The Unemployment-Risk Channel in Business-Cycle Fluctuations[*]

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Abstract

The unemployment-risk channel amplifies an initial contraction through a reduction in consumption demand by workers who fear unemployment. We show that the strength of this channel increases when accounting for the dynamic response of job separations and firm hiring to macroeconomic shocks. In response to identified demand and supply shocks, separation and job-finding rates are equally important in accounting for the overall unemployment response, but the job-finding rate responds with a sizable lag. When calibrating a tractable heterogeneous-agent new-Keynesian model with endogenous separations and sluggish vacancy creation to match these facts, we attribute twice as large a share of output fluctuations to the unemployment-risk channel relative to a more standard model with exogenous separations and free entry.

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1 Introduction

One of the key risks individuals face throughout their working lives is that of involuntary unemployment. Fluctuations in this risk of losing one's job, or of not quickly finding a new one, is a key feature of business cycles. Because workers are not perfectly insured against this risk, their consumption response to rising fear of unemployment may amplify any contractionary shock to the economy. We label this amplification mechanism the *unemployment-risk channel* (URC).[1]

While traditional macroeconomic models, typically assuming full insurance, had no room for idiosyncratic shocks in the theory of business cycles, a recent paradigm shift toward heterogeneous-agent models has pointed out the possible implications of time-varying individual risks for aggregate demand (Kaplan and Violante, 2018). In particular, a nascent "HANK-SAM" literature has integrated the canonical macroeconomic framework for studying unemployment with search-and-matching frictions (SAM) into incomplete-markets models with price rigidities (HANK), highlighting the potential role of time-varying unemployment risk for fluctuations in precautionary savings and, thus, aggregate demand. Much of this literature follows early SAM models in their focus on the job-finding rate as the source of fluctuations in unemployment. Our aim in this paper is to extend a workhorse HANK-SAM framework to account for the dynamics of unemployment risk observed in U.S. data, including fluctuations in inflows to unemployment from separations, and investigate the implications for the contribution of the URC to business-cycle fluctuations.

Our assessment begins with an empirical investigation that quantifies the role of job-loss and job-finding rates in shaping business-cycle fluctuations in unemployment. In particular, we document two stylized facts regarding the response of unemployment, and unemployment risk, to identified demand and supply shocks in US data. First, movements in the separation rate and the job-finding rate are of similar importance for the response of unemployment. Second, the separation rate peaks more than six months ahead of the trough in the job-finding rate. The importance of separations and the lagged dynamics of the job-finding rate also show in unconditional

[1] This *unemployment-risk channel* is summarized in the minutes of an FOMC meeting in the wake of the Great Recession: "fear of unemployment could well lead to further increases in the saving rate that would dampen consumption growth in the near term". See https://www.federalreserve.gov/monetarypolicy/fomcminutes20090318.htm.

times-series data.

Standard HANK-SAM frameworks cannot account for these stylized facts because they assume the typical Diamond-Mortensen-Pissarides (DMP) setup with a constant separation rate and with free entry by firms into posting vacancies (Ravn and Sterk, 2021; McKay and Reis, 2021; Challe, 2020). Free entry implies that vacancy creation is infinitely elasticity with respect to changes in job values and, hence, that vacancy creation and thus job-finding rates jump contemporaneously in response to any shock, inconsistent with the empirical findings. We study the ability of two extensions to an otherwise standard HANK-SAM framework to account for the stylized facts: endogenous separations that fluctuate in response to changing economic conditions and sluggish vacancy posting with a less than infinite elasticity to the value of a filled vacancy. Given an otherwise standard calibration of the model, and an average real wage chosen to target the volatility of unemployment in U.S. data, we show how the two stylized facts together identify the strengths of the vacancy-posting and separation elasticities.

Using our augmented HANK-SAM model, we quantify the URC, defined as the amplification arising from imperfect insurance against idiosyncratic unemployment risk. The URC accounts for about a third of unemployment fluctuations. This share is twice as large as the share in a standard HANK-SAM model without endogenous separations and sluggish vacancy creation, recalibrated to imply the same volatility of unemployment. This results from two opposing effects: endogenous separations amplify the URC while sluggish vacancy creation dampens it. Endogenous separations result in a front-loaded response of job-loss risk, which affects hosueholds' income in the short term. Finitely elastic vacancy creation results in back-loaded responses of unemployment-duration risk, which affects households' income at a longer horizon. In their precautionary-savings decisions, households care more about near-term income loss relative to long-term income loss.

Apart from making the theory consistent with the stylized facts, the estimated model has a number of other attractive properties. First, both contractionary demand and supply shocks lead to a hump shaped fall in employment, in contrast to standard new-Keynesian models (Galí, 1999), but in line with the data (Ramey, 2016).[2] This

[2] Complementary to our focus on cyclical fluctuations in income risk, Guerrieri et al. (2022) show that a HANK model with multiple sectors and acyclical income risk can also generate demand-driven

is also true for completely transitory shocks as an initial rise in separations raises the number of matches but–contrary to the standard model–not vacancies, leading to persistently lower job-finding rates.

