate that roughly 75% of the change in UN flows from the end of an expansion through a recession are due to changes in the composition of the unemployed.[20] In Section 5, below, we discuss further how controlling for composition has little effect on our finding that supply-driven flows are quantitatively important for the response of employment to a monetary policy shock.

[20]We conjecture that the greater role for composition found by Elsby et al. (2015) partly reflects their focus on the evolution of UN flows from the *end of an expansion* over the course of a recession, whereas we calculate the impulse response of UN flows starting from steady state (similar to Shimer, 2012).

FIGURE 6. Responses by Education



Note: Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. The top row reports results for individuals with at least some college education (Coll+); the bottom row reports results for individuals with at most a high-school diploma (HS-). 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.

4.2. **Heterogeneity.** While the above section shows that our results on the quantitative importance of supply-driven flows are robust to controlling for composition effects, it does not preclude heterogeneous labor supply responses across different types of workers.

In particular, we study here the labor supply responses of higher- and lower-educated workers.[21] Lower-educated workers typically have fewer financial assets with which to smooth consumption. We also establish that lower-educated workers face more severe reductions in employment in response to a monetary policy contraction, due in large part to a greater increase in the probability of being laid off. Under the interpretation that the aggregate response of supply-driven flows to a monetary contraction can be understood through precautionary behavior, we should expect a greater response of such flows from lower-educated workers. We show that this is indeed the case: lower-educated workers exhibit a greater response of supply-driven flows in the face of a monetary policy contraction, most evidently through a decrease in quits to nonparticipation.

Figure 6 reports impulse responses of the employment-population ratios and EU and EN flows for higher- and lower-educated workers, computed by extending our baseline six-variable VAR one variable at a time, as in previous sections. The left column of Figure 6

[21]We classify an individual as higher-educated if they have attended at least some college, and lower-educated if their maximum educational attainment is a high-school diploma or less.

reports IRFs for the employment-population ratio of both groups. Employment of higher-educated workers responds modestly to the contraction, reaching a maximum decline of about 0.15 percent at 20 months, while the fall in employment for lower-educated workers is roughly twice as large and remains significant even 50 months after the shock.

The middle and right columns of Figure 6 report the responses of EU and EN flow rates for each education group. The increase in EU flows following a monetary contraction is again about twice as large for lower-educated workers. Splitting by education also shows that the decline in EN flows—which we have shown is driven by a decline in quits to non-employment—is concentrated among lower-educated workers. There is little discernible drop for higher-educated workers.[22] The larger decrease in quits to non-employment among lower-educated workers is consistent with a greater response of household labor supply.

We see three important takeaways from these estimates. First, monetary policy shocks do not hit all workers equally: lower-educated workers see greater employment declines from a monetary policy contraction, in part from a more responsive layoff margin. Second, labor supply responses show important differences across groups: lower-educated workers seem to adjust their labor supply more aggressively to offset the employment impact of a monetary policy shock. Third, to the extent that this supply response is driven not only by a larger increase in layoffs but also through lower asset holdings, our findings suggest that the wealth distribution helps shape the aggregate labor supply response to a monetary policy shock.

5. Flow-based Accounting for the Dynamics of Employment

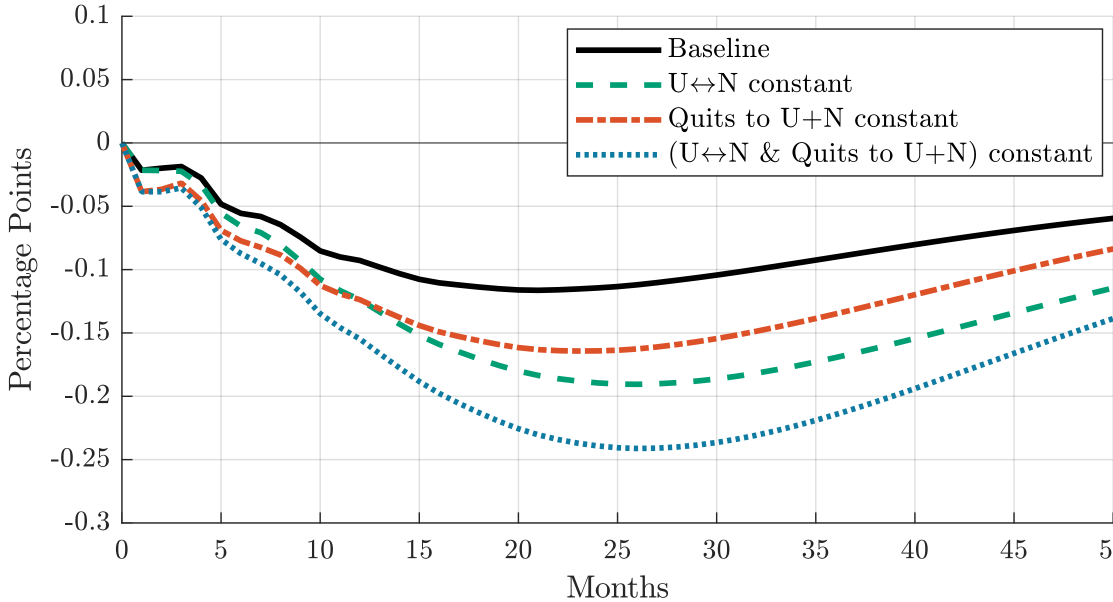
We now quantify the importance of supply-driven labor market flows for the overall response of employment to a contractionary monetary policy shock.[23] Following Shimer (2012) and Elsby et al. (2015), we account for the contribution of a particular flow by computing the hypothetical response of employment when the given flow is held fixed at its average value, using equations (1)–(2). The difference between the implied hypothetical response of employment and the actual employment response provides us with a measure of the quantitative importance of the flow for the employment response.

We perform this analysis using four scenarios: First, a baseline scenario that reports the employment response when all flows respond as estimated in our VAR in Section 3.2. Second, we shut down the responses of UN and NU flows. Third, we shut down the response of quits to non-employment. Fourth, we shut down the responses of UN and NU flows and quits to non-employment both.

[22]This is not to say that there is no labor supply response of more educated individuals: Figure C.11 of the Appendix shows a labor supply response among the higher-educated in the form of higher NU flows and lower UN flows in response to a contractionary monetary policy shock.

[23]Appendix C reports analogous results for the responses of the unemployment rate and labor force participation rate—see Figures C.14 and C.15.

FIGURE 7. Flow-Based Accounting for Employment



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.

Figure 7 plots the results. In the baseline scenario (the solid black line), employment falls a little more than 0.1 percent after about 20 months. In the second scenario, holding UN and NU flows fixed at their average values (the dashed green line), the fall in employment is almost 60% larger than in the baseline. As discussed in Section 3.3, the increase in NU flows and decrease in UN flows after a monetary contraction tilts the distribution of the non-employed from N towards U, and the UE transition rate is much higher than the NE rate (about 25.5 percent per month vs. 4.6 percent). Thus, fixing U↔N flows at their average levels reduces the rate at which workers move from non-employment to employment after the shock, generating the more pronounced employment decline in Figure 7.

In our third scenario, we shut down the response of quits to non-employment (the dashed red line). In this case, employment falls about 40% more than in the baseline, as we are now turning off the significant decline in quits to nonparticipation identified in Section 3.3.

Fourth, we shut down both the response of U↔N flows and quits to non-employment (the dotted blue line) and find that employment declines roughly twice as much relative to baseline.[24] Thus, we conclude that the response of supply-driven flows is quantitatively

[24]Note here we are not including the decline in "other separations" to nonparticipation in the labor supply response. This is a conservative assumption, given that such separations, which include retirements as well as individuals that are "tired of working", have similar cyclical properties to quits to nonparticipation and are of a similar magnitude.

very important for the overall response of employment to a monetary policy shock: if we counterfactually hold those labor-supply-driven flows constant at their average values, the response of employment would be about twice as large.

Finally, in Appendix A we show the results of the same exercise for the unemployment and labor force participation rates. We find that the labor force participation rate would decline significantly more without the response of supply-driven labor market flows, consistent with our discussion in Section 3.4. Additionally, in Appendix C.4, we repeat the exercise using our composition-adjusted flows from Section 4. We find that, when controlling for composition, holding supply-driven labor market flows constant still amplifies the decline in employment after a contractionary monetary policy shock by about 75%. This reflects the fact that, while the response of UN flows is partly muted when holding composition constant, composition adjustment has little effect on the other important supply-driven flows: NU flows and quits to non-employment.

6. A Simple Structural Model of the Labor Supply Response to Monetary Policy

In our empirical analysis, above, we documented a response of labor market flows consistent with an increase in labor supply in response to a contractionary monetary policy shock. In Section 4, we presented evidence that our main empirical results in Figures 2 and 3 are robust to controlling for cyclical changes in labor force composition and thus reflect changes in individual labor supply. In this section, we develop a simple, structural heterogeneous agent model that is also consistent with this interpretation.

More specifically, we study the household block of a heterogeneous agent New Keynesian model. We consider an incomplete-markets setting with labor market frictions where individuals make decisions over their consumption, saving, and labor supply: whether to quit, search for, or accept a job. Thus, our model builds upon the framework developed in Krusell et al. (2017) and subsequently adapted elsewhere in the literature, including Alves and Violante (2023).[25]

We consider the effect of a monetary policy shock in the model by feeding in the response of job-finding rate, the layoff rate, the real interest rate and wages to a contractionary monetary policy shock, studying the labor supply and consumption/savings response of agents in the model and their implications for aggregate labor market flows. We estimate the model's key parameters to minimize the distance between the impulse response functions for the six labor market transition rates in the model and those reported in Figure 3.

[25]Two other recent papers incorporating labor supply decisions into search models include Cairó, Fujita and Morales-Jiménez (2022) and Ferraro and Fiori (2023). These papers consider models somewhat different from our own: the former considers a representative-agent framework abstracting from quits, whereas the latter considers a framework with risk-neutral households whose flow value of leisure is assumed to be procyclical. Thus neither model admits a precautionary motive for labor supply (as we consider here).

Our model is able to closely match both the average level of each of these six transition rates and their dynamic response to a monetary policy shock. This close fit allows us to then construct a counterfactual path of employment, holding labor supply policy functions at their steady-state value. In this scenario, employment declines about 70% more than in the baseline model. This exercise provides further evidence that our empirical results are driven by true changes in labor supply at the individual level and highlights the features that general-equilibrium New Keynesian models are likely to require in order to be consistent with these results.

Importantly, we also establish that our model is quantitatively consistent with micro-level evidence on marginal propensities to consume (MPCs) and marginal propensities to earn (MPEs). In particular, an existing literature has estimated small MPEs from the labor earnings response to idiosyncratic windfalls. These estimates have been interpreted as justification for treating employment as demand-determined in the NK framework (e.g., Auclert et al., 2021), thereby implicitly ruling out the type of labor supply response that we document earlier in the paper. By simultaneously matching the estimates of labor market flows presented in Figure 2 alongside existing estimates of MPCs and MPEs, our model establishes that a modest labor supply response to an idiosyncratic transfer does not rule out a large labor supply response to an aggregate shock.

6.1. **Setting.** Time is discrete with an infinite horizon. There is a unit measure of individuals who make decisions over consumption and labor supply subject to a no-borrowing constraint and a number of exogenous shocks: First, individual labor productivity z follows an AR(1) process in logs,

$$\log z' = \rho \log z + \epsilon_z', \quad \epsilon_z' \sim N(0, \sigma_z^2)$$

with $\rho \in [0, 1)$, where employed workers receive total labor income that is proportional to their productivity. We interpret this process as capturing not only shocks to earnings, but also any other shock that affects an individual's willingness to work.

Second, for non-employed individuals, the cost of active job search, κ, is i.i.d. each period following a logistic distribution with mean μ_κ and scale s_κ. Finally, both employed and non-employed individuals make labor supply decisions in the presence of shocks to their labor market status. An individual's labor market state is either employed, non-employed but eligible for unemployment insurance (UI), or non-employed and not eligible for UI.

Employed individuals may choose to quit their job and move to UI-ineligible non-employment in the following period. If they don't quit, they may still be laid off with probability δ_L, in which case they will move to UI-eligible non-employment.

