Gross Worker Flows, Job Loss,
and Monetary Policy

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Abstract

This paper examines how monetary policy shocks in the U.S. affect the flows of workers among three labor market categories—employment, unemployment, and nonparticipation—and assesses each flow’s relative importance to changes in labor market “stock” variables like the unemployment rate. The full stock-flow accounting reveals that job loss is the largest driver of monetary policy’s effects on the labor market and that these fluctuations in job losses generate a composition effect in the stock of unemployed that plays a quantitatively important role in accounting for the dynamics of labor market variables after monetary policy shocks. I develop a New Keynesian model that incorporates these channels and show how a central bank can achieve welfare gains from targeting job loss, rather than output or unemployment, in an otherwise standard Taylor rule.

Keywords: Worker flows; monetary policy; unemployment; labor force participation.
JEL classifications: E24, E52, J6.

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1 Introduction

How does monetary policy affect the labor market? A common answer is that by directly changing interest rates, monetary policy changes the desired levels of consumption and investment and, consequently, affects output. Because short-run changes in production come primarily from changes in employment, monetary policy is ultimately able to influence the labor market. This is how the Federal Reserve describes monetary policy’s ability to influence the real economy, and much of the recent literature has focused on how monetary policy affects output and financial variables, rather than employment.

In this paper, I take a different approach to examining how monetary policy influences the labor market. Rather than focusing on output measures and arguing that employment tracks output, I study the effects of monetary policy on the full set of gross flows of workers into and out of employment, unemployment, and nonparticipation. This approach allows me to address questions such as: Does monetary policy affect the labor market by influencing job finding rates? Does it affect job loss probabilities? Do participation decisions—workers’ choices to enter or leave the labor force altogether—drive monetary policy’s impact on labor markets? As I demonstrate in this paper, the answers to these questions matter for understanding both the limits to and efficacy of monetary policy’s ability to offset macroeconomic shocks.

I find that job loss—that is, workers moving from employment to unemployment—is the most important driver of the responses of employment, unemployment, and labor force participation after monetary policy shocks; job finding plays a secondary role. Moreover, ignoring the participation margin—as is common in the literature—hides quantitatively important labor force composition effects driven by job loss. To demonstrate this, I first give a detailed characterization of the effects of monetary policy shocks on the movement of workers among employment, unemployment, and nonparticipation. I then assess the relative importance of these flows in the transmission of monetary policy shocks to the following “stock” variables: the employment-to-population ratio (EP), unemployment rate (UR), and labor force participation rate (LFP). To do so, I examine the impulse responses of worker flows and exploit the fact that they sum up to the responses of the stock variables to construct decompositions of the stock responses into the underlying flow responses. I show that the

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2 The literature quantifying the effects of monetary policy shocks on output, prices, and financial variables is too long to review in detail. Lawrence J. Christiano, Martin Eichenbaum and Charles Evans (1999) provide an overview of the early literature. Valerie A. Ramey (2016) provides a review of more recent developments.
flow of workers from employment to unemployment is the most important flow driving the responses of all three stock variables. Alternative decompositions (for example, into groups of flows) point toward the same result: job loss drives the labor market response to monetary policy shocks.

Throughout the paper, I focus on three mutually exclusive labor market states as defined by the Current Population Survey (CPS)—employment ($E$), unemployment ($U$), and nonparticipation ($N$)—and the flows of workers across these three states. To be specific, a worker who is employed one month and unemployed the next would constitute an $EU$ flow, while a worker who is out of the labor force this month but unemployed next month would be an $NU$ flow; other flows are defined in the same way. As is evident in Figure 1, substantial “churning” underlies the more familiar labor market stock measures. Although their dynamics are substantially more complicated, the flows uniquely pin down the stock variables and not vice versa; it is this appealing characteristic of the flows that I exploit in my analysis. The first contribution of this paper, therefore, is to quantify the effects of monetary policy shocks on the movement of workers between employment, unemployment, and nonparticipation.

I find that the pattern of the responses of gross worker flows to contractionary monetary policy shocks is distinctive, and qualitatively similar to the pattern observed during most recessions (see Figure 1). In particular, the $EU$ flow rises rapidly but the response is relative short-lived; the $UE$ and $UN$ flows decline much more slowly and stay lower for four years; and $EN$ and $NE$ decline modestly while $NU$ rises. As discussed above, because fluctuations in the gross flows uniquely pin down changes in the stock measures, it is relatively straightforward to assess flows’ relative contributions to stock variable fluctuations. I find that the decline in EP and LFP and the increase in UR after a contractionary shock are primarily accounted for by the $EU$ flow and to a lesser extent by the $UE$ and $UN$ flows. Half of the magnitude of the peak responses of the stock variables is accounted for by the $EU$ flow alone.

Motivated by these empirical results, I develop a model that embeds a Diamond-Mortensen-Pissarides (DMP) labor market in a New Keynesian sticky-price framework in which worker flows are well defined. The model includes endogenous job separations and labor force participation decisions. Workers differ in their degree of labor force attachment—that is, their propensity to exit the labor force. I show that this specific type of heterogeneity is necessary for the model to match the empirical flow responses. I verify that this type of heterogeneity
Figure 1: Labor Market Stocks and Flows, 1967–2017

Employment-to-Population Ratio (EP), Unemployment Rate (UR), and Labor Force Participation Rate (LFP)

Stock (upper panel, monthly) and flow (lower panel, quarterly averages) measures, June 1967 to June 2017. Vertical axes indicate minimum, mean, and maximum values of these variables over the sample period. Red lines are measured on the right axis, while black and bold black lines are measured on the left axis. Shaded dates are NBER recessions.

Stock (upper panel, monthly) and flow (lower panel, quarterly averages) measures, June 1967 to June 2017. Vertical axes indicate minimum, mean, and maximum values of these variables over the sample period. Red lines are measured on the right axis, while black and bold black lines are measured on the left axis. Shaded dates are NBER recessions.
is indeed present in the data.³ Job loss due to monetary policy shocks produces changes in the composition of workers who are unemployed—in particular, the composition shifts towards workers with higher attachment—and this composition effect is an important driver of not only the flow variables, but also the stock variables.⁴ The model is able to replicate qualitatively the responses of the labor market stocks and flows to monetary policy shocks that I estimate in the first part of the paper.

I then use the model to illustrate how a central bank that targets job loss in a simple Taylor-type rule is able to improve on welfare outcomes relative to either strict inflation targeting or a standard Taylor rule that targets both inflation and output or unemployment gaps. I find that the optimal simple Taylor-type rule targets inflation, the output gap, and the EU gap—that is the gap between EU flows and their efficient level. Moreover, the losses relative to this optimum from a simple rule that targets only the EU gap and inflation are negligible, while those from a rule that targets only the output gap and inflation, a commonly used Taylor rule in the literature, are significant.⁵ I compare this optimal simple rule to other proposed rules in similar models that do not include some of the key features necessary to match the conditional moments I identify in the empirical section of the paper. These rules, despite being optimal in similar models, deliver significantly worse outcomes than the optimal policy I derive.

More broadly, this paper contributes to at least three strands of the macroeconomic literature. The first is the literature on labor force flows. While previous papers, such as Robert Shimer (2012) and Michael W. L. Elsby, Bart Hobijn and Ayşegül Şahin (2015) have studied their unconditional moments, and Regis Barnichon and Christopher J. Nekara (2012) have explored their usefulness for forecasting labor market variables, the flows’ conditional moments have yet to be explored. This paper is the first to examine the conditional moments of the full set of gross worker flows.⁶ The methodology I introduce can easily be extended to

³Specifically, after a contractionary monetary policy shock, a larger share of the stock of unemployed is made up by workers with low dropout propensities conditional on observable characteristics such as age, gender, marital status, and reason for unemployment.

⁴Although worker heterogeneity has been cited elsewhere as a source of persistence and propagation of shocks in the DMP model (e.g., Federico Ravenna and Carl E. Walsh (2012)), this particular source of heterogeneity, described in detail in Section 4, is a novel one.

⁵David Berger, Ian Dew-Becker, Konstantin Milbrandt, Lawrence D.W. Schmidt and Yuta Takahashi (2016), using different data sources and a different model, argue that the Fed should target layoffs; my paper also shows that it indeed can affect layoffs.

⁶Claudio Michelacci and David Lopez-Salido (2007) and Fabio Canova, David Lopez-Salido and Claudio Michelacci (2007) consider the effect of technology shocks on job creation, destruction, finding, and separation, but because they do not estimate the effects on all the flows, they are not able to construct decompositions to assess the relative importance of each flow in the responses of other labor market variables.
study the effects on the labor market of other macroeconomic shocks; it can also provide a set of conditional moments that can be used to discipline a model in the spirit of Robert E. Lucas (1980) and Emi Nakamura and Jón Steinsson (2017).\footnote{Indeed, I use the empirical results on the effects of monetary policy shocks on worker flows for exactly this purpose.}

The second contribution is to the literature on the effects of monetary policy. To the extent that the empirical monetary policy literature has considered labor market effects directly, it has done so mostly by examining the responses of the stock measures only (EP, UR, and LFP). One notable exception is Helge Braun, Reinout De Bock and Riccardo DiCecio (2009), who examine the response to various shocks (including a monetary demand shock) of job separation and job finding rates; however, the exclusion of the participation margin from their analysis leads to qualitatively different results from those of this paper.

Finally, this paper contributes to the literature on optimal macroeconomic stabilization policy, specifically optimal monetary policy. The study of optimal policy in simple New Keynesian models like those described in Michael Woodford (2003) and Jordi Galí (2008) has evolved into finding optimal policy in settings with steady-state distortions along with various real and nominal frictions, as in Stephanie Schmitt-Grohé and Martin Uribe (2006) and 2007, or with a more realistic treatment of the labor market, such as in Ester Faia (2008), Jordi Galí (2011), and Federico Ravenna and Carl E. Walsh (2011). I find that simple rules that target the flow of workers from employment to unemployment improve welfare significantly relative to standard Taylor rules targeting output or unemployment gaps or strict inflation targeting.

The remainder of the paper is organized as follows. Section 2 describes the labor market flow data, from Shimer (2012) and Elsby, Hobijn and Şahin (2015), and monetary policy shock series from Christina D. Romer and David H. Romer (2004) I use throughout the paper. In this section I also discuss previous research that uses these detailed flow data series. Section 3 uses single-equation regressions and Romer and Romer’s (2004) shock series to estimate the effects of monetary policy shocks on worker transition probabilities and conducts decompositions to quantify the relative importance of each flow. Section 4 describes the model, and Section 5 discusses its implications for optimal policy. Section 6 concludes.
2 Data

This section describes the construction of gross worker flow series from the CPS, as well as the estimation of Romer and Romer’s (2004) monetary policy shock series. Alternative VAR-based shock identification strategies and the data used in these estimates are discussed in the appendix. The results are broadly consistent with the baseline estimates, which follow Romer and Romer (2004).