Second, the model generates total unemployment volatility in accordance with the data without excessively low values of the *fundamental surplus*, or steady-state match profits, in contrast to to a broad class of search-and-matching models with free entry (Shimer, 2005; Hall, 2005; Hagedorn and Manovskii, 2008; Ljungqvist and Sargent, 2017). Although introducing endogenous separations and finitely-elastic vacancy creation have opposing effects on the contribution of the URC, they both amplify the total response of unemployment for any given value of the fundamental surplus..

Third, although a substantial share of recession unemployment is accounted for by a surge in separations, vacancy creation does not surge, as in typical calibrations of free-entry models with endogenous separations. The model thus produces a standard Beveridge-curve relationship.

After a brief literature review, the rest of the paper is structured as follows. In Section 2, we present our two stylized facts. In Section 3, we outline the model. In Section 4, we characterize and discuss the model propagation mechanism, in particular the URC. In Section 5, we show how the stylized facts can be accounted for by having endogenous separations and finitely-elastic vacancy creation, and how these features matter for quantifying the unemployment-risk channel. Section 6 concludes.

Related literature. Our study is most related to the literature on HANK-SAM models, in particular Ravn and Sterk (2021), but also Den Haan et al. (2018), McKay and Reis (2021), Challe (2020), Gornemann et al. (2021), Kekre (2022) and Jung (2023). We share an ambition to quantify the importance of unemployment risk in a general-equilibrium framework with Cho (2023) and Graves (2020). Cho (2023) reports an "MPC puzzle" where a calibration to the empirical estimates of the marginal propensity to consume generates counterfactually volatile aggregate consumption in a HANK-SAM framework. Graves (2020) studies a two-asset model and find that aggregate shocks are amplified through a flight-to-liquidity mechanism. In relation to these two papers, our focus and contribution is with respect to the calibration of the labor-market dynamics, introducing sluggish vacancy creation together with endogenous

recessions from contractionary supply shocks.

separations.

In addition, our paper is related to several other bodies or work. First, the importance of fluctuations in the separation rate for unemployment fluctuations in unconditional time-series data is discussed extensively in Fujita and Ramey (2009) and Shimer (2012). Elsby et al. (2009), Barnichon (2012) and Elsby et al. (2015) argue that separations are more important when unemployment starts to increase from a low point or begin to fall from a peak. Mueller (2017) shows that the separation rate of high-wage earners is particularly highly counter-cyclical. We add to this literature by providing new evidence on the response of separations to identified demand and supply shocks.

Second, the study of finitely elastic vacancy creation goes back at least to Fujita and Ramey (2005). Several recent papers have explored related aspects of labor-market dynamics under the lens of finitely elastic vacancy creation, and also provided other micro-foundations. See, e.g., Coles and Kelishomi (2018), Leduc and Liu (2020), Haefke and Reiter (2020), Mercan et al. (2021), Engbom (2021) and Den Haan et al. (2021). We add to this literature both in terms of providing new evidence from identified demand and supply shocks, where we show that the delay between the peak of the separation rate and the trough of the job-finding rate identifies the entry elasticity in our model, as well as by analyzing the implications of sluggish vacancy creation for business-cycle dynamics in a model with both incomplete markets and pricing frictions, thus having an unemployment-risk channel.

Third, our paper, together with the aforementioned HANK-SAM papers, builds a bridge between two existing new-Keynesian literatures which respectively either have heterogeneous agents but no search-and-matching frictions (see, e.g., Oh and Reis, 2012; McKay and Reis, 2016; Guerrieri and Lorenzoni, 2017; Bayer et al., 2019; Hagedorn et al., 2019; Auclert et al., 2020; Luetticke, 2021)[3] or search-and-matching frictions but a representative agent (see, e.g., Walsh, 2005; Krause and Lubik, 2007; Gertler et al., 2008; Trigari, 2009; Gertler and Trigari, 2009; Galí, 2010; Ravenna and Walsh, 2012; Christiano et al., 2016, 2021). With a real business cycle model, Den Haan

[3] Bayer et al. (2019) highlight the portfolio rebalancing channel of cyclical income risk, which, through its effect on firms' financing costs, may partly explain a delayed response in vacancy creation. Another closely connected literature has explored counter-cyclical income and unemployment risk as a driver of aggregate demand, see, e.g., Challe and Ragot (2016), McKay (2017) and Harmenberg and Öberg (2021).

et al. (2000) also stressed the importance of endogenous separations for business-cycle fluctuations, but through an interaction with capital adjustment costs rather than household saving decisions as in our paper. Jung and Kuester (2015) characterize optimal labor-market policies in a similar framework with endogenous search effort.