Non-employed individuals can choose to actively search for a job. Active search raises an individual's job-finding rate, but is subject to the stochastic cost described above. For the UI-eligible non-employed, active search is also required for there to be any possibility of UI-eligibility in the next period. If non-employed individuals receive a job offer, they face a job acceptance decision. For the UI-eligible non-employed who search and either do not receive a job offer, or who reject one, there is an exogenous probability of UI expiry, δ_{UI}.

6.2. **Value Functions.** Let $V_E(a,z)$, $V_U(a,z,\kappa)$, and $V_N(a,z,\kappa)$ represent the values of being employed, UI-eligible non-employed, and UI-ineligible non-employed, defined over assets a, productivity z, and, in the case of non-employed agents, their cost of active job search, κ. For clarity, we describe here the model equations in steady-state and thus suppress time subscripts.[26]

An employed worker chooses consumption c, asset holdings a', and whether or not to quit. Accordingly, $V_E(a,z)$ can be expressed as follows:

$$V_E(a,z) = \max_{c,a'} \Big\{ u(c) + \beta \max\Big\{ \mathbb{E}\, V_N(a',z',\kappa'), \mathbb{E}\Big[\delta_L V_U(a',z',\kappa') + (1-\delta_L)V_E(a',z')\Big]\Big\}\Big\} \tag{11}$$

subject to

$$c + a' = \bar{R}a + (1-\tau)wz + T, \quad a' \geq 0, \tag{12}$$

where the mathematical expectation operator $\mathbb{E}$ is conditional on the state (a,z), the max operator is over the values of quitting and not quitting, β denotes the worker's discount factor, $\bar{R}$ the gross real interest rate, τ the tax rate on labor income, w the real wage, and T a real lump-sum transfer. If a worker quits, she moves to UI-ineligible non-employment. If she chooses not to quit, she still faces a risk of losing her job exogenously with probability δ_L, in which case she moves to UI-eligible non-employment.

A UI-eligible non-employed worker chooses consumption c, asset holdings a', whether or not to search, and whether or not to accept a job should she receive an offer. Thus, the value $V_U(a,z,\kappa)$ satisfies

$$V_U(a,z,\kappa) = \max_{c,a'} \Big\{ u(c) + \max\Big\{ (1-\kappa)\psi + \beta \mathcal{V}_U^{s}(a',z), \psi + \beta \mathcal{V}_U^{ns}(a',z) \Big\}\Big\} \tag{13}$$

subject to

$$c + a' = \bar{R}a + (1-\tau)\min\{\phi w z, \bar{\phi}\} + T, \quad a' \geq 0, \tag{14}$$

where ψ denotes the flow utility value of non-employment, ϕ denotes the replacement rate from unemployment insurance, with a maximum possible UI benefit of $\bar{\phi}$. The max operator is taken over the values of searching—in which case the worker receives flow utility $(1-\kappa)\psi$

[26]We refer to UI-eligible and UI-ineligible workers with subscripts U and N, reflecting that UI-eligible non-employed have greater incentive to search (and thus are more likely to be classified as unemployed, U) compared to the UI-ineligible, who are thus are more likely to be nonparticipants, N.

and continuation value $\mathcal{V}_U^s(a',z)$—and not searching—in which case the worker receives flow utility ψ and continuation value $\mathcal{V}_U^{ns}(a',z)$.

The terms $\mathcal{V}_U^s(a',z)$ and $\mathcal{V}_U^{ns}(a',z)$ appearing in (13) reflect the expected continuation values associated with searching and not searching:

$$\mathcal{V}_U^s(a',z) = f_s \cdot \max\{\mathbb{E}\, V_E(a',z'), \mathbb{E}\, \tilde{V}_U(a',z',\kappa')\} + (1-f_s)\,\mathbb{E}\, \tilde{V}_U(a',z',\kappa') \tag{15}$$

$$\mathcal{V}_U^{ns}(a',z) = f_{ns} \cdot \max\{\mathbb{E}\, V_E(a',z'), \mathbb{E}\, V_N(a',z',\kappa')\} + (1-f_{ns})\,\mathbb{E}\, V_N(a',z',\kappa'), \tag{16}$$

where searchers find jobs at a higher probability, $f_s > f_{ns} > 0$, and $\tilde{V}_U(a,z,\kappa)$ expresses the expected value of unemployment taking into account the realization of exogenous benefit exhaustion:

$$\tilde{V}_U(a,z,\kappa) = \delta_{UI} V_N(a,z,\kappa) + (1-\delta_{UI}) V_U(a,z,\kappa). \tag{17}$$

The presence of $\tilde{V}_U$ in (15) but not (16) reflects that the worker is additionally incentivized to search to retain access to UI benefits. Note that the values defined by (15) and (16) encode the worker's optimal decision of whether or not to accept a job offer (if received) through the max operator.

Finally, a UI-ineligible non-employed worker faces the same menu of decisions as a UI-eligible non-employed individual, with

$$V_N(a,z,\kappa) = \max_{c,a'} \left\{ u(c) + \max\left\{ (1-\kappa)\psi + \beta \mathcal{V}_N^s(a',z), \psi + \beta \mathcal{V}_N^{ns}(a',z) \right\} \right\} \tag{18}$$

subject to

$$c + a' = \bar{R}a + T, \quad a' \geq 0, \tag{19}$$

and the law of motion for z and the distribution of κ, where

$$\mathcal{V}_N^s(a',z) = f_s \cdot \max\{\mathbb{E}\, V_E(a',z'), \mathbb{E}\, V_N(a',z',\kappa')\} + (1-f_s)\,\mathbb{E}\, V_N(a',z',\kappa') \tag{20}$$

$$\mathcal{V}_N^{ns}(a',z) = f_{ns} \cdot \max\{\mathbb{E}\, V_E(a',z'), \mathbb{E}\, V_N(a',z',\kappa')\} + (1-f_{ns})\,\mathbb{E}\, V_N(a',z',\kappa'). \tag{21}$$

As in the case of the UI-eligible non-employed, a UI-ineligible non-employed individual faces a tradeoff between the potential utility benefit of not searching with higher job-finding probabilities, summarized by the terms $\mathcal{V}_N^s$ and $\mathcal{V}_N^{ns}$ (similar to (15) and (16), but without implications for future UI benefits).

6.3. **Calibration and Estimation.** Our estimation procedure broadly follows Christiano, Eichenbaum and Evans (2005) and Auclert, Rognlie and Straub (2020): we set a number of our model parameters based on clear external evidence or consensus in the literature and estimate the remainder to minimize the distance between the model and our empirical impulse response functions. The model period is one month. We assume $u(c) = c^{1-\gamma}/(1-\gamma)$ and $f_{ns} = \alpha f_s$.

The parameters that we calibrate are $\theta_{EXT} \equiv \{\gamma, \beta, \bar{R}, w, \alpha, \delta_{UI}, \phi, \bar{\phi}, \tau, T\}$. We set $\gamma = 2$, a standard value, and $\beta = 0.988$, in order to generate a quarterly MPC in the model in the range of 7-8%.[27] In Section 6.4 we will discuss the recent literature that supports this target. We set $\bar{R}$ to imply a steady-state real interest rate of 1% and normalize the real wage w to 1. We calibrate the rate at which nonparticipants receive job offers to 60% of that at which job searchers receive offers, consistent with the average transition rate among nonparticipants who want a job relative to the average UE transition rate.[28] We set $\delta_{UI} = \frac{1}{6}$, implying that UI lasts six months on average, as in most states in the US in normal times. The UI replacement rate and upper bound, income tax rate, and lump-sum transfer are set to match US evidence, as described in Auclert, Bardóczy and Rognlie (2021) and Graves (2023).[29]

We estimate the remaining parameters, $\theta_{EST} \equiv \{\rho_z, \sigma_z, \mu_\kappa, \sigma_\kappa, \psi, \delta_L, f_s\}$, which govern the idiosyncratic productivity and search cost processes, the value of leisure, and the steady-state layoff and job-finding rates. In most cases, these parameters do not have a clear mapping to a single moment, and thus must be jointly estimated. For example, the job-finding rate f_s in the model is distinct from the UE rate in the data, as an endogenous fraction of job offers will be rejected by unemployed agents in the model.

Starting from steady state, we consider the effects in the model of an unanticipated monetary policy shock, which leads to changes in the real interest rate, job-finding rate, layoff rate and wage that match those shown in Figures 1–2 (i.e., the responses to a 25bp monetary tightening). We feed these paths $\{R_t, f_{s,t}, \delta_{L,t}, w_t\}_{t=0}^{T}$ into the model and calculate the responses of the six labor market transition rates: $J(\theta_{EST}) = \{EU_t, EN_t, UE_t, UN_t, NE_t, NU_t\}_{t=0}^{50}$.[30]

Denoting by $\hat{J}$ the impulse response functions estimated in the data, our estimator is

$$\min_{\theta_{EST}} (J(\theta_{EST}) - \hat{J})' \Sigma^{-1} (J(\theta_{EST}) - \hat{J}), \tag{22}$$

where Σ is a diagonal matrix containing the estimated variances of the empirical impulse responses. As in Christiano et al. (2005) and Auclert et al. (2020), standard errors for our estimated parameters are calculated using the delta method. The externally calibrated and internally estimated parameters are reported in Table 4.[31]

[27] See Kaplan and Violante (2022) for a discussion of methods of calibrating discount factors and effects on implied MPCs.

[28] We report NE|Want in Table B.2 of the Appendix.

[29] In the stationary distribution of our model, unemployment insurance is equal to 1% of labor compensation. This is marginally above the figure of 0.75% reported in Krusell et al. (2017).

[30] We truncate the responses after 50 months, as in Figure 2. In order to generate smooth responses of the six transition rates, we introduce very small taste shocks for the discrete choices that individuals face over quitting or accepting jobs. Appendix C.4 describes this approach and provides further computational details.

[31] Our estimates for the labor productivity process imply a less persistent and more volatile process for labor income than seen in the data. In light of our reduced-form interpretation of this process as capturing all shocks that affect a worker's overall willingness to work, our estimates suggest a separate and potentially important role for shocks to the value of leisure or job-related amenities.

Table 4. Model Parameters

Parameter	Description	Value	Source/Target
	Calibrated		
β	Discount Factor	0.988	Quarterly MPC of 7-8%
R	Steady-State Real Interest Rate	1.001	1% Annual
γ	Risk Aversion Coefficient	2	Standard value
δ^{UI}	Benefit Exhaustion Probability	0.167	Expected duration of UI
w	Steady-State Wage	1	Normalization
α	Efficiency of Passive Search	0.6	Job-finding rate from N
ϕ	UI Replacement Rate	0.50	Graves (2023)
$\bar{\phi}$	Maximum UI Payments	1.85	Graves (2023)
τ	Labor Income Tax Rate	0.33	Auclert et al. (2021)
T	Lump-sum Transfer	0.24	Auclert et al. (2021)
	Estimated		
Parameter	Description	Value	Standard Error
ρ_z	Persistence of Labor Productivity	0.960	(0.004)
σ_z	Standard Deviation of Labor Productivity	0.362	(0.023)
μ_κ	Mean Value of Search Cost	0.783	(0.105)
σ_κ	Dispersion of Search Cost	0.167	(0.022)
ψ	Value of Leisure	0.421	(0.107)
δ	Steady-State Layoff Rate	0.019	(0.002)
f_s	Steady-State Job-Finding Rate	0.273	(0.028)

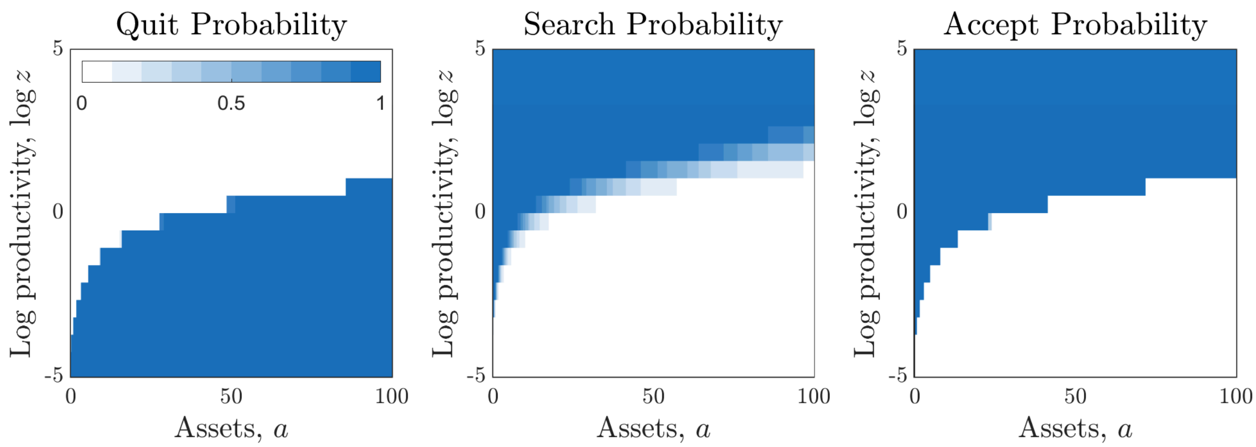
Note: Standard errors for estimated parameters are calculated using the delta method. See text for details.