2.1 Measures of worker flows

The data on worker flows I use below are measures of transition probabilities based on monthly “gross flow” data from the CPS.\(^8\) Approximately three-quarters of households interviewed as part of the CPS in a given month are re-interviewed the next month, which allows individuals’ labor force states to be tracked, which in turn allows for the calculation of the total number of transitions among the three labor force states between months.

Examining these month-to-month counts directly, however, can potentially be misleading. If for example, someone is out of the labor force when interviewed in June, begins looking for work after being interviewed, and by the July interview has found a job, she would be counted as not in the labor force in June and employed in July, even though there was a period between the interview dates during which she would have been considered unemployed, as she did not have a job and was actively seeking one. Because the survey interviews occur at discrete dates, the unadjusted gross flow data in this case “miss” a transition, counting the flow pattern \(N\) to \(U\) to \(E\) as simply \(N\) to \(E\).

The data I use have been corrected for this time-aggregation problem following Shimer (2012), and therefore represent the probability of a transition from one state to another in a given month.\(^9\) In what follows, I use the quarterly average of the monthly transition flow probabilities from 1967:Q2 to 2007:Q3. I use these years primarily because Romer and Romer’s (2004) extended monetary shock series is available from 1969 to 2008, but also because the flow data for this period have been previously tabulated in a consistent manner by Shimer (2012). I use the quarterly averages because the flow data are noisy on a

\(^8\)The quarterly flow data I use in the empirical work below are freely available on Robert Shimer’s website, https://sites.google.com/site/robertshimer/research/flows. Data from January 1976 forward were constructed by Robert Shimer. For additional details, see Shimer (2012). Data from June 1967 to December 1975 were tabulated by Joe Ritter and made available by Hoyt Bleakley. Monthly flow data back to February 1990 are available from the Bureau of Labor Statistics (BLS) website, and back to June 1967 on Bart Hobijn’s website, http://www.barthobijn.net.

\(^9\)This adjustment from the monthly data as published by the BLS is discussed in detail in Appendix A.
month-to-month basis.\textsuperscript{10} Although not used in its entirety in the baseline estimates, I have constructed an extended series of the flow transition probabilities from 1967:Q2 to 2017:Q2, which is displayed in the bottom panel of Figure 1. The details of the construction of the data are discussed in Appendix A.

The obvious cyclical patterns in the flow data have been discussed at length elsewhere;\textsuperscript{11} nevertheless a few such patterns are worth emphasizing here. During recessions, there is typically a short-lived spike in $EU$ as workers are laid off, accompanied by relatively smaller declines in $EE$ and $EN$ as workers delay retirement or find periods of recession comparatively less attractive for non-market activities. Recessions also see a slow, hump-shaped decline in $UE$ and a symmetric increase in $UU$, as unemployed workers are less likely to transition to employment; $UN$ actually declines during a recession, despite the conventional wisdom that widespread discouragement of job seekers leads more of the unemployed to drop out of the labor force. As Elsby, Hobijn and Şahin (2015) point out, this is likely due to a compositional effect: as a recession progresses, a larger share of the pool of unemployed is made up by workers with greater labor-force attachment than in normal times, implying a lower overall $UN$ transition probability.\textsuperscript{12} In Section 3, I show this same composition effect occurs after a monetary policy shock. Along the participation margin, $NE$ declines and $NU$ increases during recessions, reflecting a relative increase in the probability of entering the labor force as unemployed conditional on a transition into the labor force.

2.2 Previous research on worker flows

Early research on worker flow data from the CPS focused on the technical problems involved in actually calculating the gross flows between labor force states. John M. Abowd and Arnold Zellner (1985) noticed substantial misreporting of labor force statuses in the CPS, leading to measured transitions that were not, in fact, occurring. They and James M. Poterba and Lawrence H. Summers (1986) proposed different correction methods for this problem; however, as noted in Shigeru Fujita and Gary Ramey (2009) and Elsby, Hobijn and Şahin (2015), although correcting for potential misclassification can affect the levels of the flows, it does not alter their fluctuations or relative contributions to stock variables.

\textsuperscript{10}In the appendix, I use a high-frequency identification strategy along with the monthly flow data to relax both these restrictions. The results are essentially unchanged from the baseline.

\textsuperscript{11}See, for example, Olivier J. Blanchard and Peter Diamond (1990), Shimer (2012), Elsby, Hobijn and Şahin (2015), and Per J. Krusell, Toshihiko Mukoyama, Richard Rogerson and Ayşegül Şahin (2016).

\textsuperscript{12}Note, however, that, despite the lower $UN$ transition probability, because the actual number of unemployed workers is larger during a recession, this pattern is still consistent with the declines in labor force participation that occur during recessions.
Olivier J. Blanchard and Peter Diamond (1989) and 1990 examine the trends and cyclicality of the gross flows among employment, unemployment, and nonparticipation. In their later paper, combining their analysis with other data on manufacturing employment, they characterize much of the cyclical patterns discussed above. They also find that lower employment during recessions is due more to high rates of job destruction than low rates of job creation, while “booms” are the result more of low rates of job destruction than high rates of job creation. The question of the relative importance of worker flows in the cyclicality of labor market variables was later debated with Robert E. Hall (2005a) and 2005b and Robert Shimer (2005b) and 2012 attributing nearly all of the rise of unemployment during downturns to declines in job finding, and Shigeru Fujita and Gary Ramey (2006), 2007, and 2009 attributing a much larger share of the rise in unemployment to the job separation margin. This strand of the literature has tended, however, to focus on two labor market states: employment and unemployment (or non-employment), abstracting from the participation margin. Elsby, Hobijn and Şahin (2015) decompose historical fluctuations in the unemployment rate into the component flows, and find that slightly more of the long-run variance in the unemployment rate is attributable to UE transitions than EU transitions; they also find that UN transitions are just as important as EU transitions. In contrast to these studies, I focus on conditional moments of worker flows.

Only recently have three-state models been developed explicitly to match the flows observed in the data. Per J. Krusell, Toshihiko Mukoyama, Richard Rogerson and Ayşegül Şahin (2011) are able to match the average long-run values of the flows in a steady-state equilibrium with persistent idiosyncratic shocks meant to represent events such as wage shocks or health shocks that generate long-time separation from or attachment to the labor force. In a later paper, Krusell et al. (2016) build a similar model that—via idiosyncratic productivity shocks, random job matchings and separations, indivisible labor, and incomplete markets—reproduces the cyclical patterns in the data noted above. The driver of the cycle in this model is a pattern of correlated aggregate shocks in partial equilibrium. In neither of these models, however, does monetary policy play any role.

Perhaps closest to this paper is Braun, De Bock and DiCecio (2009) who use a structural VAR to assess the impact on job finding and job separation rates of supply and demand shocks (including non-monetary and monetary demand shocks) identified via sign restrictions. Importantly, they do not consider the effects on labor force participation. Although measuring the complete response of worker flows to a monetary shock is not the aim of their paper, the absence of the labor force participation channel in their approach leads to
conclusions on the relative importance of job finding and job separations that differ from my results accounting for labor force participation. Specifically, they find that nearly all of the increase in unemployment following a contractionary monetary policy shock is due to the decline in the job finding rate,\(^\text{13}\) while I demonstrate that when one considers the full set of worker flows—including flows into and out of the labor force—jobs loss is a larger driver of employment and unemployment.

### 2.3 Monetary policy shocks

In Section 3, I use a measure of monetary policy shocks developed by Romer and Romer (2004) and extended through 2007 to estimate the response of worker flows. Romer and Romer (2004) identify monetary policy shocks as changes to the Federal Funds target rate that are not predictable by the economic information in the Federal Reserve’s “Greenbook” forecasts.\(^\text{14}\)

The focus on monetary policy shocks is motivated by three observations. First, as shown in Olivier Coibion (2012), monetary policy shocks can account for a fairly large share of the historical fluctuations in the unemployment rate. Second, the long and well-established literature on monetary policy shocks encompasses a variety of methods for identification and estimation, which makes it a natural candidate for providing a set of “identified moments” for distinguishing between different models as suggested by Nakamura and Steinsson (2017). Finally, and related to the previous point, although empirical methods can be used to estimate the effects of *exogenous* changes in monetary policy, they cannot be used to directly estimate the responses of macroeconomic variables to *systematic* monetary policy changes; for that, a model is required. The implications of a model, such as optimal policy rules, might reasonably be thought to be more valid if that model is able to replicate the moments of interest that can be identified empirically. As Lucas (1980) put it, “The more dimensions on which the model mimics the answers actual economies give to simple questions, the more we trust its answers to harder questions.”

\(^{13}\) Although they find that job separation rates contribute almost one-half of the impact effect of the shock on unemployment, the impact effect on unemployment is small and the relative contribution of job separations quickly dies out. I find that the increase in job separations alone, once one accounts for the participation margin, also results in a persistent, hump-shaped response of unemployment.

\(^{14}\) The exact identification strategy is discussed in the appendix. I also discuss alternative methods of shock identification.
3 Single-equation regressions

This section uses a flexible single-equation specification, making use of the shock series constructed by Romer and Romer (2004) extended through 2007, discussed in Section 2.3, to quantify the effects of monetary policy shocks on worker flows. The specification below regresses the period-$t$ value of the variable of interest on its own lags as well as lags of the monetary policy shock. It is identical to that used in Romer and Romer’s (2004) estimation of the effect of a monetary policy shock on industrial production. If $y_t$ denotes the dependent variable in time $t$, the equation to be estimated is

$$\Delta y_t = c + \sum_{j=1}^{J} \beta_j \Delta y_{t-j} + \sum_{i=1}^{I} \gamma_i \hat{s}_{t-i} + \epsilon_t,$$  \hspace{1cm} (1)

where $\hat{s}_t$ is the value of Romer and Romer’s (2004) monetary policy shock series in time $t$. The number of lags of the dependent variable and the shock in the estimation below are, respectively, $J = 8$ and $I = 12$. The sample period is 1969Q1 through 2007Q3.\footnote{These lag lengths are the quarterly equivalents of those in Romer and Romer’s (2004) original estimation. The choice of sample period is dictated in part by the feasibility of the Romer and Romer (2004) shock estimation, which is not amenable to the ZLB period. In the appendix, I use high-frequency shock identification methods to include portions of the ZLB period. The results are essentially unchanged.} As I show in the appendix, the results from estimating the impulse responses using Óscar Jordà’s (2005) method of local projections are essentially identical.