Finally, our model attributes a large fraction of unemployment fluctuations to the inefficient unemployment-risk channel. While we do not analyze policy in this paper, this result potentially motivates a large role for stabilizing policy interventions, both in response to demand and supply shocks. Because the unemployment-risk channel is due to the interaction between separation decisions made in the labor market, and consumption decisions made by the households, these interventions encompass both traditional monetary and fiscal transfer policy as well as firm subsidies. In follow-up work, we quantify fiscal multipliers in response to common fiscal policy designs in a similar framework (Broer et al., 2024).[4]

2 Two stylized facts about U.S. unemployment risk

Unemployment and unemployment risk rise when either more employed workers lose their jobs or when fewer unemployed workers find new ones. In this section, we document the relative importance of these two drivers of unemployment fluctuations in the US economy. We document two stylized facts. First, fluctuations in the separation and job-finding rates on average account for similar shares of unemployment fluctuations. Second, their relative importance changes over the cycle: fluctuations in separations are more important earlier, while the job-finding rate accounts for a higher share later. In other words, fluctuations in the separation rate lead the job-finding rate. We show how these stylized facts hold both in response to identified monetary policy ("demand") shocks and TFP ("supply") shocks, as well as in unconditional time-series data.

[4] Also using HANK-SAM models, but without finitely elastic vacancy creation, McKay and Reis (2021) and Kekre (2022) show that unemployment insurance can be used to stabilize demand-driven fluctuations, while Dengler and Gehrke (2021) show correspondingly that match-saving firm subsidies can be used to stabilize demand-driven fluctuations.

(a) Unemployment (b) Transition rates (monthly)

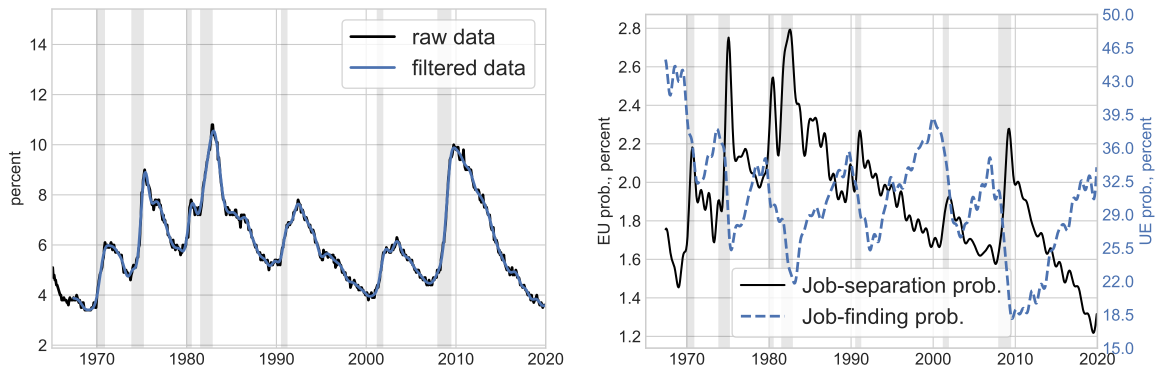


Figure 1: Unemployment and labor-market transition probabilities.

2.1 Data

Labor-market flows. Our labor-market flow data is constructed using gross flows in the Current Population Survey (CPS) micro data following the methodology in Shimer (2012). It spans 1967-06 to 2019-12.[5] The monthly transition probabilities are derived from observed flows and seasonally adjusted. To account for time aggregation, we retrieve the transition probabilities from estimating a three-state continuous-time model, where workers are either employed (E), unemployed (U) or inactive (I), i.e., out of the labor force. The monthly job-finding probability (the "UE probability") is calculated as the probability of at least one transition from unemployment to employment conditional on not transitioning out of the labor force. The separation probability (the "EU probability") is calculated in a similar manner. Although both are discrete-time probabilities and not continuous-time rates, from here one we refer to them as the job-separation rate and the job-finding rate respectively. Details are in Appendix A.

In Figure 1, we display the evolution of the unemployment rate alongside the estimated time series for the job-finding and the separation rate. For this figure, the time series are filtered using a Christiano and Fitzgerald (2003) band-pass filter where features below a periodicity of 12 months are filtered out.

[5] The data from 1967-06 to 1975-12 were tabulated by Joe Ritter and made available by Hoyt Bleakley.

Shock series. We use Romer and Romer (2004)'s monthly series of monetary policy shocks, identified using a narrative method, extended by Miranda-Agrippino and Ricco (2021). As a measure of shocks to total factor productivity (TFP), we use the first difference of the quarterly TFP series in Fernald (2015), which is adjusted for variation in capacity utilization.

Other time series. The other time series we use are standard and retrieved from the Federal Reserve Economic Data.

2.2 Impulse responses to identified shocks

We compute impulse responses for the labor-market transitions using a smoothened version of the local projection method from Jordà (2005) introduced by Barnichon and Brownlees (2019).[6] For a generic outcome Y_t, we estimate

$$Y_{t+h} = \alpha_h^Y \nu_t + \beta_h^Y X_t + \epsilon_t^Y, \tag{1}$$

separately for horizons $h \in \{0, 1, ..., T\}$, where ν_t is the shock series, X_t is a set of controls, and ϵ_t^Y is an error term. We set the smoothing parameter for the smoothened impulse responses to $\lambda = 10^4$.