Our treatment of the response of layoff and job-finding rates as inputs determined outside of the model is consistent with our focus on labor supply and affords our analysis greater clarity.[32] Moreover, while there has been important research incorporating job creation and job destruction into HANK search and matching (HANK-SAM) models, it is unclear what precise features would be required in order to match the hump-shaped and highly persistent responses of layoffs and job-finding rates implied by the response of EU and UE rates shown in Figure 2, particularly for a heterogeneous agent model such as we consider here. Thus, our approach highlights the extent to which the labor supply forces present in our model allow us to obtain a close fit to the data, without concern that the model's failure (or ability) to fit the data may reflect a simple mis-specification of the model's labor demand block.

6.4. **Results: Steady State.** Before studying the model's dynamic responses to a monetary policy shock, we briefly discuss its steady-state properties. First, we consider the model's labor supply policy functions and verify that the model matches the steady-state labor market flows from the data. We then calculate the MPC and MPE from an idiosyncratic transfer in the model and compare it to empirical estimates in the literature.

[32]In this sense, our analysis is analogous to Krusell et al. (2017), whose quantitative analysis treats business cycle variation in job-finding rates and layoffs as exogeneously determined by demand-side considerations.

FIGURE 8. Labor Supply Policy Functions



Note: The left plot shows the probability that an employed individual quits their job, for different levels of assets on the x-axis and labor productivity on the y-axis. The middle plot shows the probability that a UI-eligible individual searches for a job, before the realization of their search cost. The right plot shows the probability that a UI-eligible individual accepts a job.

6.4.1. *Labor Supply Policy Functions and Steady-State Labor Market Flows.* Here, we document the substantial heterogeneity in steady-state optimal labor supply policies, consistent with the notion that different workers maintain different levels of attachment to the labor force as a function of their underlying characteristics. Then, we show that, after aggregating labor supply decisions within labor market states, the implied labor market flows in the stationary distribution of the model match the data.

Figure 8 plots the probability of quitting a job (for employed workers), and searching for and accepting a job (for UI-eligible workers) at different levels of idiosyncratic productivity and assets. The policy functions show considerable heterogeneity in the propensity of workers to quit to non-employment, search for a job, or accept a job as a function of their wealth and labor productivity. Thus, the model displays substantial variation in labor supply policies indicative of a worker's degree of "labor force attachment" within labor market states.

As indicated in the left-most panel of the figure, individuals are more likely to quit from employment to nonparticipation (thereby making an EN transition) the lower their productivity and the higher their wealth. Comparing the left and right panels confirms that states where employed workers quit their jobs closely correspond to those where workers will not accept a job offer if non-employed. The middle panel of Figure 8 then shows that individuals are more likely to search when they have low wealth or high productivity. Note that a UI-eligible worker is a worker who was either employed and laid off, or unemployed and unsuccessful at finding a job. Thus, the middle panel illustrates which workers will move to unemployment (versus nonparticipation) after a layoff, and which workers will continue

Table 5. Average Labor Market Transition Rates

Transition Rate	Model	Data
EU	0.0143	0.0143
EN	0.0297	0.0296
UE	0.2547	0.2547
UN	0.2260	0.2262
NE	0.0462	0.0461
NU	0.0253	0.0252

Note: Transition rates are calculated in the stationary distribution of the model.

searching from unemployment (versus stopping search and moving to nonparticipation) after a period of unsuccessful job search.

The middle and right-most panels of Figure 8 make evident the existence of many intermediate combinations of wealth and productivity where individuals do not search but will accept a job if they receive an offer. When such individuals find and accept a job, it is recorded as an NE transition in the model. The model's ability to match the lower NE rate in the data (compared to the UE rate) obtains both through the lower job-finding probability of non-searchers and the distribution of non-searching workers who will not accept a job when one is offered.

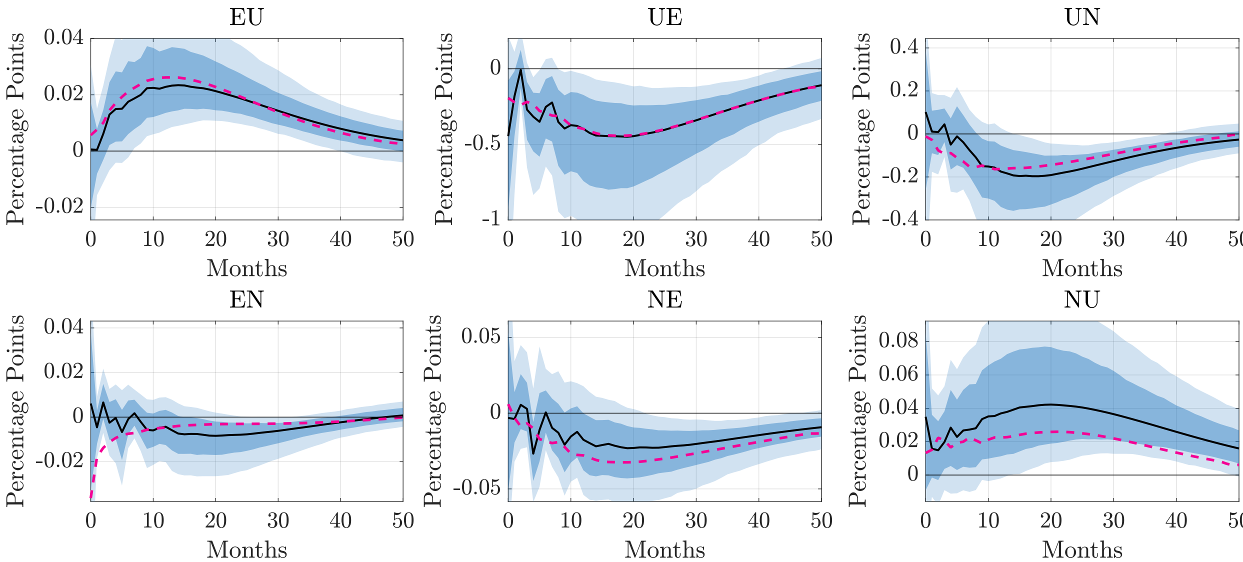
Figure 8 makes it apparent that the ability of our model to match aggregate labor market flows is mediated not only through the distribution of workers across labor market states, but also through the distribution of workers over labor productivity and wealth. Table 5 compares the steady-state labor market transition rates in the model with their average values in the data. The model closely matches the data for all six transition rates.

6.4.2. *The Marginal Propensities to Consume and Earn.* We now describe how our model matches estimates of the marginal propensity to consume (MPC) and the marginal propensity to earn (MPE), quantities describing how agents adjust their consumption and labor earnings in response to an unanticipated transfer. Our model generates a quarterly MPC of 0.073 and an annual MPE of 0.027.[33]

While lower than estimates from the earlier literature (e.g., Parker et al., 2013), the MPC implied by our quantitative model is consistent with more recent studies that have identified potential biases in the earlier estimates (e.g., Borusyak, Jaravel and Spiess, 2024; Orchard, Ramey and Wieland, 2023; Boehm, Fize and Jaravel, 2024). These more recent studies suggest that the "notional MPC"—the appropriate MPC to target for a model of

[33]We calculate these from an unexpected transfer equivalent to approximately $500 to agents in the model.

FIGURE 9. Response of Labor Market Flows: Model and Data



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 magenta lines report impulse response functions from the estimated model. See text for details.

nondurable consumption—should lie in a range between about 0.07 and 0.114.[34] Our MPC falls in this range.

Auclert, Bardóczy and Rognlie (2021) define the MPE as *"the negative of the level of the response of earned income to a one-time, unexpected unit payment, in the period of the payment"* and document a tight connection between MPCs and MPEs in models with frictionless labor markets and an intensive margin of labor supply. Drawing from an empirical literature estimating labor supply responses to lottery winnings, Auclert et al. (2021) conclude that the annual MPE lies between 0 and 0.04. The annual MPE from our model falls comfortably within this range.[35]

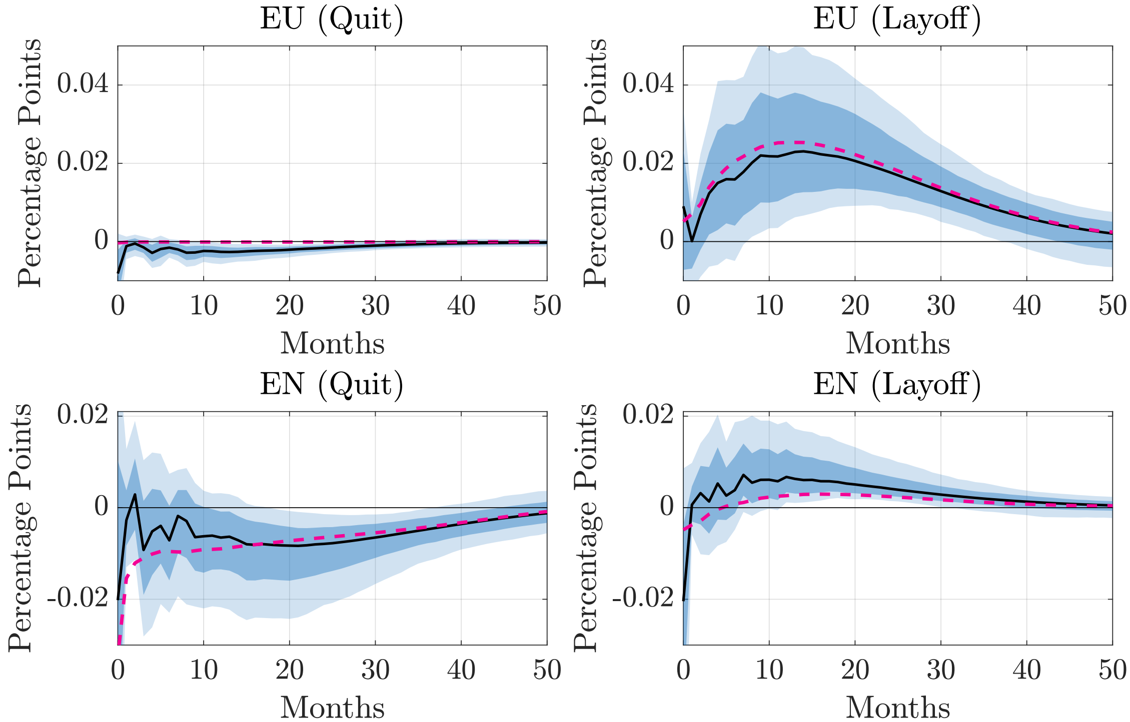
Having established that the model (*i*) generates realistic variation in labor force attachment within labor market states, and (*ii*) implies MPCs and MPEs consistent with those estimated in the existing literature, we proceed to study the model's ability to fit the response of labor market flows to a contractionary monetary policy shock.

6.5. **Results: Model Dynamics.** We now turn to the dynamic properties of the model in response to a contractionary monetary policy shock. Figure 9 reproduces Figure 2 with the

[34]Laibson, Maxted and Moll (2022) develop the "notional MPC" to address the fact that empirical estimates often include spending on durables, while most models do not. See the discussion of Table III of Boehm et al. (2024) for more details of recent estimates.

[35]The presence of labor market frictions allows our model to break the tight link between MPCs and MPEs described by Auclert et al. (2021).