Equation 1 is estimated independently for each variable of interest by ordinary least squares (OLS). The objects of interest are again impulse response functions. The cumulative response of the dependent variable one month after the shock is $\gamma_1$; two months after the shock it is $\gamma_1 + \gamma_2 + \beta_1 \gamma_1$, and so on. Standard errors for the impulse responses can be constructed by drawing repeatedly from the asymptotic distribution of the coefficients estimated by OLS, computing the impulse responses for each draw, and taking the standard deviation of these simulated responses at each horizon.\footnote{Because the error bands of impulse responses implicitly test whether the response is different from zero, as discussed in Adrian Pagan (1984), the standard errors remain valid despite the presence of a generated regressor.}

I estimate two sets of impulse responses: one for the stock variables and one for the flow transition probabilities. The stock variables I use are the employment-to-population ratio (EP), the unemployment rate (UR), and the labor force participation rate (LFP); the flow variables are the six off-diagonal transition probabilities.\footnote{The diagonal transitions (i.e., $EE$, $UU$, and $NN$) are constructed as residuals from the other flows, so estimating them in addition is redundant.}
3.1 Results

The impulse response functions of the stock variables are displayed in the top row of Figure 2. EP and LFP fall, while UR increases, all with hump-shaped responses that peak about two years after the shock; EP and UR recover fully five years after the shock. The shock has a peak effect on EP and UR of more than six-tenths of a percentage point; LFP falls by only slightly more than 0.15 percentage point, but remains at that level throughout the five-year IRF horizon. Using their average values over the time period considered, this corresponds to a decline in EP from 60.4 to 58.8 percent, an increase in UR from 6.0 to 6.6 percent, and a decline in LFP from 65.0 to 64.9 percent. The responses of EP and UR are fairly large, while that of LFP is little more than rounding error.\textsuperscript{18} As shown in Section 3.2, however, the almost negligible response of labor force participation does \textit{not} imply that the participation channel can be innocuously ignored in the understanding of monetary policy’s effects on the labor market.

The responses of the transition probabilities from the flow regressions are shown in the bottom two rows of Figure 2. Most noteworthy and statistically significant are the rapid increase in \textit{EU} and subsequent steady decline, and the slow, hump-shaped declines of \textit{UE} and \textit{UN}. Qualitatively, these responses are similar to the typical cyclical pattern noted in Section 2.1 and displayed in Figure 1. Also similar to the typical cyclical pattern of the flow rates are the responses of \textit{EN} and \textit{NE}, both of which decline slightly, while \textit{NU} increases; the responses of these three flows are at most only modestly significant.\textsuperscript{19} The response of the \textit{UN} flow is worth discussing more, as it motivates portions of the structure of the model presented in Section 4. As mentioned above, Elsby, Hobijn and Şahin (2015) argue that the \textit{unconditional} cyclical pattern in \textit{UN} is caused by larger numbers of workers with high labor force attachment being driven into unemployment during recessions. Indeed, a similar phenomenon occurs \textit{conditional} on a monetary policy shock. To assess this composition effect, I estimate impulse responses of the shares of unemployment made up by different groups of workers—specifically, for groups that have high labor force participation rates and low average \textit{UN} transition rates over the entire sample period. The groups I consider are prime-age workers (ages 25-54), married workers, those seeking full-time employment, and job losers, i.e., those who report being unemployed because they lost an existing job.


\textsuperscript{19}Responses of similar shape and magnitude are obtained using Romer and Romer’s (2004) shock series and Jordà’s (2005) local projection method of estimating impulse responses, described in the appendix.
Figure 2: Impulse Responses of Stocks and Flows to a Monetary Policy Shock

Impulse responses of stock (top row) and flow (bottom two rows) variables to a 100 b.p. contractionary Romer and Romer (2004) monetary policy shock, 1969Q1–2007Q3. Autoregressive Distributed Lag (ADL) model (Equation 1). Shaded areas are one standard deviation intervals from a bootstrap.
Figure 3 displays the impulse responses of the share of unemployment made up by these groups, estimated from (1). After a contractionary shock, these workers make up a larger share of the unemployed, with most groups’ response peaking at 1 percentage point. The share of unemployed made up by job losers increases by almost 2.5 percentage points. The average $UN$ rate of job losers over this period is 13.3 percent, compared to 27.0 percent for all unemployed workers. A back-of-the-envelope calculation suggests that the composition effect of the 2.4 percentage-point increase in job losers alone can account for two-thirds of the decline in $UN$. After a contractionary shock, the pool of unemployed shifts in composition towards workers with a lower propensity to exit the labor force, thereby driving the $UN$ flow rate down.

Because of the difficulty in interpreting the importance of the impulse responses of the flow variables, in the next section I construct decompositions of the stock impulse responses into the underlying flows.

3.2 Decompositions

The quantitative importance of the effects of a monetary shock on flow variables is unclear from the impulse responses of the transition probabilities alone. The peak response of $EU$ is an increase of 0.1 percentage point, which is approximately a 4% increase relative to its average value over the sample period. Similarly, the peak declines of $UE$ and $UN$ are also around 3-4% of their average values. To assess the impact of a monetary shock on these flows in terms of more familiar variables, one can exploit the fact that the flows sum to the stocks to calculate the stock impulse responses that would occur if only specific flows responded to the shock.

I do this in a manner similar to Shimer’s (2012) assessment of the historical contribution of each flow probability to the unemployment rate. Specifically, I shut down the effect of the shock on particular flows by fixing them at their average values throughout the horizon of the impulse response. Other flows move according to the responses estimated from (1). I then re-calculate the implied stock responses from this new pattern of flow responses with one or more flows fixed at their average values. These counterfactual responses answer the question, “What would the stock impulse response look like if only certain flows responded

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20 This calculation considers the 2.4 percentage-point increase in job losers as a share of the unemployed and applies the average $UN$ transitions over the full time sample. Ideally, one would estimate the transition rates for each group directly; unfortunately, small sample sizes prevents doing this at monthly or quarterly frequencies (the full set of flows for all workers, even before examining different groups, shrinks the sample sizes to one-twelfth of the full CPS sample).
Impulse responses of the *share* of unemployed workers made up by various groups to a 100 b.p. contractionary Romer and Romer (2004) monetary policy shock, 1969Q1–2007Q3. Autoregressive Distributed Lag (ADL) model (Equation 1). Shaded areas are one standard deviation intervals from a bootstrap.
The first set of decompositions I consider looks at the contribution of each flow individually to the responses of the three stock variables. The results are presented in Table 1. Each row within a panel of the table displays, at yearly horizons, the value of the impulse response of the stock variable if only the indicated flow responded to the shock. The final column visually depicts the same information across all horizons. Within each panel, each column sums to the total response of the stock variable at that horizon. The importance of the $EU$ flow is immediately evident. It contributes the most to the decline in EP for nearly the entire horizon; the most to the increase in UR for the first two years, after which it contributes almost equally to $UE$; and the most to the decline in LFP two to four years out. The $UE$ flow contributes to the responses of these variables for only the later periods of the IRFs. The decomposition of stock variables into the individual flows demonstrates that the $EU$ flow is the most important driver of labor market variables’ responses to monetary policy.

It should also be noted that the offsetting forces of the many of the flows are evident in the decomposition of EP and, especially, LFP. As discussed in Section 3, the small response of LFP to a monetary policy shock masks the importance of participation; the flat response of the stock is the outcome of large, but offsetting flow responses.

Other decompositions can also be considered. The top and bottom panels of Figure 4 display the decomposition of stock variables into, respectively, inflows and outflows. Similar to Table 1, the red counterfactual IRFs in each column sum to the total response (in black). As above, these counterfactuals also depict the response of stock variables if only these flows responded to the shock. Inflows into unemployment ($EU + NU$) account for about half the decline in EP (more at early horizons, less at later) and nearly all of the increase in UR, while inflows to employment contribute roughly equally to EP and nothing to UR. Outflows from employment ($EU + EN$) account for most of the decline in EP and more than half of the increase in UR; outflows from unemployment produce very little change in any stock variable. In these alternative decompositions, it is inflows to unemployment and outflows...
Table 1: Contribution of Individual Flows to Stock Impulse Responses

<table>
<thead>
<tr>
<th>Stock</th>
<th>Flow</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<td>EP ratio</td>
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<td>-0.30</td>
<td>-0.29</td>
<td>-0.17</td>
<td>-0.12</td>
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<td></td>
<td>EN</td>
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<td>-0.07</td>
<td>-0.02</td>
<td>0.03</td>
<td>0.04</td>
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<tr>
<td></td>
<td>UE</td>
<td>-0.03</td>
<td>-0.15</td>
<td>-0.23</td>
<td>-0.17</td>
<td>-0.11</td>
<td></td>
</tr>
<tr>
<td></td>
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<td>0.01</td>
<td>0.07</td>
<td>0.09</td>
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</tr>
<tr>
<td></td>
<td>NE</td>
<td>-0.01</td>
<td>-0.08</td>
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<td>-0.12</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>+ NU</td>
<td></td>
<td>0.02</td>
<td>0.07</td>
<td>0.13</td>
<td>0.12</td>
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<tr>
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<tr>
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<tr>
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<td>-0.07</td>
<td>-0.02</td>
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<td>0.04</td>
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<tr>
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<tr>
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<td>0.11</td>
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<tr>
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<td>-0.12</td>
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</tr>
<tr>
<td>+ NU</td>
<td></td>
<td>0.06</td>
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<td>0.20</td>
<td>0.13</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
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<td>-0.11</td>
<td>-0.14</td>
<td>-0.15</td>
<td>-0.15</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Bold numbers indicate largest contributions, red numbers indicate gross contribution in the opposite direction of stock IRF. Rows in each columns sum to totals. Rightmost column depicts the full counterfactual impulse response. See Section 3.2 for details.
from employment that drive most of the response of labor market variables to monetary policy shocks. These “grouped” decompositions are both consistent with job loss being the primary driver of these responses.\footnote{In the last columns, the offsetting contributions of flows to the response of LFP is again evident.}

Figure 5 shows the contribution of flows into and out of the labor force. While the majority of the response of EP is accounted for by $EU$ and $UE$ flows, participation decisions play a larger role in the response of UR, accounting for about one third of its increase in response to contractionary monetary policy shocks. The two groups of flows have partially offsetting effects on LFP.

The last decomposition I consider divides the flows into two groups: the first group, $EU + EN + UN$, are labeled “separation”; the second, $UE + NE + NU$, are labeled “finding.” This division is motivated by the results from Section 3 that the response of $UN$ is largely driven by a compositional change in the pool of unemployed workers driven by job loss. I therefore group it with separations from employment. I group $NE$ and $NU$ with $UE$ because their responses measure the rate of transitioning to employment conditional on entering the labor force. The results are displayed in Figure 6. The “separations” group accounts for most of the decline in EP and half the increase in UR. “Finding” only contributes to the EP decline at the end of the response. As with the other decompositions considered above, these two groups have partially offsetting effects on LFP.

The decompositions considered in this section point to three conclusions. First, job loss—regardless of whether one considers the $EU$ flow alone, inflows into unemployment, outflows from employment, or $EU$, $EN$, and $UN$ all together—is the most important driver of the labor market’s response to monetary policy. Second, flows into and out of the labor force account for roughly one third of the response of UR to monetary policy shocks. And, finally, flows tend to have partially offsetting effects on LFP; a focus on the stock variable alone masks large responses in the underlying flows, indicating that monetary policy shocks can have large effects on participation decisions despite its modest impact on overall LFP.