Our specifications of Equation (1) follows Ramey (2016). For the analysis of monetary policy shocks, the controls include the contemporaneous value and two lags of log industrial production, the unemployment rate, the log of consumer prices, and the log of commodity prices. We also include two lags of the nominal interest rate and the monetary shock series.[7] Including contemporaneous controls amounts to imposing a recursiveness assumption: with this specification, we assume that innovations to monetary policy do not affect the unemployment rate in the same month. In the case of TFP shocks, we include as controls a quadratic time trend, two lags of the shock (to account for serial correlation in the shock series) as well as the following variables: log real GDP per capita, log real stock prices per capita, log labor

[6] Plagborg-Møller and Wolf (2021) show that local projection and VARs estimate the same impulses responses when the lag structure is unrestricted. Li et al. (2021) show in a large Monte Carlo study that smoothing is beneficial in terms of lower variance for a moderate increase in bias.

[7] For commodity prices we use the CRB Commodity Price Index as in Coibion (2012).

productivity (equal to real GDP divided by total hours worked), and the dependent variable. The estimation period is 1969-01 to 2007-12 for the responses to monetary policy shocks and 1967Q4 to 2015Q4 for the TFP shocks. We compute standard errors using a Newey and West (1987) correction for autocorrelation, and report 90 percent confidence intervals. The presented impulse responses are normalized so that a monetary policy shock (TFP shock) generates an increase (decrease) in the nominal interest rate (TFP) of one percent on average over the first year. When computing these impulse responses, we do not impose any filter but use the raw data directly.

In Figure 2, we display the estimated responses of unemployment, the job-separation (EU) rate, and the job-finding (UE) rate, as well as the nominal interest rate, in response to a contractionary monetary policy shock. The monetary shock generates a hump-shaped increase in unemployment, an increase in the job-separation rate and a decrease in the job-finding rate. On impact, the separation (job-finding) rate falls (rises) slightly before it increases (decreases). In Appendix A, we show that these impulse responses are very similar when excluding the control variables but that the sizes of the impact responses vary across specifications and are, in general, not significant.

In Figure 3, we display the estimated responses of unemployment, the job-separation rate, the job-finding rate, as well as of TFP, to a negative TFP shock. As with the contractionary monetary policy shock, the negative productivity shock generates a hump-shaped increase in unemployment, an increase in the job-separation rate and a decrease in the job-finding rate. On impact, we also see that the separation (job-finding) rate falls (rise) slightly before it increases (declines). Again, these responses are not much affected by the control variables, except that the size and the sign of the impact responses vary, see Appendix A.

2.3 Stylized facts

Fact 1: Separations account for a significant share of unemployment fluctuations. In order to quantify the importance of changes in the separation rate and job-finding rate to fluctuations in unemployment, we use the static decomposition proposed by Shimer (2012). We calculate the steady-state unemployment rate implied by current probabilities of separation (EU_t) and job finding (UE_t) rate using the formula