FIGURE 10. Decomposition of EU and EN Responses: Model and Data



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 magenta lines report impulse response functions from the estimated model. See text for details.

model-generated impulse response functions overlaying the empirical estimates as dashed magenta lines. The labor market flows implied by the estimated model are remarkably close to those of the data, with the models' impulse responses lying within the 68% confidence bands for almost all labor market flows and horizons.

Note that the close fit of the model to the data is not guaranteed, but is instead achieved through the optimal labor supply response of workers to the change in the path of job-finding probabilities, layoff rates, interest rates, and wages. The contribution of labor supply decisions to the fit of the impulse responses is most evident in the responses of UN and NU flows (the right column of the figure), showing a decrease in UN transitions and increase in NU transitions in the model and the data. Figure D.2 shows that the response of NU and UN flows can be understood as largely driven by the response of job-finding and layoff rates (rather than by the response of the real interest rate or wages).

To understand how the model generates an increase in NU flows (and a decrease in UN flows) after a monetary contraction, consider a non-employed worker in the model who finances their consumption through previously accumulated savings. The reduction in job-finding probabilities from unemployment and nonparticipation (i.e., NE and UE) increases the expected duration of non-employment, forcing such non-employed workers to stretch their savings over a longer period, thereby reducing expected consumption. By engaging in active job search, the worker can shorten their expected spell of joblessness, mitigating the necessary reduction in consumption over their non-employment spell and ameliorating other forms of consumption risk.

Although the model offers implications for the response of quits to nonparticipation, these are not easily seen in Figure 9, which only shows the response of aggregate EN flows. Figure 10 compares the responses of quits and layoffs to unemployment and nonparticipation to our empirical estimates from Figure 3. While these impulse responses are not targeted in the estimation, the fit of the model here is also good, with the model doing particularly well in matching the the prolonged decline in EN quits after a monetary contraction. As in the data, the model implies that the share of laid-off workers who move to unemployment (rather than nonparticipation) increases. Indeed, both in the model and in the data the layoff rate to nonparticipation declines on impact. Figures D.2 and D.3 of Appendix D.3 shows that the response of EN flows is largely driven by the the response of job-finding and layoff rates to a contractionary monetary policy shock.

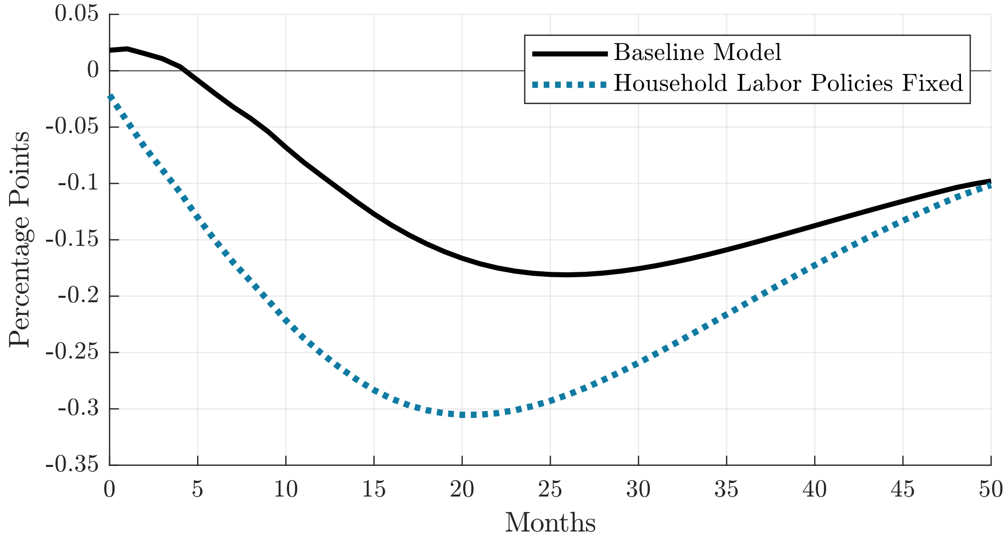
The fall in EN quits in the model can be understood as individuals prolonging their employment spells to maintain consumption. Given the fall in job-finding probabilities from non-employment (i.e., NE and UE), the expected duration of non-employment increases: thus, a worker who may have otherwise been able to temporarily quit to non-employment and maintain their consumption through accumulated savings may no longer able to do so, given the necessity of stretching the same amount of savings over a longer anticipated spell of nonemployment.

6.6. **The Role of Labor Supply.** The previous section shows that the model offers an excellent fit to our estimates of the response of labor market flows to a contractionary monetary policy shock. We also describe how the response of supply-driven labor market flows can be understood to reflect an increase in labor supply among workers possessing limited assets by which to self-insure and smooth consumption. Here, we establish that the model's ability to match the data occurs through such a labor supply response, rather than a shift in the composition of workers across labor market states.

More specifically, it is in theory possible that the response of these flows could be occurring due to changes in the distribution of employed and non-employed individuals, interacting with the heterogeneity in labor supply policy functions shown in Figure 8. For example, an increase in layoffs could shift the the composition of workers in non-employment towards workers who are more attached to the labor force.

Here, we show that the ability of our model to match the response of labor market flows reflects a broad-based increase in labor supply (as opposed to a shift in the composition of

FIGURE 11. The Employment Response with Fixed Labor Supply



Note: The black solid line shows the overall response of the employment-population ratio to a contractionary monetary policy shock in the estimated model. The blue dotted line shows the response if labor supply policy functions are held at their steady-state values.

non-employed workers towards those with greater labor market attachment). We solve for a counterfactual path of aggregate employment where labor supply policy functions (as a function of worker characteristics) do not respond to the shock, while consumption/savings policy functions evolve as in the baseline model. To the extent that the ability of the model to match the data is generated through composition (rather than a shift in labor supply behavior), the counterfactual fixed-labor-supply path of employment should closely resemble the response of employment implied in the baseline model.

Figure 11 shows the response of employment under the full model and under the restricted fixed-labor-supply counterfactual.[36] The two paths diverge considerably, with employment declining by about 70% more under the fixed-labor-supply counterfactual. The steeper decline in the counterfactual employment path indicates that the baseline model fits the data through a broad-based increase in labor supply, via reductions in quits to non-employment and increases in search activity.[37]

[36]Figure D.1 in the Appendix confirms that the path of employment in the baseline model is very close to that estimated in the data.

[37]Note that this analysis is distinct from the flow-based accounting exercise in Section 5, where we held supply-driven labor market flows fixed at their steady-state levels. Here, we instead hold individual labor supply policies fixed, potentially allowing aggregate labor market flows to vary as the composition of the labor force changes. While distinct, both exercises are complementary in illustrating the importance of labor supply considerations for the employment response to monetary policy.

7. Conclusion

This paper offers new empirical evidence of a sizeable response of supply-driven labor market flows to a contractionary monetary policy shock. Using high-frequency identified monetary policy shocks from FOMC announcements and Fed Chair speeches, we show that a contractionary monetary policy shock decreases the rate at which workers quit jobs to non-employment and stimulates job-seeking behavior among the non-employed. In doing so, we develop a novel decomposition of transitions from employment to nonparticipation into quits and layoffs, and we offer new evidence that a large and procyclical component of EN flows reflects quits.

Our estimates imply a quantitatively important role for labor supply considerations in shaping the employment response to a monetary policy shock: Holding the response of such supply-driven labor market flows fixed, the decline in employment from a monetary contraction would be about twice as large. These results contrast with much of the New Keynesian literature, where labor supply plays almost no role in the response of employment to monetary policy. Thus, our paper highlights a potentially important shortcoming of such models.

To better understand our new empirical findings, we estimate a heterogeneous agent model with frictional labor markets and an active labor supply margin. The estimated model provides an excellent fit to our new empirical evidence and points to an important role for labor supply in moderating the response of employment to a monetary policy shock. Additionally, we show that our model is consistent with existing empirical evidence on the responses of consumption and labor earnings to idiosyncratic transfers. Given its ability to match both micro and macro facts, we view our modeling framework as a promising foundation for general equilibrium analysis of monetary policy and other policy interventions.

Indeed, incorporating an active labor supply margin in New Keynesian models may prove to be helpful for understanding the recent U.S. labor market experience since the pandemic: a sequence of unprecedentedly large stimulus payments in 2020 and 2021 was soon followed by a period of weak labor force participation and an unexpectedly high quit rate (the "Great Resignation").[38] Existing models are well-placed to consider the effects of such stimulus on consumption, but less suited to considering how such policies may affect labor supply, or how the labor supply response to such policies might have contributed to the rise in inflation.

We thus view endogenizing the layoff and job-finding rates in a fully-fledged New Keynesian model with an active labor supply margin as a promising topic for future research.

[38]Adopting our methodology for decomposing flows from employment to nonparticipation, Michaels (2024) documents that quits to non-employment account for a disproportionate share of the increase in quits during this period.

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ONLINE APPENDIX TO "THE LABOR DEMAND AND LABOR SUPPLY CHANNELS OF MONETARY POLICY"

SEBASTIAN GRAVES, CHRISTOPHER HUCKFELDT, AND ERIC T. SWANSON

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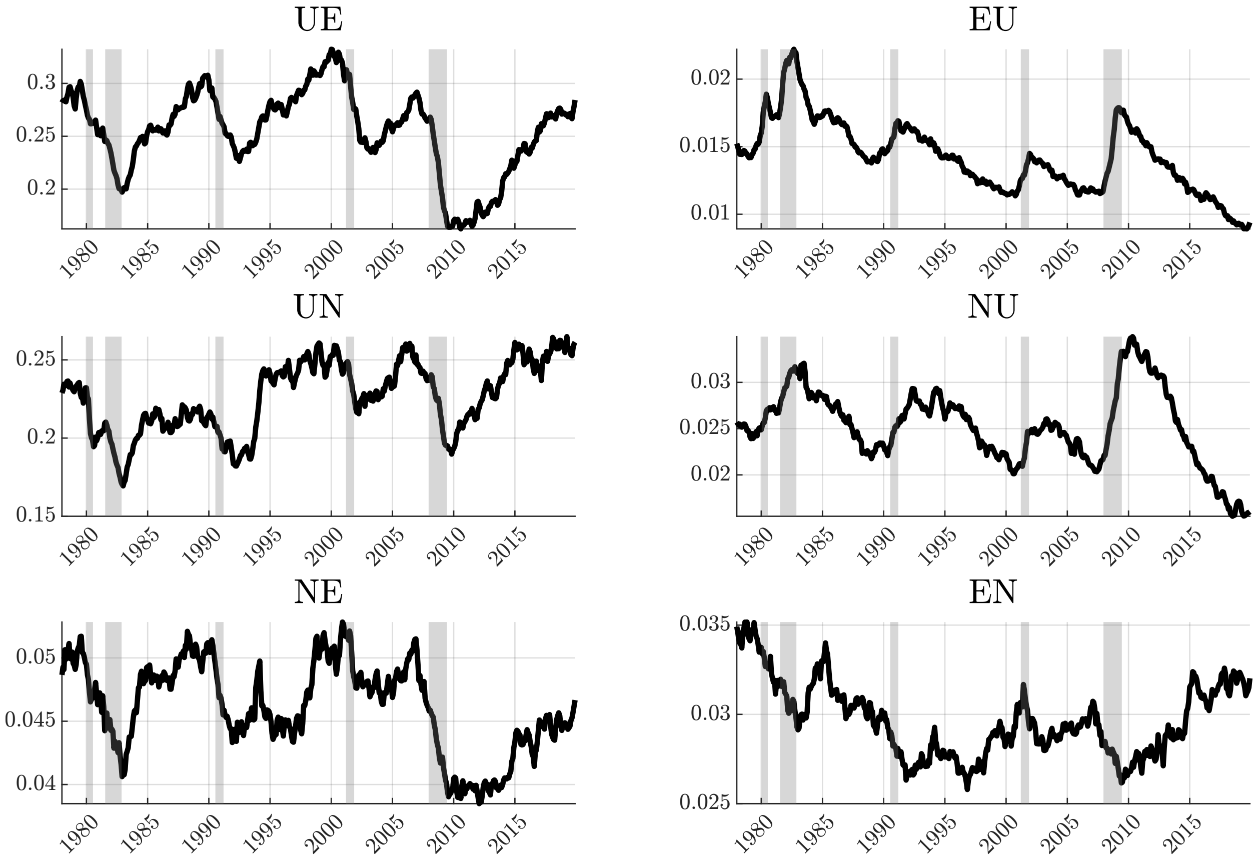
Appendix A. Time series: Labor Market Flows and Intensive Margins of Job Search