The first result—that job loss drives the labor market’s response to monetary policy shocks—is particularly striking considering the importance of the job finding rate in accounting for unconditional labor market moments.\footnote{For discussions on the importance of the job finding channel, see, for example, Hall (2005a), Hall (2005b), Shimer (2005b), and Shimer (2012).} My results are not necessarily in conflict with that literature, however, as I focus on conditional moments. The results that flows into and out of the labor force contribute to about one third of the increase in UR after a contractionary monetary policy shock and that flows have offsetting effects on LFP are, however,
Figure 4: Contribution of Inflows and Outflows to Stock Impulse Responses

Contribution of inflows (upper panel) and outflows (lower panel) to stock variable responses to a 100 b.p. Romer and Romer (2004) monetary policy shock. In each row, red lines are counterfactual responses in which only those flows are responding. Within each panel, the red lines in each column sum to the black lines (baseline stock IRFs). See Section 3.2 for details.
Figure 5: Contributions of Participation Flows to Stock Impulse Responses

Actual and counterfactual IRFs. Upper panel: Only flows between E and U ($EU + UE$) respond. Lower panel: Only direct participations flows ($EN + UN + NE + NU$) respond. Shaded areas are one standard deviation bootstrap intervals. (Equation 1).

Figure 6: Contribution of Job Separation and Job Finding to Stock Impulse Responses

Actual and counterfactual IRFs. Upper panel: Only job separation ($EU + EN + UN$) responds. Lower panel: Only job finding ($UE + NE + NU$) responds. Shaded areas are one standard deviation bootstrap intervals. (Equation 1).
in line with the unconditional decompositions described in Elsby, Hobijn and Şahin (2015).

The results from this section motivate the construction of a model that can accurately replicate these conditional moments in order to conduct policy experiments. The structure of the model I describe below is informed by the results on the importance of job loss, participation decisions, and composition effects in accounting for both the stock and flow responses to monetary policy shocks. The model I build therefore includes a search model of the labor market with endogenous separations, labor supply decisions that include a nontrivial role for nonparticipation, heterogeneity in labor force attachment, and a role for monetary policy to affect the real economy. The next section describes this model in detail and discusses its policy implications.

4 Model

The model consists of a representative household made up of two types of workers indexed by \( i \in \{ h, \ell \} \) and representative firms. Ex ante, the two types of workers differ only according to their participation in the labor market. Workers of each type are subject to search frictions and idiosyncratic productivity shocks. “Wholesale” firms produce using labor of each type and sell their output in competitive product markets to monopolistically competitive “retail” firms that are subject to price stickiness.

4.1 Households

The setup of the household sector follows Monika Merz’s (1995) “large family” construct, in which workers are able to perfectly insure their consumption against idiosyncratic shocks. The household receives utility from an aggregate consumption good \( C_t \) and leisure from nonparticipants. Each worker is either employed \( (E) \), unemployed and searching for work \( (U) \) or not in the labor force \( (N) \). Each period, each non-employed worker of type \( i \) draws a nonparticipation utility \( x_t \) from a distribution with c.d.f. \( G^i(x) \). The household receives wages from employed workers, which depends on workers’ match-specific productivity drawn from \( F^i(a) \) when employed, and an unemployment benefit from unemployed workers, and trades in risk-free nominal bonds. Both productivity and nonparticipation utility shocks are assumed to be serially uncorrelated.

The household solves the following problem:
\[
\max_{C_t, B_t, x^*_t} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ u(C_t) - \sum_i \gamma^i \left[ \chi E^i_t - (1 - E^i_t) \int_{x^*_t}^{\infty} v(\chi) \, dG^i(\chi) \right] \right\} \\
\text{s.t. } P_t C_t + Q_t B_t = D_t + B_{t-1} + P_t T_t,
\]

and the laws of motion of the labor market, described below, where \( \gamma^i \) is the measure of type \( i \) workers, \( B_t \) is the risk-free nominal bond with price \( Q_t \) equal to the inverse of the gross nominal interest rate, \( T_t \) are transfers, including lump-sum taxes and firm profits, and \( P_t \) is the aggregate price level. \(^{24}\) Consumption \( C_t \) is a Dixit-Stiglitz aggregate across retail goods. Importantly, \( x^*_t \) is the reservation utility for workers of type \( i \), the utility above which they do not participate in the labor market. \( D_t \) is total labor market income given by

\[
D_t = P_t \sum_i \gamma^i \left[ b U^i_t + \frac{E^i_t}{1 - F^i(a^*_i)} \int_{a^*_i}^{\infty} w^i_t(\alpha) \, dF^i(\alpha) \right],
\]

where \( b \) is the (real) unemployment benefit, which is assumed to be independent of worker type, \( w^i_t(\alpha) \) is the wage function of type-\( i \) workers with match-specific productivity \( a_t \), and \( a^*_i \) is the threshold productivity level, below which employed workers separate endogenously from their matches. \(^{25}\)

### 4.2 Labor market

The labor market is characterized by DMP-style search frictions. At the start of any period workers are subject to idiosyncratic separation and utility shocks; at the end of any period, a worker is in one of three states: employment, unemployment, and nonparticipation.

At the start of period \( t \), unemployed workers are matched with firms according to an aggregate matching function \( m(U^i_{t-1}, V^i_{t-1}) \), which matches unemployed workers to vacant firms. \(^{26}\) After these matches occur, all matched workers of type \( i \)—including both these newly matched workers and workers employed from the previous period—separate with exogenous

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\(^{24}\)Note that utility to the household from nonparticipation is simply a transformed equation for the expected value of the utility draw conditional on its being above the threshold \( x^*_t \) times the number of nonparticipants.

\(^{25}\)As will be seen below, because of Nash-bargained wages, this threshold will be the value such that the total match surplus is zero.

\(^{26}\)The timing assumption implies that searching workers and firms are only matched and able to produce in the period after they begin their search. The timing convention follows Michael U. Krause and Thomas A. Lubik (2010), who study parameter regions for determinacy in this class of models.
probability $\delta^i$. Those who survive this separation draw a new idiosyncratic productivity from $F^i(a)$ and they separate endogenously if this draw is sufficiently low. The law of motion for employment of type-$i$ workers can, therefore, be written as

$$E^i_t = (1 - \delta^i)(1 - F^i(a^i_{t+1}))(E^i_{t-1} + f^i_{t-1}U^i_{t-1})$$

where $f^i_t \equiv f(\theta^i_t)$ is the probability a type-$i$ unemployed worker is matched with a vacant firm, which is a function of $\theta^i_t \equiv \frac{V^i_t}{U^i_t}$.

After exogenous and endogenous separations occur, all unmatched workers draw non-participation utilities from c.d.f. $G^i(x)$. Workers who get a sufficiently high draw exit (or remain out of) the labor force, and the household gets their utility realization but forgoes the opportunity of forming a match next period. Workers who draw a low non-participation utility become (or remain) unemployed, and the household forgoes their utility draw, obtains the unemployment benefit $b$, and has the opportunity to be matched next period. Unemployment and nonparticipation in period $t$ are, therefore, given by

$$U^i_t = G^i(x^i_t)(1 - E^i_t),$$
$$N^i_t = (1 - G^i(x^i_t))(1 - E^i_t).$$

The model uniquely pins down all the flows described in Section 2 with the exception of $NE$. All flows vary endogenously via the matching function and endogenous thresholds $a^i_t$ and $x^i_t$.

### 4.3 Firms

Firms are owned by the household. The wholesale firm produces using only labor, which is assumed to be perfectly substitutable across types. It hires labor by posting vacancies for each type of labor ($V^i_t$) in separate matching markets. Wholesale output is linear in labor, and the firm sells its output to retail firms at relative price $\frac{P^w}{P^r}$. Let $\mu_t \equiv \frac{P^w}{P^r}$ denote the retail markup over wholesale prices. Firms maximize profits discounted by the household’s stochastic discount factor.

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27 As discussed above, although in reality a very large number of workers enter employment directly from nonparticipation, this flow is of minor importance in the transmission of monetary policy shocks. Therefore, the model presented here abstracts from this mechanism.

28 Perfect substitutability and linear production assures that the “one firm, many workers” assumption made here is identical to a “one firm, one worker” assumption.
The wholesale firm’s time-
t problem can be written as
\[
\max_{V_t} \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j \sum_i \left[ E_t^i \left( \frac{\tilde{A}_t^i Z_t^i}{\mu_{t+j}^i} - \tilde{w}_t^i \right) - \kappa^i V_{t+j}^i \right],
\]

s.t. \( E_t^i = (1 - \delta^i)(1 - F_t^i(a_t^{i*})) \left[ E_{t+1}^i + q_{t+1}^i V_{t+1}^i \right], \)

where \( q_t^i \equiv q(\theta_t^i) \) denotes the probability a type-\( i \) vacancy is matched with a searching worker, \( \lambda_t \) is the household’s marginal utility of consumption, and \( \tilde{w}_t^i \equiv \mathbb{E} [w_t^i(a) | a \geq a_t^{i*}] = (1 - F_t^i(a_t^{i*}))^{-1} \int_{a_t^{i*}}^{\infty} w_t^i(\alpha) dF_t^i(\alpha) \), and \( \tilde{A}_t^i \equiv \mathbb{E} [a | a \geq a_t^{i*}] \) is evaluated similarly. \( Z_t \) is an aggregate labor productivity shock and \( \kappa^i \) is the flow vacancy cost. The assumption of perfect substitutability of the wholesale good produced by different types of labor ensures that \( \mu_t \) does not depend on \( i \).

### 4.4 Wage setting

Wages are determined by period-by-period generalized Nash bargaining, which gives rise to the surplus sharing rule
\[
\eta_t S_t^{iF} = (1 - \eta_t) S_t^{iH},
\]

where \( \eta_t \in (0, 1) \) is the time-varying bargaining power of workers, and \( S_t^{iF} \) and \( S_t^{iH} \) denote the match surplus to the firm and household, respectively.\(^\text{29}\) Shocks to the worker’s bargaining weight enter as “cost-push” shocks to the New Keynesian Phillip’s Curve and are the source of inefficient fluctuations in the optimal policy experiment in Section 5.2.

### 4.5 Retail firms and monetary policy

There is a continuum of monopolistically competitive retail firms, indexed by \( j \), that transform the wholesale good into the retail good according to the production function
\[
Y_t^r(j) = \sum_i Y_t^i(j).
\]

Retail firms are subject to staggered price setting as in Guillermo A. Calvo (1983); in each period retail firms can reset their prices with probability \( 1 - \phi \). These firms maximize expected discounted profits subject to price stickiness and a demand function arising from

\(^{29}\)The surplus in the Nash bargain is given by the marginal value of employed workers in the household’s and firm’s problems.
the Dixit-Stiglitz consumption aggregator. Thus, the retail firm’s problem is identical to that of the standard New Keynesian model\textsuperscript{30} with linear production and real marginal cost equal to $1/\mu_t$; therefore, a detailed derivation is omitted.