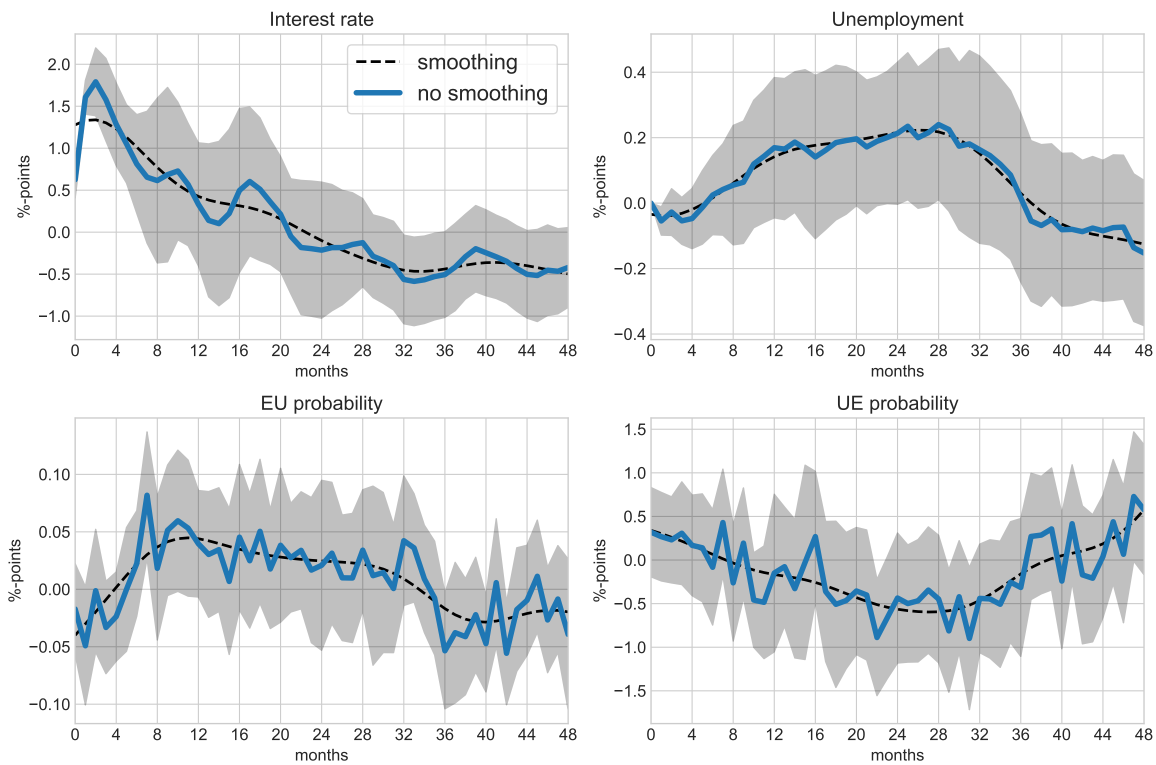


Figure 2: Responses to a monetary policy shock.

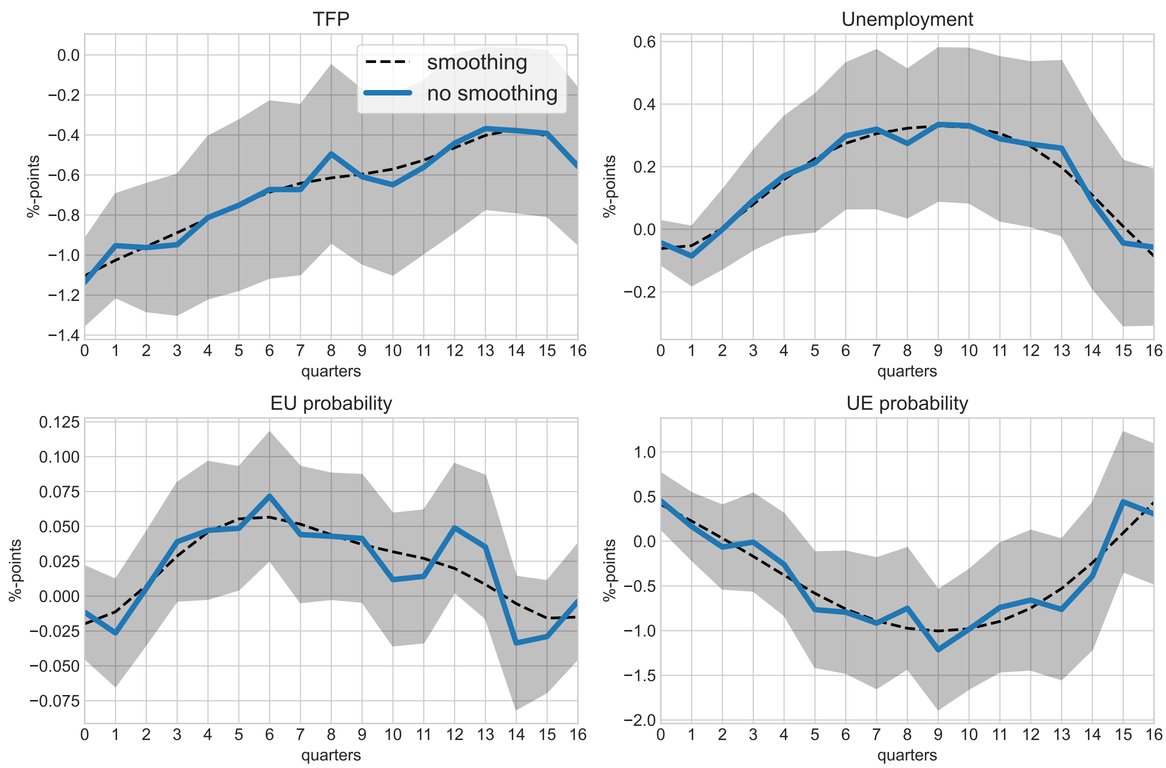


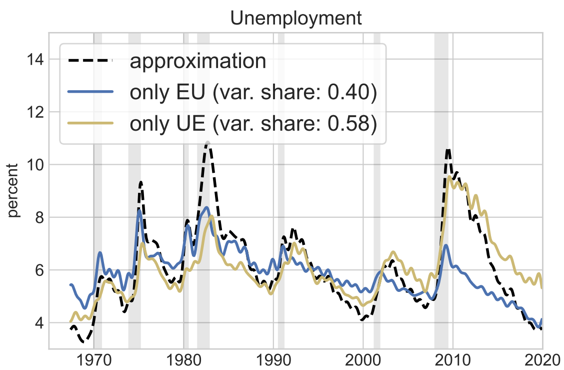
Figure 3: Responses to a TFP shock.

$u_t^{ss} = \frac{EU_t}{EU_t+UE_t}$, which, given the high value of the US job-finding rate, approximates actual unemployment very well. We approximate the share of fluctuations in the unemployment rate stemming from movements in the job-separation rate as $\frac{EU_t}{EU_t+UE^{ss}}$, thus holding the job-finding rate constant at its average value. Correspondingly, the variation in the unemployment rate stemming from movements in the job-finding rate equals $\frac{EU^{ss}}{EU^{ss}+UE_t}$.