Figure A.1. Time Series of Labor Market Flows



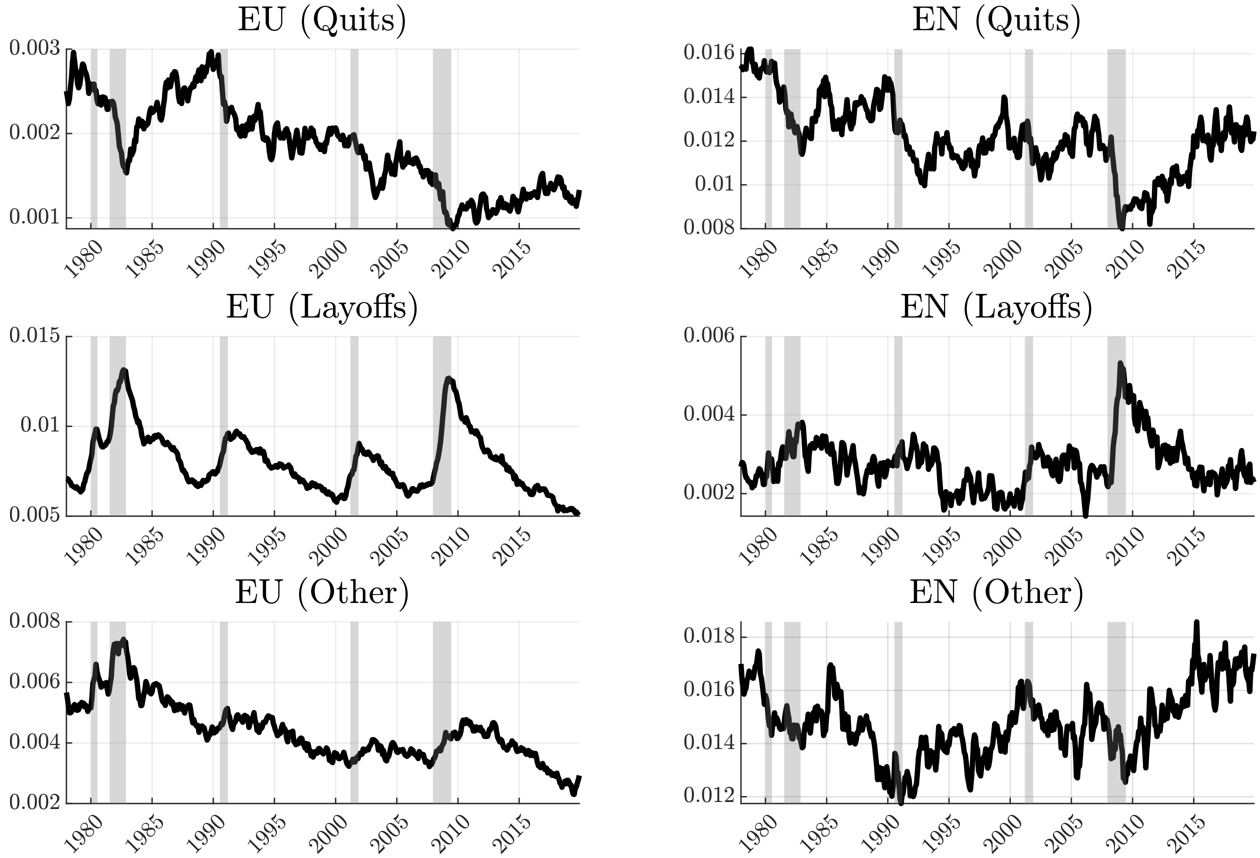
Note: Transition rates are calculated using CPS microdata. All series are smoothed using a centered 5-month moving average.

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



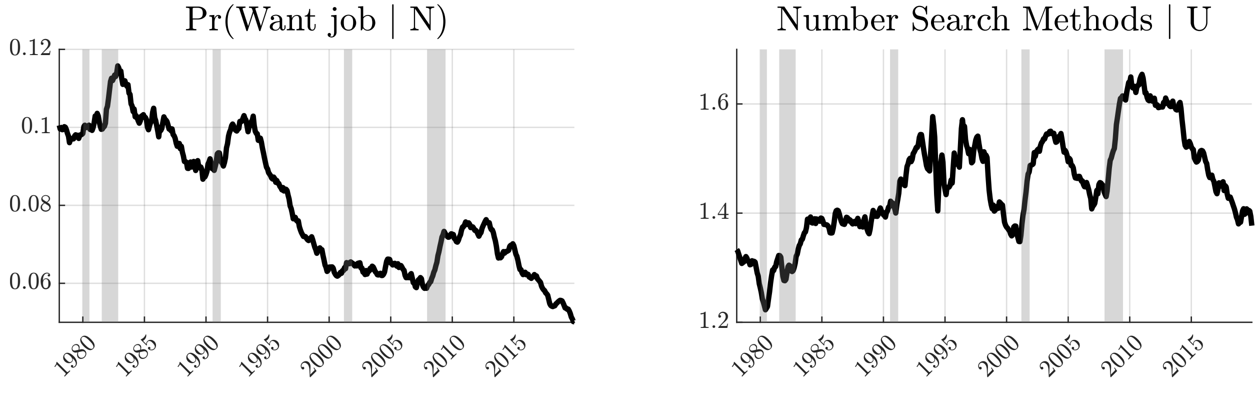
Note: Employment-unemployment (EU) and employment-nonparticipation (EN) flows are decomposed into quits, layoffs and other separations as explained in Appendix B.1.1. All series are smoothed using a centered 5-month moving average.

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.[1] 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

[1]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.

FIGURE A.3. Intensive Margins of Labor Supply



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 Quits 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.[2] 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.

[2]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”.[3]

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

[3]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.[4]

To create a harmonized series, we restrict our attention to individuals who report having worked in the past 12 months.[5] We label an EN transition as a quit if the reason for leaving the job is "personal, family or school" or "unsatisfactory work arrangements".[6] 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.[7] 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.

[4]For technical background on these changes, see U.S. Census Bureau (2019, pg. 111).

[5]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.

[6]These are the possible answers from before 1994. After 1994 we define such transitions analogously.

[7]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

	To		
From	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.[8] 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

[8]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

Sample period	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

	From	*To* 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

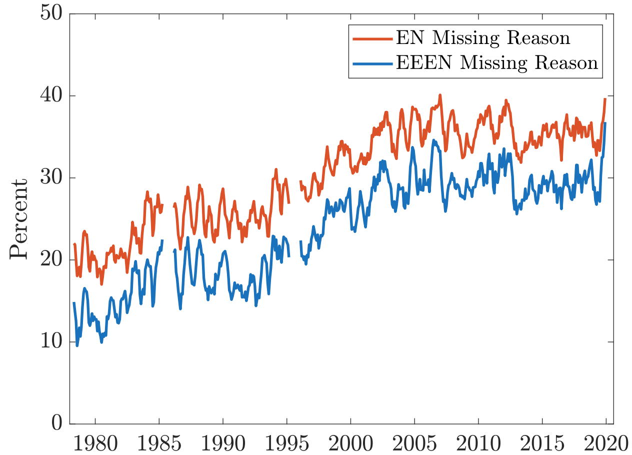
Note: Transition rates are shown for individuals that are in their second month of unemployment following an employment spell, split by reason for unemployment, as defined in Appendix B.1.1. The rates are computed for the period prior to the 1994 CPS redesign.

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.[9] 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

[9]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.

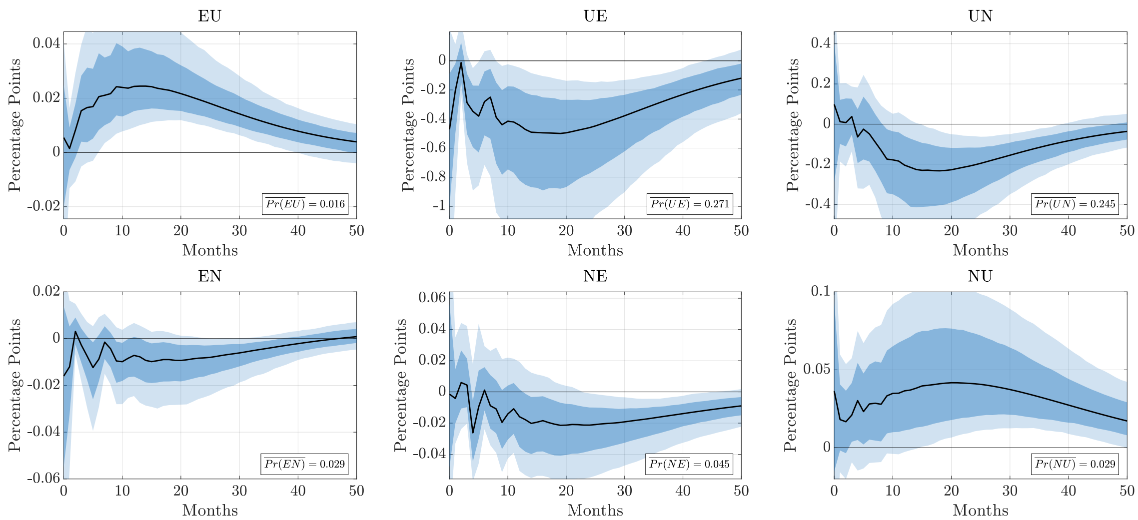
First, we find that the share of EN transitions with missing data on reason for leaving a job does not change significantly across subgroups of workers where one might expect meaningful variation in the fraction of workers who are coded as having not worked in the requisite prior time period (e.g., individuals 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.

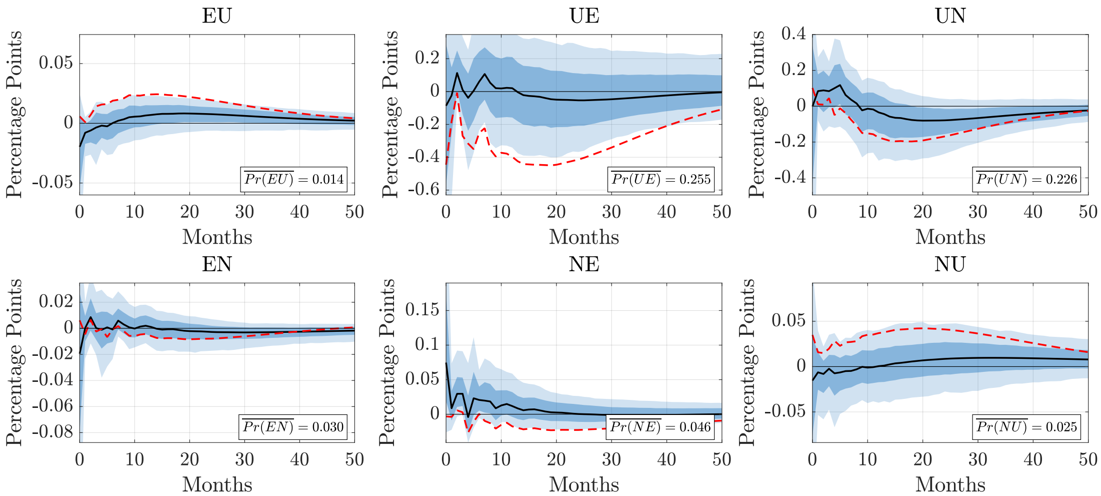
Appendix C. Additional VAR Results

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.