Finally, in the baseline model, the central bank is assumed to follow a Taylor rule of the following form:\textsuperscript{31}

$$\beta(1 + \dot{i}_t) = (\beta(1 + \dot{i}_{t-1}))^{\rho_i} \left[ (1 + \pi_t)^{\phi_\pi} \left( \frac{Y_t}{Y^ss} \right)^{\phi_Y} \right]^{1-\rho_i} \epsilon_{t}^{mp},$$

where $\dot{i}_t$ is the nominal interest rate, $\pi_t$ is inflation, $Y^ss$ is steady-state output of the final good, $\phi_Y > 0$ and $\phi_\pi > 1$, $\rho_i \in [0, 1)$ is an interest-rate smoothing parameter, and $\epsilon_{t}^{mp}$ is a monetary policy shock.

### 4.6 Parameterization

The model as described above is fairly general and flexible, accommodating potentially many types of workers differing in their average productivities and drawing idiosyncratic shocks from several combinations of distributions. While most parameters can be calibrated to standard values from the literature, there is, however, a degree of freedom in choosing the distributions of idiosyncratic shocks, $G^i(x)$ and $F^i(a)$, and the degree to which types differ from one another. In order to keep the model as simple as possible, I make stark assumptions on these differences.

I focus exclusively on the case with two types of workers, denoted “high” and “low.” The conceptual mapping between the model and the data is that high-type workers correspond to prime-age workers, those between 25 and 54, while low-type workers correspond to those aged 16-24 or over 55. In the U.S., almost exactly half of the civilian noninstitutional population over 16 is between the ages of 25 and 54, so I assume equal measure of each type of worker in the household.\textsuperscript{32}

Furthermore, because the labor force participation rate of workers between 25 and 54 is very high in the U.S. (above 80 percent), while that of the other group is roughly half that (44.6 percent in April, 2017), I assume that only low-type workers are able to receive utility from nonparticipation. This difference in labor force attachment (low-type workers choose whether or not to participate in the labor market, while high types always participate) is the

\textsuperscript{30} Described, for example, in Galí (2008).
\textsuperscript{31} Section 5.2 considers alternative simple Taylor rules.
\textsuperscript{32} The mapping of worker types to age groups follows the approach taken in Ravenna and Walsh (2012).
only difference between the two types of workers.

Separating the participation decision across worker types in this way will ensure that the model produces cyclical variation in the composition of the unemployed, which was shown to respond to monetary policy shocks above in Section 3, and which Elsby, Hobijn and Şahin (2015) argue is an important driver of the cyclicality of the flow of workers from unemployment to nonparticipation. In particular, after a contractionary monetary policy shock, the value of employment falls, which in turn may decrease the threshold value of nonparticipation \( x_i^* \), causing low type workers to exit the labor force. Thus, after a contractionary shock, a larger share of the pool of unemployed is made up by high-type workers, just as in the data.\(^{33}\)

The distributions \( F^l(a) = F^h(a) \) are assumed to be Type II Pareto distributions.\(^{34}\) This distribution has two attractive features. First, the distribution of income is often estimated to have a Pareto tail. Second, as illustrated in Figure 7, the elasticity of separations with respect to the (endogenous) idiosyncratic productivity threshold \( a_i^* \) is higher for lower values of the threshold. This gives the model a reasonable chance to match Mueller’s (2017) observation that the separation rate of prime-age workers’ is lower but responds more to the business cycle than those of other age groups. I choose \( F^i(\cdot) \) to have an unconditional mean of 1 and variance of 3.\(^{35}\)

Given this functional form for the idiosyncratic productivity shocks, other parameters are chosen to match U.S. labor market data. Utilities from nonparticipation for low types are drawn from \( G^l(x) \), which is assumed to be a uniform distribution with support on \([x, \bar{x}]\). The lower bound is assumed to be zero, and the upper bound is chosen to match the U.S. labor force participation rate (see below). Because the idiosyncratic shocks are serially uncorrelated, it is necessary to have low values in the support of these distributions to induce endogenous flows into and out of the labor force and endogenous separations.\(^{36}\) Because high-type workers do not receive nonparticipation utility draws, the exact functional form of \( G^l(\cdot) \) matters little; the first and second moments are what matter for participation decisions in the model.

\(^{33}\)Andreas I. Mueller (2017) argues that the pool of unemployed workers shifts towards high-productivity, high-wage workers during recessions, while I focus on compositional changes with respect to labor force attachment.

\(^{34}\)That is, Pareto distributions shifted to have support on \([0, \infty)\).

\(^{35}\)This implies a scale parameter of 2 and a curvature parameter of 3, so the CDF is given by \( F^i(x) = 1 - (1 + \frac{x}{\bar{x}})^{-3} \).

\(^{36}\)If, for example, the lower bound of the support of idiosyncratic productivity shocks was sufficiently high, workers would never separate endogenously, implying a constant EU flow.
Table 2: The Calibration of Parameters in the Baseline Model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>High Value</th>
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<tbody>
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<td>$\beta$</td>
<td>Discount factor</td>
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</tr>
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<td>Unemployment benefit</td>
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<td>0</td>
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<tr>
<td>$\kappa$</td>
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</tr>
<tr>
<td>$\bar{x}$</td>
<td>Maximum utility from nonparticipation</td>
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<tr>
<td>$\epsilon$</td>
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<tr>
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</tr>
</tbody>
</table>

Notes: The column labeled “High Value” displays the parameter values assigned to high-attachment workers, while the column labeled “Low Value” displays the values assigned to low-attachment workers.

Finally, I let $u(C_t) = \log(C_t)$ and $v(x) = \psi \log(x)$, and the matching function is assumed to be the standard, Cobb-Douglas form:

$$m(U_t, V_t) = m U_t^\alpha V_t^{1-\alpha},$$

so that the vacancy matching rate is given by

$$q(\theta_t) = m^{\theta_t^{-\alpha}}$$

and $f(\theta_t) = \theta_t q(\theta_t) = m^{\theta_t^{1-\alpha}}$.

Many parameters are calibrated to values standard in the literature; this facilitates straightforward welfare comparisons across comparable models discussed in Section 5.2. The full parameterization is presented in Table 2.

The parameters of the distributions of the idiosyncratic shocks are chosen so that the steady state stock variables match their counterparts in the data. However, because high-attachment workers in the model always participate, I target the relative participation rate of prime-age workers to non-prime-age workers. Between 1990–2017, the labor force partici-
ipation rate of prime-age workers averaged 83 percent while that of non-prime-age workers averaged 45 percent. To match the relative participation rates, I therefore target a steady-state participation rate for low types of 54 percent. The matching efficiency parameter $m$ is chosen to match a target unemployment rate. Following Antonella Trigari (2009), because labor force participation is higher in the model than in the data, I target a broader measure of unemployment than the official unemployment rate. Specifically, I target the U-6 unemployment rate, which includes not only the unemployed, but also marginally attached workers and those working part time for economic reasons. This measure has an average value of 10.6 percent since 1994, the first year in which it was published.

4.7 Monetary policy shocks

The baseline model is solved by a second-order approximation around a zero-inflation, non-stochastic steady state.\textsuperscript{37} The experiment I first consider is a monetary policy shock that raises the (annualized) nominal interest rate by 100 basis points on impact.

After a contractionary shock, labor market tightness $\theta^t_i$ falls in both markets. This reduces the job-finding rates $f^t_i$ but increases the vacancy-matching rates $q^t_i$ since there are more unemployed workers. The match surplus is lower for a firm (because value of being vacant is higher due to the higher $q^t_i$). Wages fall and, because wholesale prices are flexible, so does relative price of the labor produced intermediate good. This is the marginal cost of the retails firm, so the markup of prices over marginal cost $\mu_t$ rises. Prices must fall to return to the desired level of markups, producing deflation. Lower wages and job-finding rates reduce the value of employment—and, consequently, unemployment—causing low-type workers to exit the labor force. Lower match surplus increases the threshold for endogenous separations for both types. Because these thresholds differ for each type of worker, responses of these thresholds—even of the same magnitude—imply changes in separations of differing magnitudes across types. Figure 7 illustrates this mechanism. These separations combined with low types exiting the labor force cause a change in the composition of the unemployed.

The model impulse responses for stock variables—EP, UR, and LFP—and the empirical estimates from Section 3 are presented in Figure 8. EP and LFP fall while UR rises, matching, in a qualitative sense, their empirical counterparts. The magnitude of the responses are also roughly equivalent, although somewhat smaller in the model than in the data, at roughly two-thirds the peak magnitudes.\textsuperscript{38}

\textsuperscript{37}A second-order approximation is required for the welfare calculations in Section 5.2.

\textsuperscript{38}As is well known, the very persistent and hump-shaped empirical responses are difficult to match without
The separations resulting from a given increase in the idiosyncratic productivity thresholds $a^*$ for a lower initial value (left) and a higher initial value (right), under the assumption that the productivities are drawn from a Type II Pareto distribution with density $f(a)$. The separations resulting from the same increase in the threshold are higher for a lower initial value of $a^*$. 
Figure 8: Impulse Responses of Stock Variables—Data vs. Model

Model impulse responses of the EP, UR and LFP to a contractionary monetary policy shock that raises the nominal interest rate by 100 basis points. Percentage-point deviation from steady state.
The model impulse responses for the flow variables EU, EN UE, and UN are displayed in Figure 8. All match, qualitatively, their empirical counterparts. EU increases and returns quickly to steady state, while UE and UN decline and are more persistent and hump-shaped, an unsurprising result since these two measures are driven by compositional changes. The EN response is modest. The initial increase in UN (also present in the data) is the initial exit from the labor force of unmatched low-type workers. As seen in Figure 10, the share of the unemployed made up by high types increases in response to the shock, as does the share of high-type vacancies among all vacancies. This shift in the makeup of vacancies increases the volatility of labor market tightness in the low-attachment sector, which in turn impacts the cyclicality of low-attachment workers’ participation in the labor market.

Additionally, because new matches are long lasting, this shift in vacancies toward high-type workers produces a more persistent decline in the employment of low types. This is displayed in Figure 11, which displays the employment response of each type. High-type employment returns to steady-state after 6 quarters, while low-type employment takes about twice as long.\footnote{The fact that low-type employment does not decline on impact arises because endogenous productivity shocks are assumed to occur only in the high-type market, a simplifying assumption that can be relaxed.}

This highlights a new role for heterogeneity in contributing to the persistence of monetary policy shocks. Although Ravenna and Walsh (2012) emphasize the role of heterogeneity in their model’s persistent response to shocks, the mechanism is slightly different. In their model, the unemployment pool shifts systematically toward low-productivity workers in responses to a contractionary shock, reducing firms’ incentives to post vacancies. In the model presented here, on the other hand, compositional shifts in the pool of unemployed induce firms to shift their vacancies toward different types of workers. After a contractionary shock, high-type workers make up a larger share of all unemployed workers, increasing the probability of a vacancy being matched with a worker in the high-type market relative to the low-type market. Persistence in this model comes from the resulting long-lasting employment matches of firms and high-type workers, rather than reduced incentives to post vacancies as in Ravenna and Walsh (2012).