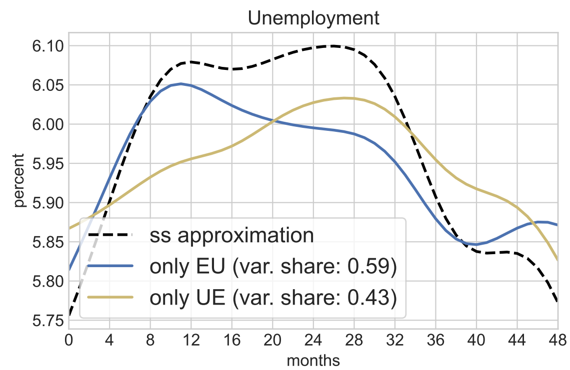
Figure 4 shows the evolution of the steady-state unemployment rate and the respective contributions of the labor-market flows. Panel (a) uses the unconditional time series data. Here, the variation in the job-separation rate contributes 40 percent and the variation in the job-finding rate contributes 58 percent, respectively (because of the non-linearity in the definition of the steady-state unemployment rate, the contributions do not exactly sum to 100 percent). In panel (b), we show the evolution of the same variables in response to a monetary policy shock. Here, the job-separation rate contributes 59 percent and the job-finding rate contributes 43 percent. Finally, in panel (c), we show the evolution of the steady-state unemployment rate and the respective contributions in response to a productivity shock. The job-separation rate contributes 47 percent and the job-finding rate contributes 58 percent. We conclude a broad pattern: movements in the job-separation rate account for a substantial share of fluctuations in the unemployment rate.

Fact 2: The separation rate leads the job-finding rate. Figure 5 illustrates the lead-lag relationship between the job-separation rate and the job-finding rate in the data. In panel (a), we show the correlation structure of the unconditional time series of the job-separation rate and the job-finding rate. The correlation peaks when the job-finding rate lags the job-separation rate by 6 months. In panel (b), we show the smoothened impulse responses to a monetary policy shock. Separations peak after 11 months while the trough for the job-finding rate occurs after 27 months, implying that the job-separation rate leads the job-finding rate by 16 months in response to a monetary policy shock. In panel (c), we show the smoothened impulse responses to a TFP shock. Separations peak after 6 quarters while the trough for the job-finding rate occurs after 9 quarters, implying that the job-separation rate leads the job-finding rate by 9 months in response to a productivity shock. Again, we conclude that there is a broad pattern: movements in the job-separation rate significantly lead movements in the job-finding rate.

(a) Unconditional data



(b) Monetary policy shock



(c) TFP shock

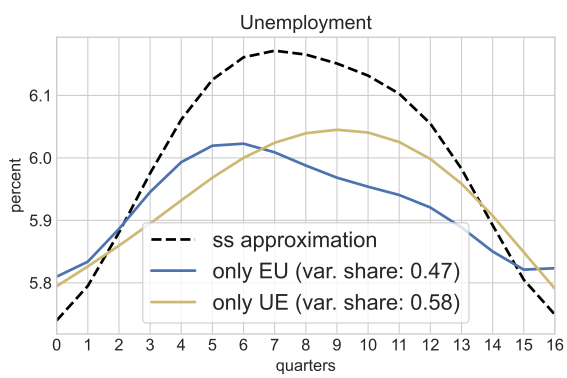
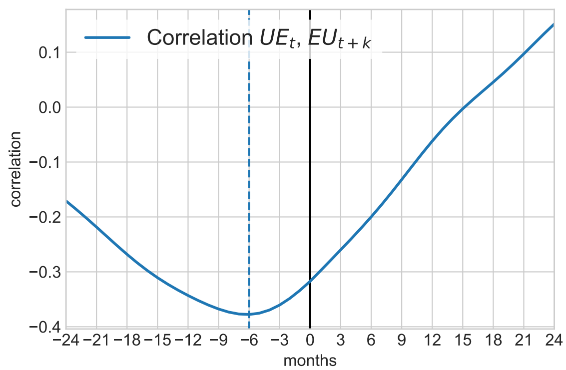
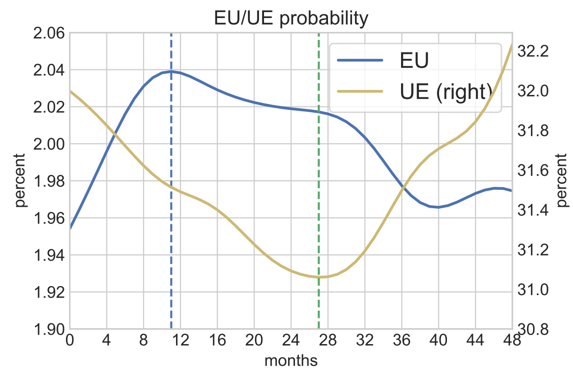


Figure 4: Variance decomposition of unemployment.