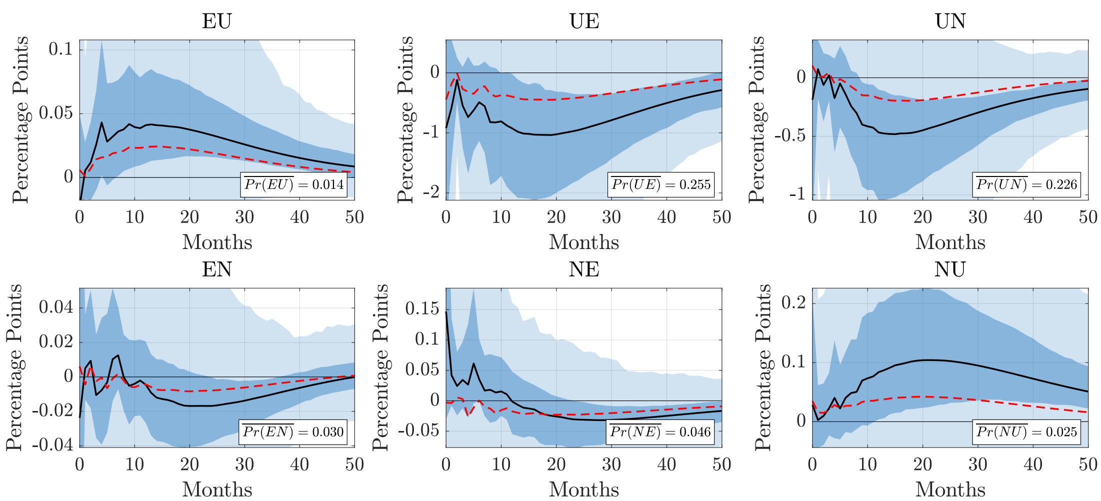
Figure C.2. Labor Market Flows: Non-Orthogonalized Shocks, No Chair Speeches



Robust F-statistic from Baseline VAR: 9.30

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.

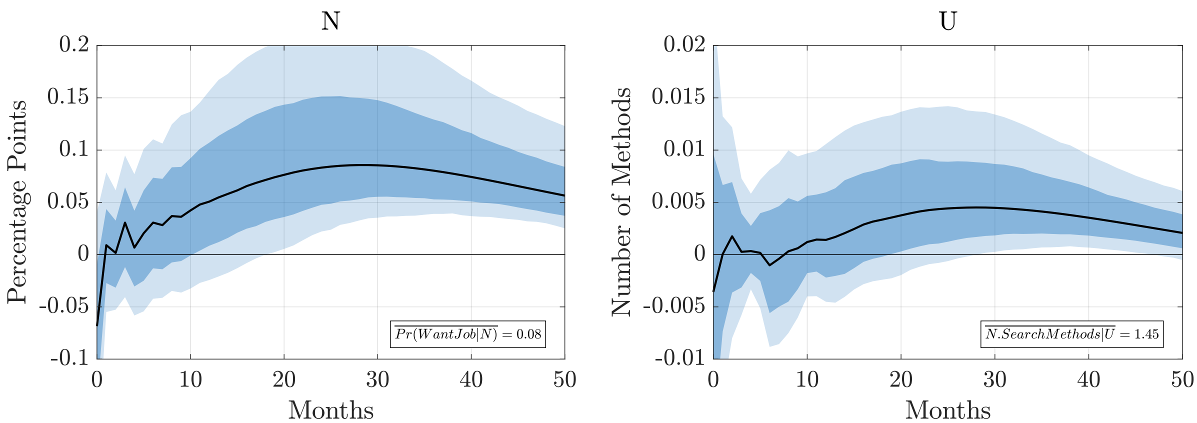
Figure C.3. Labor Market Flows: Orthogonalized Shocks, No Chair Speeches



Robust F-statistic from Baseline VAR: 0.48

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 an 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.

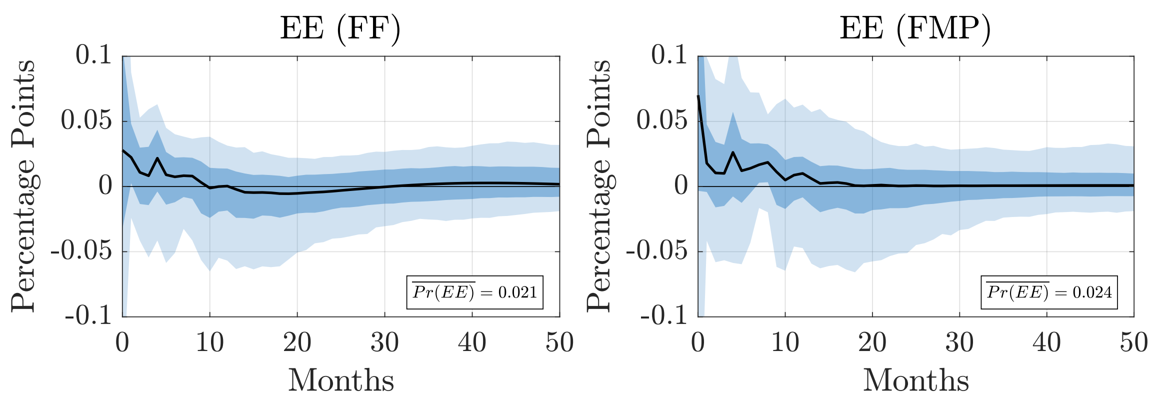
Next, we look at the number of job search methods used by workers in unemployment. This metric has been adopted elsewhere in the literature and has been shown to be highly correlated with time spent looking for a job, e.g., Mukoyama, Patterson and Şahin (2018). Moreover, unemployed workers who use two 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.

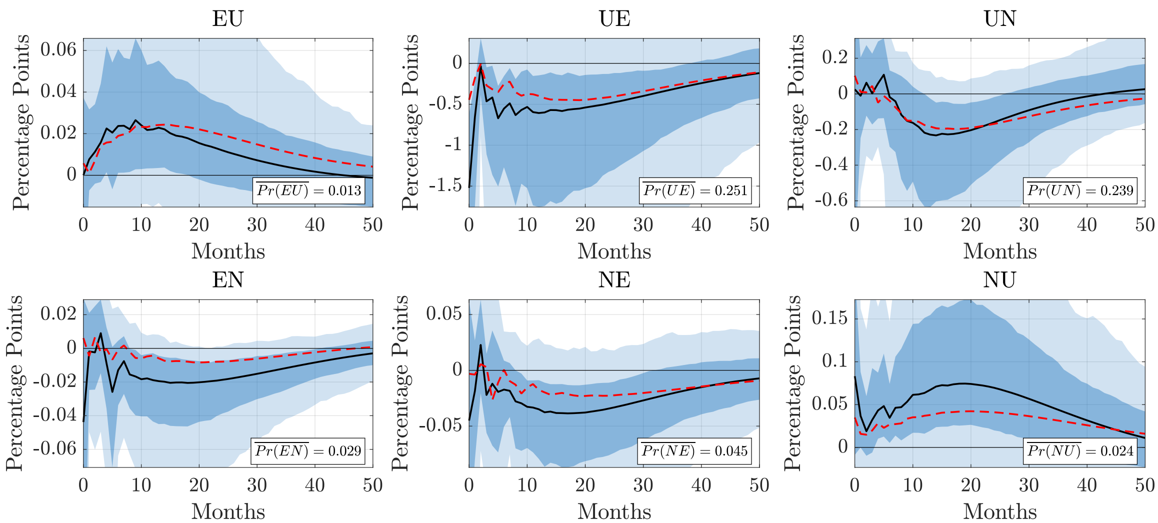
Figure C.5. Response of Job-to-Job Transitions



Robust F-statistic from Baseline VAR: 5.44

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

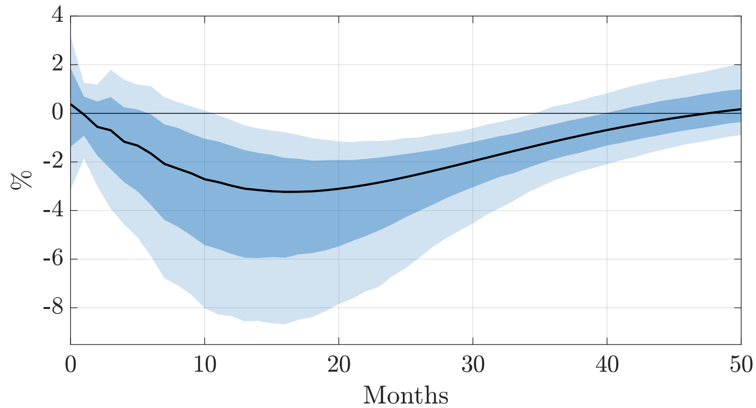


Note: Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given labor market flow variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence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

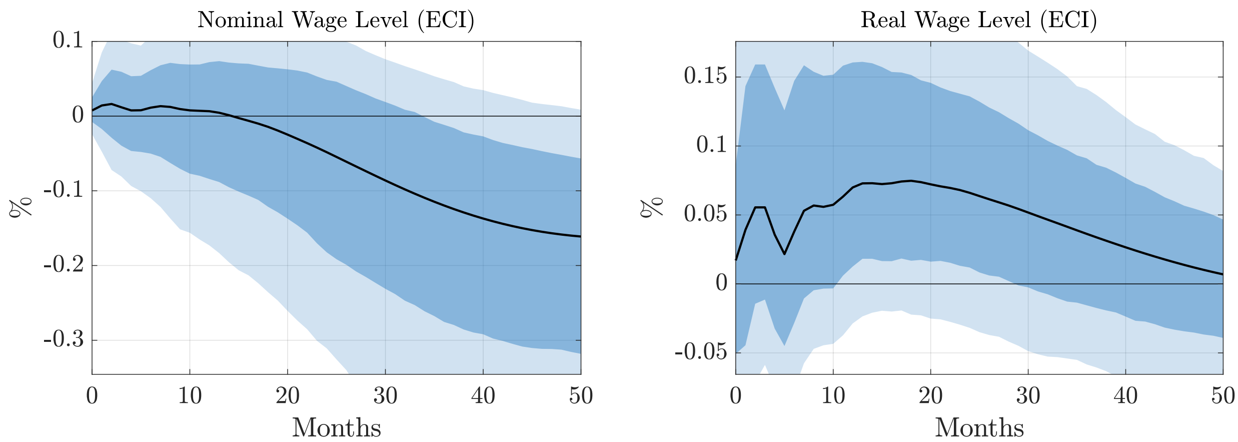
Thus, it is possible that a series measuring job-to-job changes to higher-paying jobs might offer a more robust series by which to assess the offer-matching theory of inflation.

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



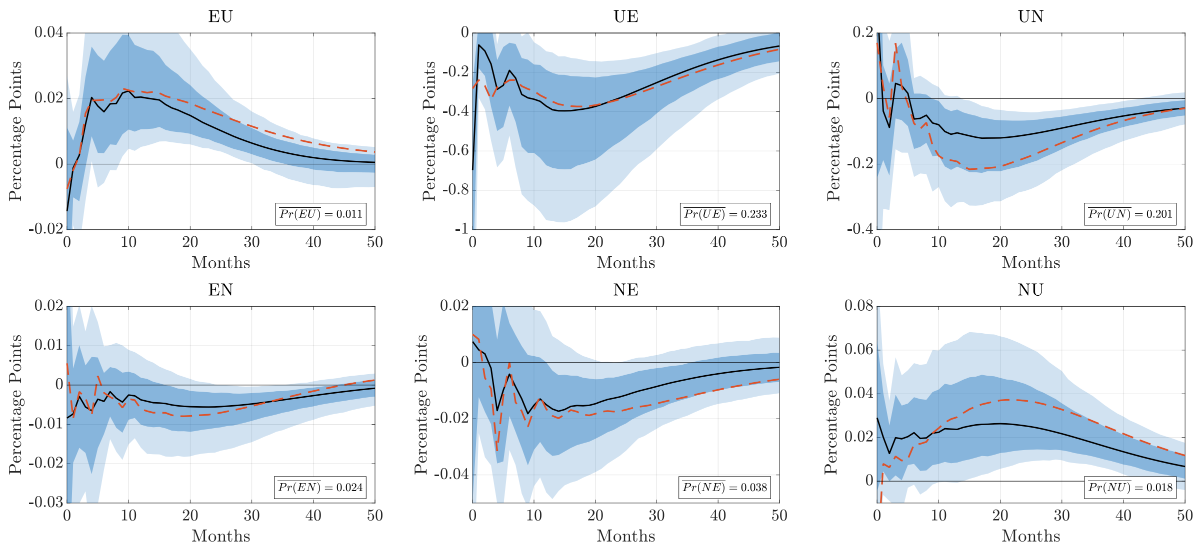
Note: Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Real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

C.4. **Composition.** In this section, we discuss further results when using composition-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).