\footnote{a variety of additional frictions, as discussed in, for example, Lawrence J. Christiano, Martin Eichenbaum and Charles Evans (2005).}
Figure 9: Impulse Responses of Flow Variables—Data vs. Model

Top row: Empirical and model impulse responses of $EU$ and $EN$ flows to a contractionary monetary policy shock that raises the nominal interest rate by 100 basis points. Percentage-point changes. Bottom row: Empirical and model impulse responses of $UE$ and $UN$. 

*Top row:* Empirical and model impulse responses of $EU$ and $EN$ flows to a contractionary monetary policy shock that raises the nominal interest rate by 100 basis points. Percentage-point changes. *Bottom row:* Empirical and model impulse responses of $UE$ and $UN$. 

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Figure 10: Model Impulse Responses of Unemployment Shares

Model impulse responses of the share of the unemployed made up by high-type workers and the share of vacancies made up by high-type vacancies to a contractionary monetary policy shock that raises the nominal interest rate by 100 basis points. Percentage-point deviation from steady state.

Figure 11: Model Impulse Responses of Employment by Worker Type

Model impulse responses of employment of each type of worker to a contractionary monetary policy shock that raises the nominal interest rate by 100 basis points. Percent deviation from steady state.
5 Welfare

The baseline model is able to replicate some of the key moments identified in the empirical section of the paper. It produces reasonably accurate responses to monetary policy shocks of both the stock and flow variables in the labor market. In this section I use the model as a normative tool to solve for optimal monetary policy within a class of simple Taylor-type rules of the form described in Section 4.

5.1 Sources of inefficiency

There are two sources of inefficiencies in the steady state of the model. The first, a familiar source in the labor search literature, occurs if the worker’s share in the Nash bargain differs from the elasticity of the matching function with respect to vacancies (i.e., \( \eta \neq \alpha \)). This is the well-known Arthur J. Hosios (1990) condition. The second is inefficiency low output due to monopolistic competition, which occurs in standard New Keynesian models in the absence of a production subsidy.

If these two conditions are met in the steady state, and if the only shocks are to aggregate productivity \((Z_t)\), it is straightforward to show that a strict inflation targeting rule is able to replicate the social planner’s solution and achieve first best. Following Ravenna and Walsh (2011), I introduce exogenous shocks to \( \eta \), the worker’s share in the Nash bargain. These shocks are meant to capture some of the inefficiencies introduced from deviations from the Hosios condition without taking a stance on the particular type of wage rigidity or bargaining differences present. Because the Hosios condition holds in the steady state, however, these shocks are more similar to the wage rigidities in Hall (2005a) or Olivier J. Blanchard and Jordi Galí (2010) than to Marcus Hagedorn and Iourii Manovskii’s (2008) alternative calibration of Robert Shimer’s (2005a) model.

5.2 Wage bargaining shocks and welfare

This section considers the economy described above in an efficient steady state that is hit with shocks to productivity \( Z_t \) and \( \eta_t \) the worker’s bargaining weight in wage determination and compares welfare across simple Taylor-type rules. I calibrate the variance and persistence of these shocks to values suggested in Ravenna and Walsh (2011), where the standard deviations of innovations are 0.32 percent for productivity, and 3.87 percent for the bargaining weight, in terms of deviations from steady state.
I compare the baseline Taylor rule with a number of alternatives. To do so, I approximate the model to second order around the non-stochastic steady state and simulate the model for 10,000 periods. I compare alternative policies according to the share of average consumption\textsuperscript{40} the household would be willing to forgo (or would need to receive) in order to be indifferent between the policies. Specifically, letting variables with tildes denote the values in the solution to a social planner’s problem and those without denote the competitive equilibrium values, I solve for the value of $\Lambda$ that satisfies

$$\tilde{v}_0 \equiv \sum_{t=0}^{\infty} \beta^t \left\{ u(\tilde{C}_t) - \sum_i \gamma^i \left[ \chi \tilde{E}^i_t - (1 - \tilde{E}^i_t) \int_{\tilde{x}^*_i}^{\infty} v(\chi) dG^i(\chi) \right] \right\}$$

$$= \sum_{t=0}^{\infty} \beta^t \left\{ u((1 + \Lambda)C_t) - \sum_i \gamma^i \left[ \chi E^i_t - (1 - E^i_t) \int_{x^*_i}^{\infty} v(\chi) dG^i(\chi) \right] \right\}. $$

Under the assumption of log utility from consumption, it is straightforward to show that

$$\Lambda = \exp \left\{ \left( \tilde{v}_0 - v_0 \right) (1 - \beta) \right\} - 1,$$

where $v_0$ denotes the time-zero expected present discounted value of utility under the competitive equilibrium allocation. The value of $\Lambda$ is the share of average equilibrium consumption the household would have to be given to be indifferent between the decentralized equilibrium (under a given policy rule) and the social planner’s constrained efficient allocation.

### 5.3 Optimal simple rules

I first find the optimal simple Taylor-type rules. This exercise is equivalent to computing a Ramsey-optimal policy in which the policymaking instrument is restricted to be a class of simple Taylor-type reaction functions to variables within the model. I consider four classes of Taylor rules. Each allows for interest-rate smoothing and include inflation targets,\textsuperscript{41} in addition to the following variables:

1. Output or unemployment gaps.\textsuperscript{42}
2. The employment-to-unemployment flow ($EU$) gap.

\textsuperscript{40}Because the model is solved by a second-order approximation, certainty equivalence fails, and average consumption does not equal consumption in the deterministic steady state.

\textsuperscript{41}Reactions to inflation are necessary to ensure that there exists a unique equilibrium.

\textsuperscript{42}That is, the difference between their equilibrium and efficient levels.
Table 3: Optimal Simple Rules and Associated Welfare Losses

<table>
<thead>
<tr>
<th>Rule</th>
<th>$\phi_\pi$</th>
<th>$\phi_Y$</th>
<th>$\phi_U$</th>
<th>$\phi_{EU}$</th>
<th>$\rho_i$</th>
<th>Abs. Loss (%)</th>
<th>Rel. Loss (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y$-gap</td>
<td>1.1</td>
<td>2.18</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.0182</td>
<td>20.52</td>
</tr>
<tr>
<td>$U$-gap</td>
<td>1.09</td>
<td>-</td>
<td>-3.3</td>
<td>-</td>
<td>0</td>
<td>0.0175</td>
<td>15.89</td>
</tr>
<tr>
<td>$\Delta Y$</td>
<td>1.06</td>
<td>3.3</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.019</td>
<td>25.83</td>
</tr>
<tr>
<td>$\Delta U$</td>
<td>1.01</td>
<td>-</td>
<td>-0.81</td>
<td>-0.2</td>
<td>0.2</td>
<td>0.0189</td>
<td>25.17</td>
</tr>
<tr>
<td>$Y$-gap, $EU$-gap</td>
<td>1.1</td>
<td>0.56</td>
<td>-</td>
<td>-0.33</td>
<td>0</td>
<td>0.0151</td>
<td>0</td>
</tr>
<tr>
<td>$U$-gap, $EU$-gap</td>
<td>1.01</td>
<td>-</td>
<td>0</td>
<td>-0.17</td>
<td>0</td>
<td>0.0152</td>
<td>0.66</td>
</tr>
<tr>
<td>$EU$-gap</td>
<td>1.01</td>
<td>-</td>
<td>-</td>
<td>-0.17</td>
<td>0</td>
<td>0.0152</td>
<td>0.66</td>
</tr>
</tbody>
</table>

Notes: Optimal simple rules and associated welfare losses compared to the efficient allocation (“Abs. Loss”) and relative to the optimal simple rule (“Rel. Loss”), expressed as percentages of average consumption (see Section 5.2 for details).

3. Output or unemployment gaps and the $EU$ gap.

4. Changes in output or unemployment.

The first of these classes of rules is the standard Taylor-type rule. The second and third are motivated by the empirical findings from Section 3 that monetary policy affects the labor market primarily through the $EU$ flow. The last class of rules are motivated by Schmitt-Grohé and Uribe’s (2006) observation that a desirable aspect of policy is that it be based on observables, as opposed to gaps of variables relative to some unknown steady-state or efficient value.

The results are displayed in the upper panel of Table 3. The column titled “Absolute loss” displays the loss relative to the efficient allocation expressed as a percent of average consumption ($100 \times \Lambda$, in the notation of the previous section). The “Relative loss” column displays the percentage loss relative to the optimal simple rule. The optimal rule responds modestly to inflation, and reacts to both the output gap and the $EU$ gap. The best rule that targets only the $EU$ gap features losses of about two-thirds of one percent relative to the optimal rule, while the best rule that targets only the output gap has losses of more than 20 percent relative to the optimal simple rule.43

I also compare the welfare losses across other Taylor-type rules commonly used in the literature. These include Taylor rules that respond to inflation and output gaps (relative

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43As is typically the case, the losses due to deviations from the efficient allocation are relatively small; the optimal rules of each form all involve losses of less than two-tenths of one percent of average per-period consumption. There are, however, substantial differences across rules relative to the optimum.
Table 4: Alternative Simple Rules and Associated Welfare Losses

<table>
<thead>
<tr>
<th>Rule</th>
<th>$\phi_\pi$</th>
<th>$\phi_{Y^{ss}}$</th>
<th>$\phi_Y$</th>
<th>$\phi_U$</th>
<th>$\rho_i$</th>
<th>Absolute Loss (%)</th>
<th>Relative Loss (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.125</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.0258</td>
<td>70.86</td>
</tr>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.125</td>
<td>-</td>
<td>-</td>
<td>0.8</td>
<td>0.0220</td>
<td>45.70</td>
</tr>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.5</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.0238</td>
<td>57.62</td>
</tr>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.5</td>
<td>-</td>
<td>-</td>
<td>0.8</td>
<td>0.0216</td>
<td>43.05</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.125</td>
<td>-</td>
<td>0</td>
<td>0.0256</td>
<td>69.54</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.125</td>
<td>-</td>
<td>0.8</td>
<td>0.0218</td>
<td>44.37</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.5</td>
<td>-</td>
<td>0</td>
<td>0.0232</td>
<td>53.64</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.5</td>
<td>-</td>
<td>0.8</td>
<td>0.0209</td>
<td>38.41</td>
</tr>
<tr>
<td>Strict inflation</td>
<td>$\infty$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.0268</td>
<td>77.48</td>
</tr>
<tr>
<td>Faia (2008)</td>
<td>3</td>
<td>-</td>
<td>-0.15</td>
<td>0</td>
<td></td>
<td>0.0265</td>
<td>75.50</td>
</tr>
<tr>
<td>Galí (2011)</td>
<td>1.51</td>
<td>-</td>
<td>-0.1</td>
<td>-0.025</td>
<td>0</td>
<td>0.0264</td>
<td>74.83</td>
</tr>
</tbody>
</table>

Notes: Alternative simple rules and associated welfare losses compared to the efficient allocation (“Abs. Loss”) and relative to the optimal simple rule (“Rel. Loss”), expressed as percentages of average consumption (see Section 5.2 for details).

to both steady state and the efficient level of output), a regime of strict inflation targeting, and optimal simple rules derived in the models of Faia (2008) and Galí (2011), both of which feature labor market frictions. These results are displayed in Table 4. A few patterns emerge from Tables 3 and 4. First, interest-rate smoothing can be welfare improving for sub-optimal rules, but the optimal rules of various forms feature no interest-rate smoothing. Second, the optimal rules derived in models only slightly different from the one described above deliver outcomes worse than even simple, commonly used Taylor rules. Finally, aside from ensuring determinacy, rules that feature a strong inflation response deliver inferior welfare outcomes. Indeed, a regime of strict price stability performs the worst of all the alternative rules considered. The optimal rules all feature inflation responses on the low end of the region of determinacy.