(a) Unconditional data



(b) Monetary policy shock



(c) TFP shock

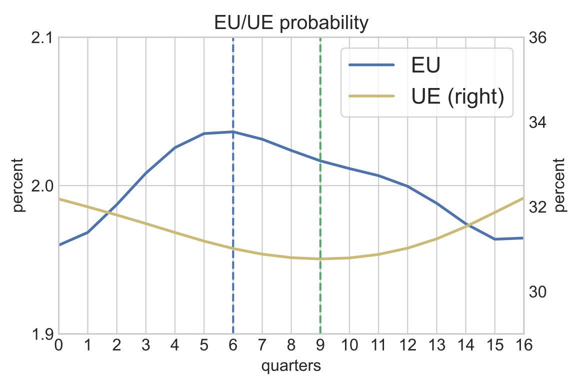


Figure 5: The job-separation (EU) rate leads the job-finding (UE) rate.

In sum, we have documented two stylized facts, which hold true both in unconditional time series data and in response to two identified and conceptually different business cycle shocks. First, fluctuations in the separation rate accounts for a sizable share of unemployment fluctuations, ranging between 40 and 59 percent across the different settings. Second, the relative importance of separations changes over the cycle: fluctuations in separations are more important earlier, while those in the job-finding rate account for a higher share later, with the separation rate leading the job-finding rate by between 6 and 16 months. These two facts will discipline our business-cycle model, presented in the next section.

Relation to the literature. The stylized facts documented here are in broad accordance with findings in the existing literature. Starting with the facts in the unconditional US time series, Fujita and Ramey (2009) (FR) and Rogerson and Shimer (2011) similarly document that fluctuations in the separation rate lead the job-finding rate. Using the same gross-flow data up until 2004, FR document that fluctuations in the separation share account for 41 percent of the fluctuations in the unemployment rate.[8] Shimer (2012) documents a smaller contribution of fluctuations in the separation rate of 28 percent when using the same gross flow data.[9] These differences likely reflect slight differences in how the final data set is constructed, but all findings point to a substantial role of fluctuations in the separation rate in accounting for unemployment fluctuations.[10] Two choices in particular may affect the results of this exercise with unconditional time-series data. First, FR document that the contribution of the separation rate increases to 55 percent when the data are detrended by taking first differences, rather than calculating deviations from an HP-filter trend. This raises the question whether our decomposition is sensitive to the detrending

[8] Elsby et al. (2009) document that the separation rate is even more cyclical when restricting to involuntary job loss.

[9] Using transition rates estimated from unemployment duration data, Shimer (2012) finds an even smaller share: 24 percent. We opt for using gross-flow data, as duration-based data is confounded by flows in and out of the labor force when measuring the transition rates.

[10] In Shimer (2012), the sample period stops in 2010, in FR it stops in 2004, whereas it runs to 2019 in our data. Shimer (2012) and FR aggregate the monthly data to a quarterly frequency, whereas we work directly with monthly data. FR corrects the data for margin error, whereas we and Shimer (2012) do not. FR calculates the contribution of the separation rate using a slighlty different formula, which yields an exact decomposition, as opposed to the approximate decomposition used here and in Shimer (2012).

method. In Appendix A, we show that the two facts that we document are robust to replacing the bandpass filter with an HP filter, a one-sided HP filter or a linear trend. Second, both Shimer (2012) and FR show that the contribution of the separation rate falls when restricting the sample to the post-1987 period. In Appendix A, we show that this also holds for our analysis: in this shorter, more recent, sample, the contribution of the separation rate is 28 percent, which is smaller but nevertheless sizable. Neither the filtering method nor the sample period affect the result that the separation rate leads the job-finding rate.

Regarding the findings to identified shocks, Graves et al. (2023) document a similar lead-lag pattern between separation rates and job-finding rates to monetary policy shocks retrieved through high-frequency identification. Oh and Picco (2020) show that the same pattern holds also for identified macro uncertainty shocks.

For TFP shocks, Galí (1999) and Basu et al. (2006) documented that hours rise in response to negative TFP shocks in contrast to the rise in unemployment documented here. These findings are thoroughly discussed in Ramey (2016), here we briefly summarize why our results differ.Basu et al. (2006) use an annual series of Solow residuals cleaned for variation in capacity utilization. The updated quarterly counterpart of that series, provided by Fernald (2015), is what we use here. With this updated series, Ramey (2016) shows that hours fall in a hump-shaped manner, mimicking the rise in unemployment documented here.Galí (1999) used long-run restrictions to identify technology shocks in a bivariate VAR. The resulting shock series, however, does not pass an over-identifying restriction test (Francis and Ramey, 2004), can be forecasted with other macroeconomic variables (Ramey, 2016), and the finding that hours rise to these shocks is not robust to assuming that hours worked per capita is stationary in the long-run (Christiano et al., 2003). Francis et al. (2014) provide a shock series building on the same idea of using long-run restrictions, but in a manner that overcomes many of these problems. In particular, they identify technology shocks by maximizing the contribution of such shocks to the forecast-error variance of labor productivity at a long but finite horizon. In Appendix A, we show that we get similar results as the ones documented above when using this shock series.