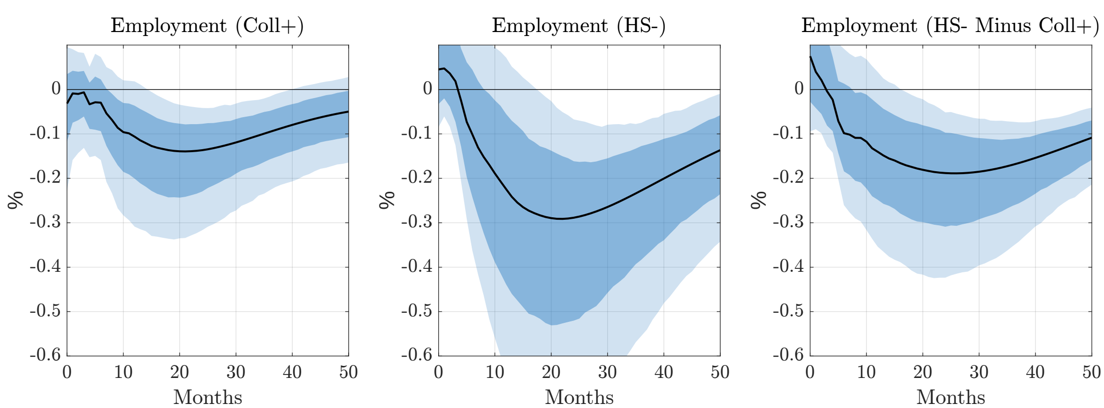
FIGURE C.9. Response of Composition-Adjusted Flows: Full EHS Controls



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.

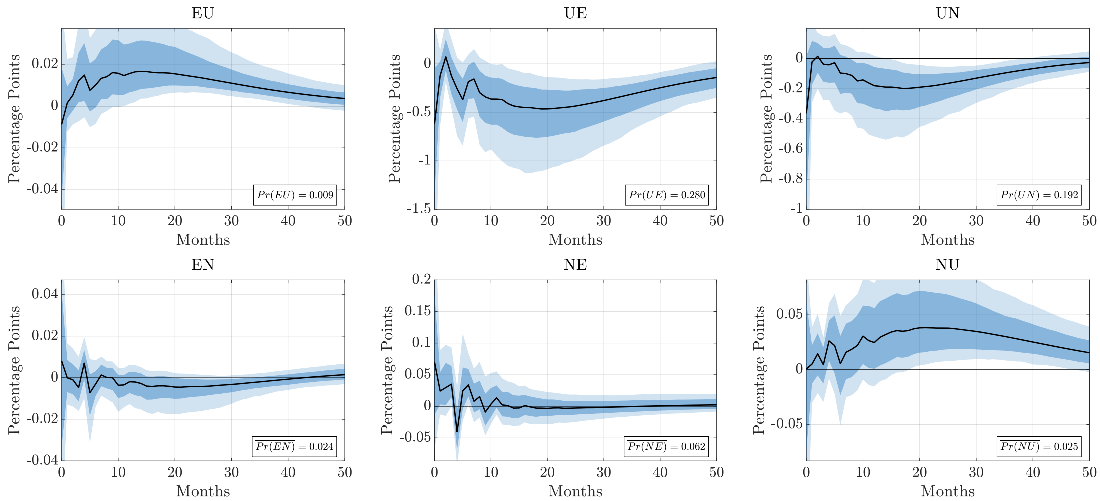
C.5. **Heterogeneity.** Here, we show additional results from Section 4.2. In Figure C.10, we again show the impulse response of employment for higher– and lower-educated workers, but we also show that the greater percentage decline in employment for lower-educated workers is significantly significant.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



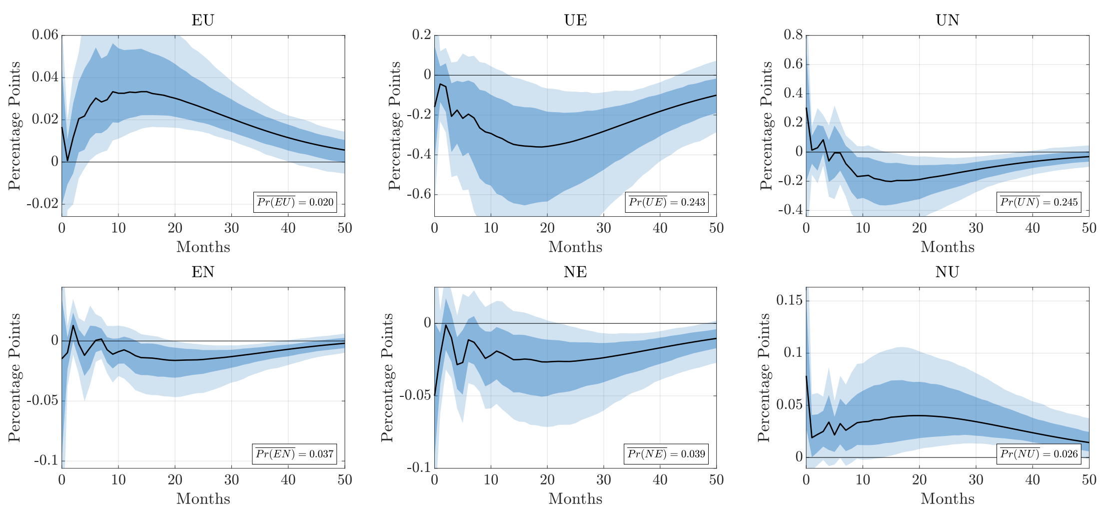
Note: Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals.

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



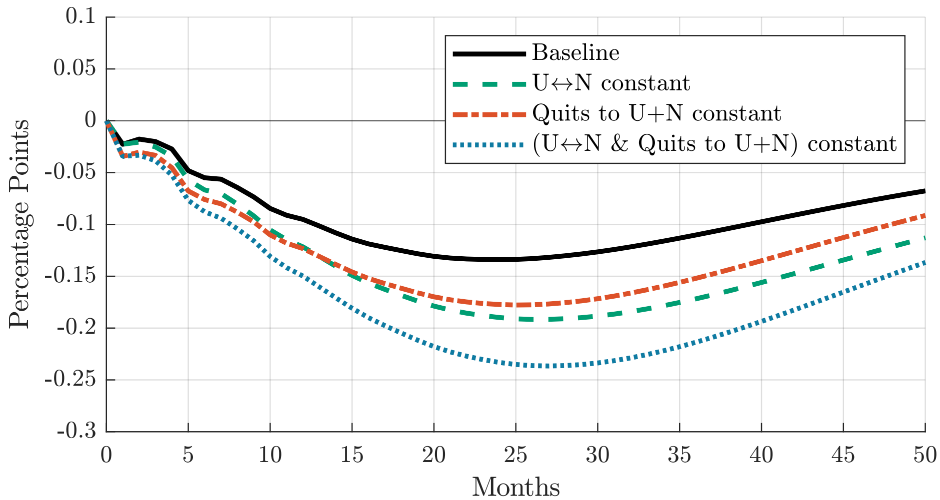
Note: Estimated impulse responses to a 25bp monetary policy tightening shock, computed by appending the given variable to the baseline VAR from Figure 1. Solid black lines report impulse response functions while dark and light shaded regions report bootstrapped 68% and 90% confidence intervals. Inset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



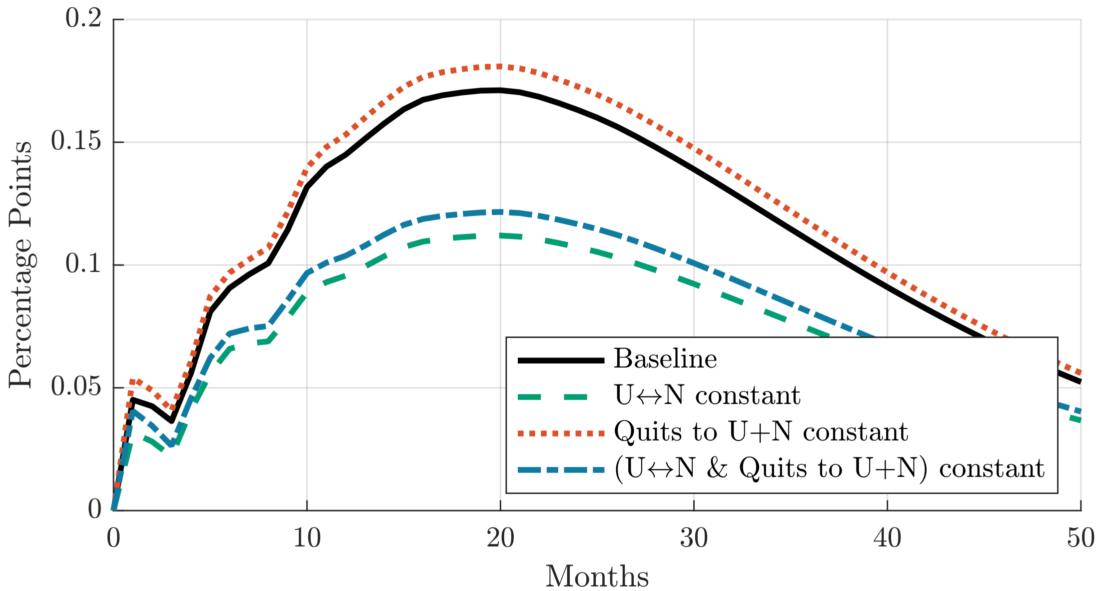
Note: The black solid line shows the overall response of the employment-population ratio to a contractionary monetary policy shock. The green dashed line shows the response if both UN and NU rates are held constant. The red dot-dashed line shows the response if quits to U or N are held constant. The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

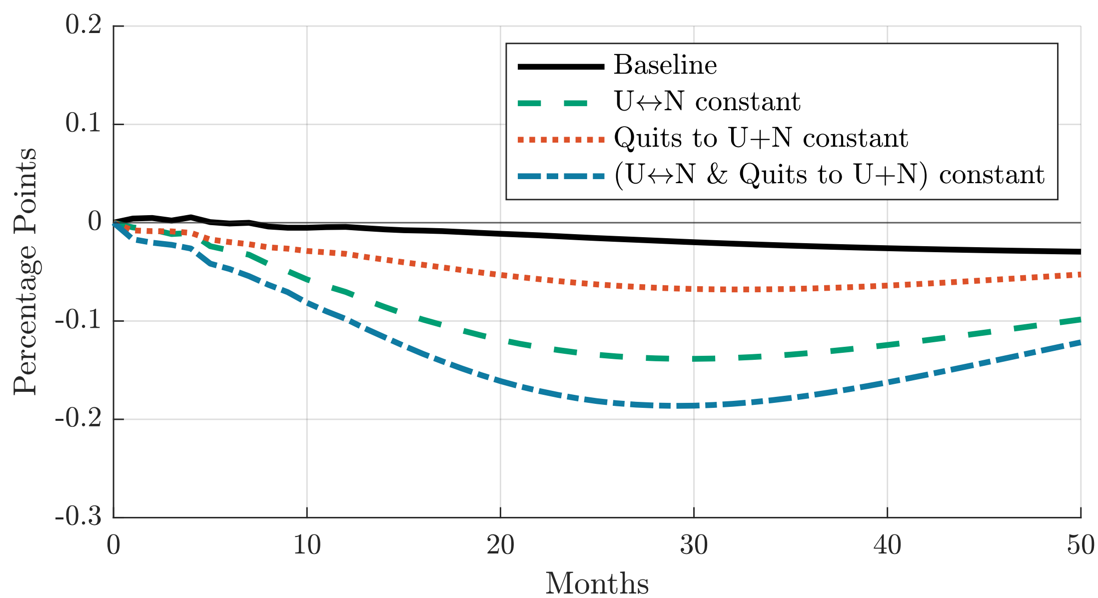
C.6.2. *Unemployment and Participation.* Here, we show the results of applying the accounting methodology discussed in Section 5 to unemployment and participation. We see to broad takeaways: first, quits are more important for shaping the response of employment than of unemployment or participation.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