This last result is particular striking, since a strong inflation response is a common feature of optimal policy in other models. In the optimal simple rule in Schmitt-Grohé and Uribe (2006), the coefficient on inflation is 3, while that on output is 0.01. The optimal policies derived in Faia (2008) and Galí (2011) both involve strong inflation responses, and Ravenna and Walsh (2011) find that strict price stability is very close to the fully optimal policy with commitment. Ravenna and Walsh’s (2011) model is almost identical the one presented above, but it does not feature endogenous separations, labor force participation, or heterogeneity.
The relative simplicity of their model facilitates an algebraic derivation of the optimal policy using a linear-quadratic approach, but the absence of the key model features described above leads to a very different policy implication. Indeed, a policy that is nearly optimal in their model ranks among the worst of the policies I consider.

While these results highlight the importance of model specification in deriving optimal policies, another way to approach the question is to ask how these rules perform when the model outcomes are ranked according to a different welfare criterion. Table 5 displays the losses from two alternative loss functions: the quadratic loss functions from the textbook New Keynesian model and Ravenna and Walsh’s (2011) simple search model. The loss function from these models all involve parameters and endogenous variables that have counterparts the baseline model. Specifically, I simulate the model using a given rule and compute the welfare losses implied by the loss functions from these other models. Strict inflation targeting delivers the best outcome for both of these alternative loss functions, while the actual optimal policy ranks very near the bottom for each alternative measure. This highlights the importance of comparing policies using model-consistent welfare measures.

6 Conclusion

The experience of the U.S. labor market during the Great Recession has highlighted the importance of a full characterization of labor market dynamics in understanding the business cycle. In this paper, I examine the effects of monetary policy shocks on three labor market states—employment, unemployment, and nonparticipation—and the flows of workers among them. A close examination of these labor market dynamics reveals the importance of job loss in understanding the effects of monetary policy on the labor market. Decompositions of labor market variables reveal that the flow of workers from employment to unemployment (EU) is the largest contributor to the increase in the unemployment rate and declines in the employment-to-population ratio and labor force participation rate after a contractionary monetary policy shock. Other decompositions lead to the same conclusion: job loss drives the labor market’s response to monetary policy.

These decompositions also demonstrate the important role played by participation decisions. Although labor force participation responds relatively little to monetary policy, this is the outcome of large but offsetting responses of worker flows into and out of the labor force. Of particular interest is the response of flows from unemployment to nonparticipation, which are driven by a composition effect. After a contractionary monetary policy shock, job loss
Table 5: Losses from Alternative Welfare Measures

<table>
<thead>
<tr>
<th>Rule</th>
<th>$\phi_\pi$</th>
<th>$\phi_{Y^{**}}$</th>
<th>$\phi_Y$</th>
<th>$\phi_U$</th>
<th>$\phi_{EU}$</th>
<th>$\rho_i$</th>
<th>Loss NK</th>
<th>Loss R&amp;W</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strict inflation</td>
<td>$\infty$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>0.014</td>
<td>0.5053</td>
</tr>
<tr>
<td>Opt. $Y$-gap</td>
<td>1.1</td>
<td>2.18</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.6142</td>
<td>0.6142</td>
<td>0.5112</td>
</tr>
<tr>
<td>Opt. $U$-gap</td>
<td>1.09</td>
<td>-</td>
<td>-3.3</td>
<td>-</td>
<td>0</td>
<td>1.3226</td>
<td>1.3226</td>
<td>0.515</td>
</tr>
<tr>
<td>Opt. $\Delta Y$</td>
<td>1.06</td>
<td>3.3</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.5026</td>
<td>0.5026</td>
<td>0.51</td>
</tr>
<tr>
<td>Opt. $\Delta U$</td>
<td>1.01</td>
<td>-</td>
<td>0.81</td>
<td>-</td>
<td>0.2</td>
<td>0.4624</td>
<td>0.4624</td>
<td>0.5093</td>
</tr>
<tr>
<td>Opt. $Y$-gap, $EU$-gap</td>
<td>1.1</td>
<td>0.56</td>
<td>-</td>
<td>-0.33</td>
<td>0</td>
<td>1.7645</td>
<td>1.7645</td>
<td>0.5221</td>
</tr>
<tr>
<td>Opt. $U$-gap, $EU$-gap</td>
<td>1.01</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>-0.17</td>
<td>0</td>
<td>1.7741</td>
<td>0.5219</td>
</tr>
<tr>
<td>Opt. $EU$-gap</td>
<td>1.01</td>
<td>-</td>
<td>-</td>
<td>-0.17</td>
<td>0</td>
<td>1.7741</td>
<td>1.7741</td>
<td>0.5219</td>
</tr>
<tr>
<td>Galí (2011)</td>
<td>1.51</td>
<td>-</td>
<td>-0.1</td>
<td>-0.025</td>
<td>0</td>
<td>0.1683</td>
<td>0.1683</td>
<td>0.5076</td>
</tr>
<tr>
<td>Faia (2008)</td>
<td>3</td>
<td>-</td>
<td>0</td>
<td>-0.15</td>
<td>0</td>
<td>0.0484</td>
<td>0.0484</td>
<td>0.5061</td>
</tr>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.125</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.1848</td>
<td>0.1848</td>
<td>0.5076</td>
</tr>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.125</td>
<td>-</td>
<td>-</td>
<td>0.8</td>
<td>0.1472</td>
<td>0.1472</td>
<td>0.5070</td>
</tr>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.5</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0.3251</td>
<td>0.3251</td>
<td>0.5086</td>
</tr>
<tr>
<td>Taylor (SS)</td>
<td>1.5</td>
<td>0.5</td>
<td>-</td>
<td>-</td>
<td>0.8</td>
<td>0.2512</td>
<td>0.2512</td>
<td>0.5076</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.125</td>
<td>-</td>
<td>0</td>
<td>0.159</td>
<td>0.159</td>
<td>0.5075</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.125</td>
<td>-</td>
<td>0.8</td>
<td>0.1223</td>
<td>0.1223</td>
<td>0.5068</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.5</td>
<td>-</td>
<td>0</td>
<td>0.2123</td>
<td>0.2123</td>
<td>0.5077</td>
</tr>
<tr>
<td>Taylor (gap)</td>
<td>1.5</td>
<td>-</td>
<td>0.5</td>
<td>-</td>
<td>0.8</td>
<td>0.1344</td>
<td>0.1344</td>
<td>0.5067</td>
</tr>
</tbody>
</table>

Notes: Welfare losses from alternative models. “Loss NK” is the implied loss from the simple New Keynesian model described in Galí (2008), while “Loss R&W” is the loss from Ravenna and Walsh’s (2011) model, which includes labor market frictions, but no heterogeneity, endogenous separations, or participation. Both “Loss NK” and “Loss R&W” are in units of utility. Strict inflation targeting is the best simple-rule policy by both of these criteria, while it ranks worst among simple rules by the model-consistent welfare criterion.
drives workers with high labor force attachment (low dropout propensities) into the pool of unemployed, lowering the overall $U$-to-$N$ transition rate. In addition, transitions into and out of the labor force account for one third of the increase in the unemployment rate after a contractionary monetary policy shock. These results show that participation decisions also play an important role in the labor market’s response to monetary policy.

A model designed to match these empirical conditional moments features a search-and-matching labor market with endogenous separations and nontrivial participation decisions, heterogeneity in labor force attachment, and sticky prices to allow monetary policy to affect the real economy. Policy experiments in this model suggest that a central bank can target job loss (or EU transitions) in a simple Taylor-type rule to achieve better welfare outcomes in response to macroeconomic shocks than under either strict inflation targeting or a standard Taylor rule that targets both inflation and output. This policy rule is attractive not only for its theoretical simplicity, but also in a practical sense since the data on job loss are available from multiple sources and at high frequencies. Layoffs, therefore, are a measure of the labor market that the Federal Reserve can target to achieve better outcomes, while staying within its mandate to promote full employment.

Obviously, the questions this paper addresses are not motivated solely by theoretical curiosity; they have arisen precisely because these issues have become increasingly important in real-world monetary policy decisions. Federal Reserve Chairs Janet Yellen and Ben Bernanke and other Federal Open Market Committee members have repeatedly made reference to worker flows—in particular, the relative contributions of flows into and out of the labor force to changes in the unemployment rate—when discussing the efficacy of monetary policy in internal deliberations, policy speeches, press conferences, and congressional testimony. The results of this paper demonstrate that a solid foundation for understanding the effects of monetary policy on labor market flows is not merely an academic pursuit, but rather a real-world necessity.
References


Appendices

A Data Adjustments for Time Aggregation

Previous work has attempted to account for the time-aggregation problem in the following way. If one views the transition rates (that is, the number of transitions that occur to each state expressed as a percentage of the pool of workers in the beginning state) as discrete-time Markov transition probabilities, while the underlying true flow pattern is governed by a continuous-time Markov chain, as shown by Shimer (2012), generically, there is a one-to-one mapping between the implied transition matrices. That is, the instantaneous flow hazard rates can be backed out from the directly observed gross flows.

Following Shimer (2012), assume the observed month-to-month transition rates define a 3 x 3 Markov matrix, so that the evolution of the observed numbers of workers employed, unemployed, and not in the labor force evolve as a discrete-time Markov chain:

\[
\begin{bmatrix}
E_{t+1} \\
U_{t+1} \\
N_{t+1}
\end{bmatrix} = \begin{bmatrix}
\pi_t^{EE} & \pi_t^{UE} & \pi_t^{NE} \\
\pi_t^{EU} & \pi_t^{UU} & \pi_t^{NU} \\
\pi_t^{EN} & \pi_t^{UN} & \pi_t^{NN}
\end{bmatrix}
\begin{bmatrix}
E_t \\
U_t \\
N_t
\end{bmatrix} =: \Pi_t s_t, \tag{2}
\]

where \( \pi_t^{XY} \) denotes the observed transition rate in month \( t \) from state \( X \) to state \( Y \). However, these are just the discrete observations. Assume that the true (but unobserved) labor market evolves according to a continuous-time Markov chain

\[
\dot{s}_{t+\tau} := \frac{d}{d\tau} \begin{bmatrix}
E_{t+\tau} \\
U_{t+\tau} \\
N_{t+\tau}
\end{bmatrix} = \lambda_t s_{t+\tau}, \forall \tau \in [0, 1), \tag{3}
\]

where \( \lambda_t \) is such that it produces the observed discrete-time process given by Equation 2. The mapping between the matrix of observed month-to-month transition rates (\( \Pi_t \)) and the flow transition hazards that are the off-diagonal terms of \( \lambda_t \) is derived below; it is based on a simple decomposition of \( \Pi_t \) into a product of matrices of its own eigenvalues and eigenvectors. Given the matrices \( \lambda_t \), the implied month-to-month transition probabilities after correcting for this time-aggregation issue are therefore given by \( 1 - \exp(-\lambda_t^{ij}) \) for \( i \neq j \).
Derivation of $\lambda$ from $\Pi$

The derivation of $\lambda_t$, the matrix of instantaneous transition hazards, from $\Pi_t$, the matrix of (discretely) observed month-to-month transition rates, follows Shimer (2012), with the notation slightly adjusted to that I use in this paper. Beginning with the discrete-time process in Equation 2, divide each time period into $\Delta$ intervals where the relationship between states $\frac{1}{\Delta}$ time apart for some $\tau \in [0, 1)$ is given by

$$s_{t+\tau + \frac{1}{\Delta}} = \Pi_{t, \Delta} s_{t+\tau},$$

(4)

for some matrix $\Pi_{t, \Delta}$. Starting at $\tau = 0$ and iterating this expression forward $\Delta$ times gives

$$s_{t+1} = \Pi_{t, \Delta}^\Delta s_t,$$

(5)

establishing a relationship between $\Pi_t$ and $\Pi_{t, \Delta}$, i.e., $\Pi_t = \Pi_{t, \Delta}^\Delta$. Subtracting $s_t$ from both sides of Equation 4 at $\tau = 0$ and dividing both sides by $\frac{1}{\Delta}$ gives

$$\frac{s_{t+\frac{1}{\Delta}} - s_t}{\Delta} = \left(\Pi_{t, \Delta} - I_{[3\times3]}\right) s_t,$$

(6)

where $I_{[n\times n]}$ denotes the $n \times n$ identity matrix. The limit as $\frac{1}{\Delta} \to 0$ of the left-hand side is simply $\lambda_t$. Therefore, the limit of the term multiplying $s_t$ on the RHS is $\lambda_t$. That is, re-writing in terms of the observed $\Pi_t$,

$$\lambda_t = \lim_{\frac{1}{\Delta} \to 0} \frac{\Pi_{t, \Delta}^\Delta - I_{[3\times3]}}{\frac{1}{\Delta}}.$$

(7)

The matrix $\Pi_t$ can be written as $\Pi_t = V_t \Lambda_t V_t^{-1}$ where $\Lambda_t$ is a diagonal matrix of the eigenvalues of $\Pi_t$ and $V_t$ is the matrix whose columns are the corresponding eigenvectors. Plugging in this for $\Pi_t$ above and pre- and post-multiplying each side by $V_t^{-1}$ and $V_t$, respectively, gives

$$V_t^{-1} \lambda_t V_t = \lim_{\frac{1}{\Delta} \to 0} \frac{\Lambda_t^\Delta - I_{[3\times3]}}{\frac{1}{\Delta}}.$$

(8)

Since $\Lambda_t$ is diagonal, all off-diagonal terms on the right-hand side will be zero in the limit as well, and each diagonal term is given by $\lim_{\frac{1}{\Delta} \to 0} \frac{(\Lambda_t^{ii})^{\frac{1}{\Delta}} - 1}{\frac{1}{\Delta}} = \ln (\Lambda_t^{ii})$, $i = 1, 2, 3$. Therefore,
we have

\[ \lambda_t = V_t \Lambda_t^{\log} V_t^{-1}, \]  

(9)

where \( \Lambda_t^{\log} \) is the matrix with diagonal terms given by \( \ln (\Lambda_t^{ii}) \) and zeros everywhere else. This establishes the mapping between the observed transition rates and the unobserved transition probabilities that are used in the regressions in this paper.

### B Derivation of Stock Responses from Flows

This section is reproduced from and closely follows Elsby, Hobijn and Şahin (2015), adjusted to the notation I use throughout this paper.

The first step is to normalize \( E_t + U_t + N_t \equiv 1 \) for all \( t \), so each stock variable is a share of the total population, which is normalized to 1. Next, rewrite Equations 2 and 3 in terms of the new state vector containing only \( E \) and \( U \). These equations become

\[ \tilde{s}_{t+1} := \begin{bmatrix} E_{t+1} \\ U_{t+1} \end{bmatrix} = \begin{bmatrix} \pi_t^{EE} - \pi_t^{NE} & \pi_t^{UE} - \pi_t^{NE} \\ \pi_t^{EU} - \pi_t^{NU} & \pi_t^{UU} - \pi_t^{NU} \end{bmatrix} \tilde{s}_t + \begin{bmatrix} \pi_t^{NE} \\ \pi_t^{NU} \end{bmatrix} =: \tilde{\Pi}_t \tilde{s}_t + \xi_t, \]  

(10)

and

\[ \tilde{\dot{s}}_t := \begin{bmatrix} \dot{E}_t \\ \dot{U}_t \end{bmatrix} = \begin{bmatrix} \lambda_t^{EE} - \lambda_t^{NE} & \lambda_t^{UE} - \lambda_t^{NE} \\ \lambda_t^{EU} - \lambda_t^{NU} & \lambda_t^{UU} - \lambda_t^{NU} \end{bmatrix} \tilde{s}_t + \begin{bmatrix} \lambda_t^{NE} \\ \lambda_t^{NU} \end{bmatrix} =: \dot{\lambda}_t \tilde{s}_t + \epsilon_t, \]  

(11)

where \( \lambda^{EE} \) and \( \lambda^{UU} \) are such that the columns of \( \lambda \) (the matrix of transition hazards in the 3-state, un-normalized setting) sum to zero. Equation 10 gives the evolution of the observed unemployment and employment levels. The impulse responses, however, give the response of \( 1 - \exp(-\lambda^{ij}) \), the probability a transition from \( I \) to \( J \) occurs during a month, conditional on having begun the month in state \( I \). These obviously define unique responses of each \( \lambda^{ij} \), so all that is needed is to translate these responses to the \( \pi^{ij} \) terms. This is straightforward using the mapping from \( \Pi \) to \( \lambda \) above.

Specifically, since the impulse response functions are for the variables \( x^{ij} = 1 - \exp(-\lambda^{ij}) \), we can write \( \lambda^{ij} = -\ln (1 - x^{ij}) \). Then the response of \( \lambda^{ij} \) can be found by noting that up to first order

\[ \Delta \lambda^{ij} = \frac{1}{1 - x^{ij}} \Delta x^{ij} = \frac{\Delta x^{ij}}{\exp(-\lambda^{ij})}. \]  

(12)

Using \( \lambda_t^{ij} = \lambda_{t-1}^{ij} + \frac{\Delta x_t^{ij}}{\exp(-\lambda_{t-1}^{ij})} \) as the entries for \( \lambda_t \) and using the mapping from the previous section gives the sequence of \( \pi_t^{ij} \) terms from which \( \tilde{\Pi}_t \) and \( \xi_t \) can be calculated directly, giving
the implied paths for $\tilde{s}_t$ and $\tilde{s}_t^*$ (since $\tilde{s}_t^* = (I_{2 \times 2} - \tilde{\Pi}_t)^{-1} \xi_t = -\tilde{\lambda}_t^{-1} \xi_t$).


In Section 3, I use a measure of monetary policy shocks developed by Romer and Romer (2004) and extended through 2007 to estimate the response of worker flows. Romer and Romer (2004) identify monetary policy shocks as changes to the Federal Funds target rate not predictable by the economic information in the Federal Reserve’s “Greenbook” forecasts. Specifically, their monetary policy shock series is given by the residuals of the following regression:

$$\Delta ff_m = \alpha + ff_{fb_m} + \sum_{i=-1}^{2} \gamma_i \tilde{\Delta}y_{mi} + \sum_{i=-1}^{2} \lambda_i \left( \tilde{\Delta}y_{mi} - \tilde{\Delta}y_{m-1,i} \right) + \sum_{i=-1}^{2} \varphi_i \tilde{\pi}_{mi} + \sum_{i=-1}^{2} \theta_i \left( \tilde{\pi}_{mi} - \tilde{\pi}_{m-1,i} \right) + \rho \tilde{u}_{m0} + \varepsilon_m,$$

where $m$ indexes FOMC meeting dates, $ff_{fb_m}$ denotes the level of the Federal Funds target rate at the time of meeting $m$, $\tilde{\Delta}y_{mi}$ denotes forecasts of real output growth, $\tilde{\pi}_{mi}$ denotes forecasts of inflation, $\tilde{u}_{m0}$ denotes forecasts of current unemployment, and $\varepsilon_m$, the residual, is the monetary policy shock. The index $i$ is the horizon of the forecast, and horizon $i = -1$ may be a true forecast or a realized value of the variable, depending on when the actual data were available.

D Alternative Estimation and Identification

D.1 Estimation by Jordà’s (2005) Method of Local Projections

As a robustness check, I have estimated the responses to monetary policy shocks using Jordà’s (2005) method of local projections. The results are displayed below and are broadly similar to those estimated in the main text.
Impulse responses of stock (top row) and flow (bottom two rows) variables to a 100 b.p. contractionary Romer and Romer (2004) monetary policy shock, 1969Q1–2007Q3. Local projection estimates. Shaded areas are one standard deviation intervals.
D.2 High-Frequency Identification and Estimation by Proxy VAR

As another robustness check, I use Mark Gertler and Peter Karadi’s (2015) hybrid-VAR method that utilizes high-frequency identification strategies combined with standard VAR techniques. I estimate the responses to a shock that has the same effect on impact to the one-year Treasury rate as the Romer and Romer (2004) shock. I include each measure in an independently estimated VAR in addition to the variables in Gertler and Karadi’s (2015) VAR. The results are displayed below and are broadly consistent with the results in the main text.
Figure 13: Impulse Responses Estimated by Proxy VAR

Impulse responses of stock (top row) and flow (bottom two rows) variables to a contractionary monetary policy shock from Gertler and Karadi (2015) that increases the 1-year nominal interest rate by 100 b.p. on impact. July, 1979 through June, 2012, monthly data. Shaded areas are 95 percent confidence intervals from a bootstrap.