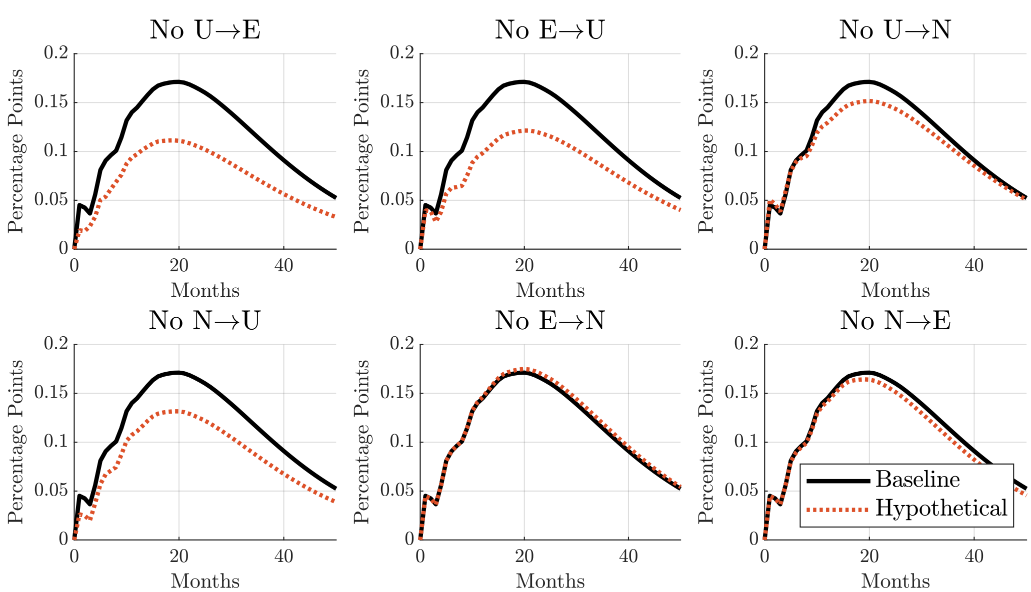


Note: The black solid line shows the overall response of the participation rate to a contractionary monetary policy shock. The green dashed line shows the response if both UN and NU rates are held constant. The red dot-dashed line shows the response if quits to U or N are held constant. The blue dotted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

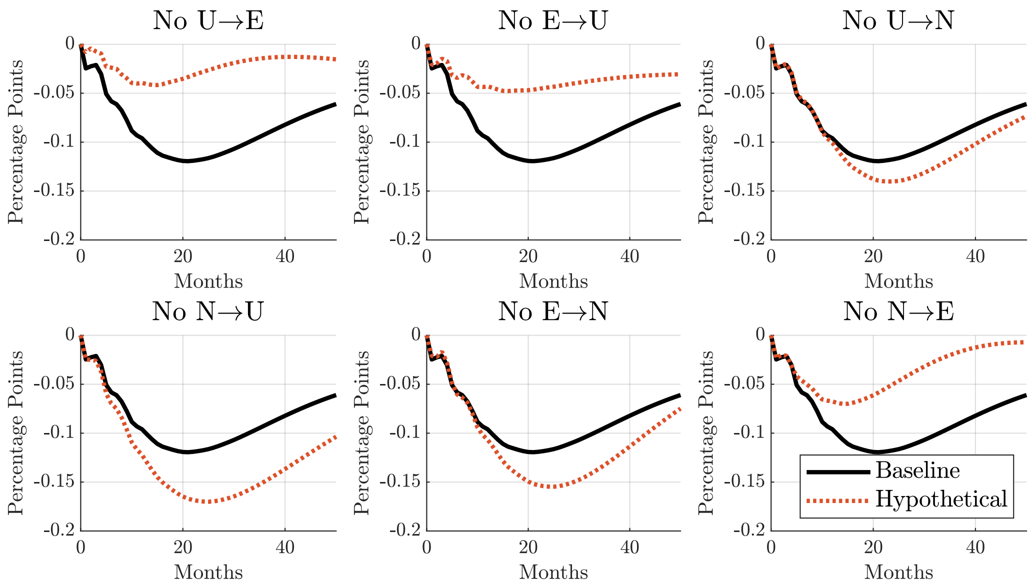
The hypothetical impulse response functions for the unemployment rate are plotted in Figure C.16. The solid black lines show the IRF for the unemployment rate estimated from our baseline VAR, while the dotted red line in each panel shows the hypothetical IRFs generated when we "turn off" the response 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



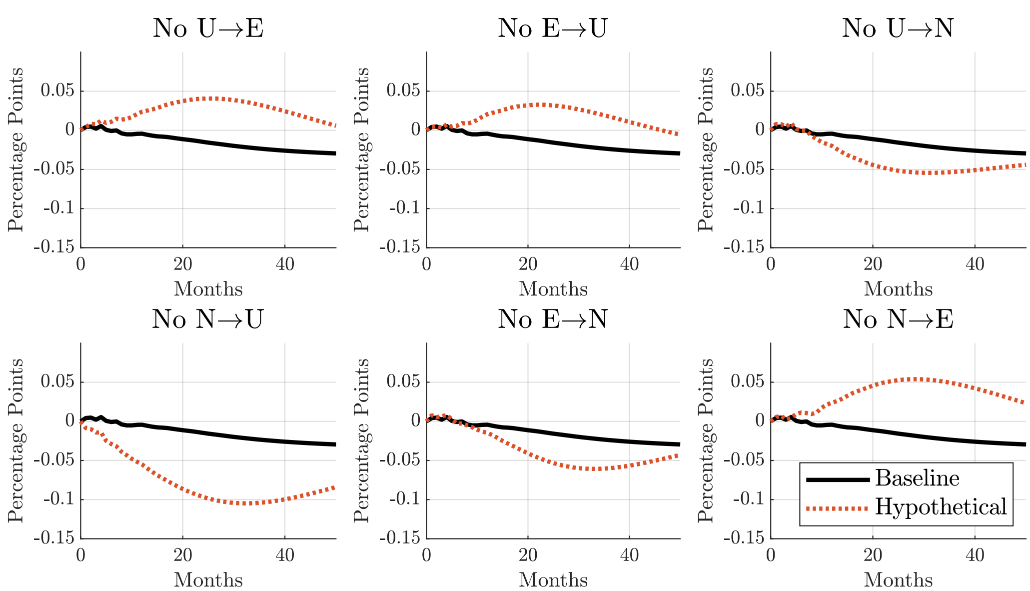
Note: The black solid line shows the overall response of the unemployment rate to a contractionary monetary policy shock. The red dotted lines show the response if the specified flow rate is held constant at its average level.

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:

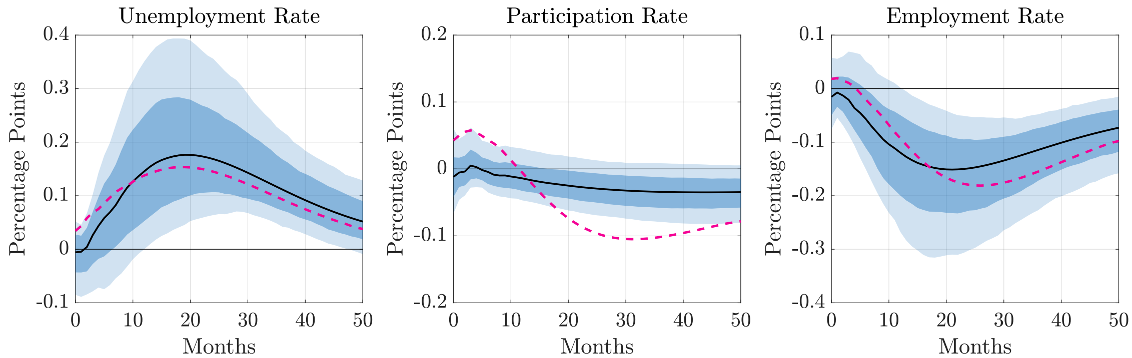
(1) All individuals draw a new value of productivity, z. Non-employed individuals draw an i.i.d. search cost, κ.
(2) Employed individuals make consumption/saving decisions and choose whether or not to quit their job. Non-employed individuals make consumption/saving decisions and choose whether or not to search for a job.
(3) Employed individuals who do not quit are exogenously laid off with probability δ. Non-employed individuals receive job offers with probabilities f_s of 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 δ_{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, ϵ_Q from a logistic distribution. They then make their quit decision taking into account this taste shifter in their binary choice:

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

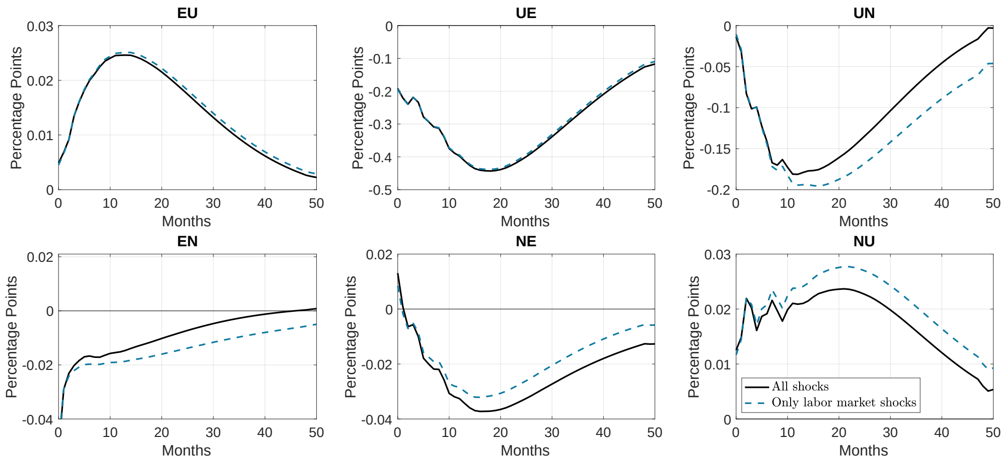
The scale of these shocks is calibrated to be as small as possible. We assume that these taste shocks are drawn from a logistic distribution with mean 0 and scale 0.005. (This scale parameter is nearly two orders of magnitude smaller than that which we estimate for the stochastic search cost, κ.) The 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

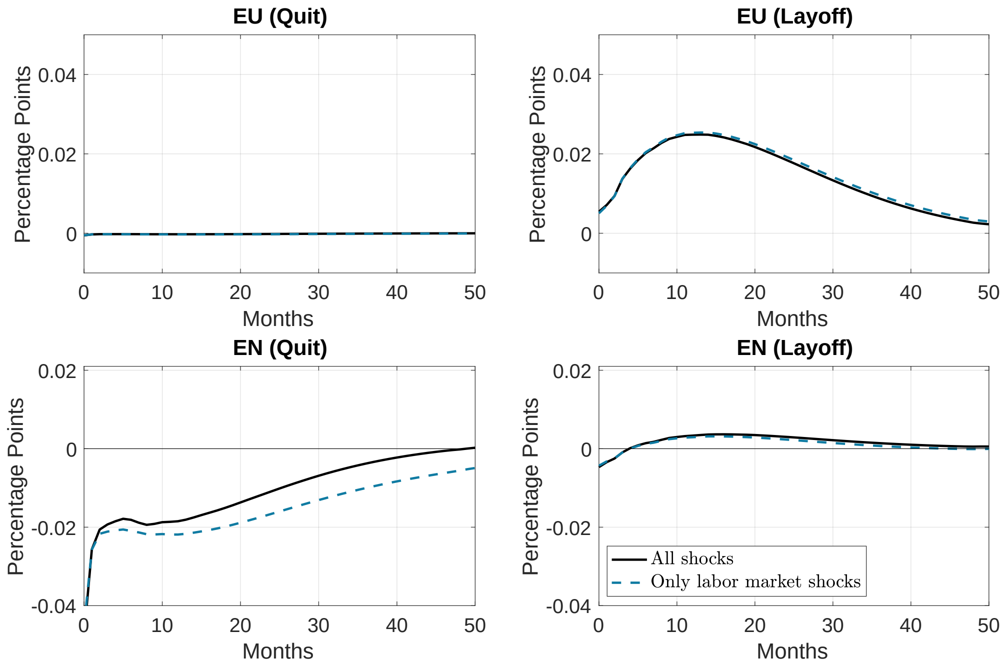


Note: The black solid line shows the response of each flow feeding in the responses of job-finding and layoff rates, real interest rates, and real wages following a contractionary monetary policy shock in the estimated model. The blue dotted line shows the responses of each flow feeding in only the responses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