3 Model

In this section, we present a tractable equilibrium model that can match the evidence presented in Section 2 and be used to quantify the importance of the unemployment-risk channel for business cycle fluctuations. We do not aim to match all the features of the impulse responses in Section 2, which would call for many additional ingredients, but only the highlighted stylized facts.[11]

We build on Ravn and Sterk (2021)'s framework that combines labor-market frictions and nominal frictions.[12] The demand side is purposefully kept simple and analytically tractable. Markets are incomplete: households can save but not borrow in a risk-free bond which is in zero net supply.[13] In consequence, higher unemployment risk increases savings and reduces the demand for goods. On the supply side, firms employ workers in a Diamond-Mortensen-Pissarides frictional labor market, and sell their output in a standard new-Keynesian environment with monopolistic competition and price-setting frictions. In this framework, a fall in the demand for goods reduces the value of a filled job thus making both existing and new matches less valuable. Firms are therefore more likely to fire existing workers, and less likely to post vacancies, which implies less hiring. The framework thus contains a reinforcing feedback loop from unemployment risk to, first, the demand for goods, and then the demand for labor, and therefore back to unemployment risk. We label this feedback loop the *unemployment-risk channel*.

Relative to previous studies of Heterogenous Agent New Keyenesian models with a Search-And-Match labor market (HANK-SAM models), the distinguishing feature of our model is the combination of endogenous rather than exogenous separations and sluggish vacancy creation rather than free entry. In Section 5 we show how these two elements are necessary to match the stylized facts of unemployment dynamics

[11] To capture the general hump-shape in all response variables, and not only the delayed response of job-finding rate, the model needs to expanded, e,g., to include habit formation.

[12] See also Den Haan et al. (2018), McKay and Reis (2021), Challe (2020) and Gornemann et al. (2021).

[13] The combination of no borrowing and zero supply of liquidity allows an analytical aggregation that makes the equilibrium dynamics particularly transparent and easy to compute. These convenience assumptions were used in the context of asset pricing by Krusell et al. (2011) and has been used extensively in the HANK literature since, see, e.g., Werning (2015); McKay and Reis (2021); Broer et al. (2020); Bilbiie (2019, 2021); Ravn and Sterk (2021). Acharya and Dogra (2020) use CARA utility to retain analytical tractability with positive liquidity.

documented in Section 2, and that they are crucial when quantifying the importance of the unemployment-risk channel.

3.1 Overview

The economy consists of infinitely-lived workers indexed by $i \in [0,1]$, and infinitely-lived capitalists indexed by $i \in (1, 1 + \text{pop}_c]$,with $\text{pop}_c \ll 1$. The workers have CRRA preferences with discount factor β and risk aversion σ. The capitalists are risk neutral with discount factor β and own all firms. Production has three layers:

1. Intermediate-good producers hire labor in a frictional labor market with search and matching frictions. Matches produce a homogeneous good sold in a perfectly competitive market.
2. Wholesale firms buy intermediate goods and produce differentiated goods that they sell in a market with monopolistic competition. The wholesale firms set their prices subject to a Rotemberg adjustment cost.
3. Final-good firms buy goods from wholesale firms and bundle them in a final good, which is sold in a perfectly competitive market.

We first describe the within-period timing in the model, then the determination of vacancy posting and job separations in the frictional labor market, then the price-setting mechanism in the wholesale and final goods market, and finally the households' consumption-saving decisions.

3.2 Timing and labor-market dynamics

Step 0: Stocks and shocks. At the beginning of each period t, all aggregate shocks are revealed. The endogenous state variables are the (beginning-of-period) stocks of unemployed workers u_{t-1} and of vacancies v_{t-1}.

Step 1: Separations and entry. Firms are exposed to an idiosyncratic continuation cost shock. After observing the shock they decide whether to continue or exit, which implies an endogenous, time-varying separation rate δ_t in a manner that we describe below. Vacancies are destroyed with rate δ_{ss}, which for simplicity we assume to be constant and exogenous, and have the same value as the steady state separation rate. Firm-specific costs of entering the labor market are realized. Firms that pay the cost post a new vacancy. The endogenous, time-varying vacancy entry rate is denoted ι_t. The resulting stocks of unemployment and vacancies are given by

$$\tilde{u}_t = u_{t-1} + (1 - u_{t-1})\delta_t, \tag{2}$$

$$\tilde{v}_t = (1 - \delta_{ss})v_{t-1} + \iota_t. \tag{3}$$

Step 2: Search and match. Unemployed workers and vacancies randomly match. The matching technology is Cobb-Douglas with matching elasticity α. Denoting market tightness by

$$\theta_t = \frac{\tilde{v}_t}{\tilde{u}_t}, \tag{4}$$

the job-filling rate λ_t^v and job-finding rate λ_t^u are

$$\lambda_t^v = A\theta_t^{-\alpha}, \tag{5}$$

$$\lambda_t^u = A\theta_t^{1-\alpha}. \tag{6}$$

The labor-market stocks after matches are formed are

$$u_t = (1 - \lambda_t^u)\tilde{u}_t, \tag{7}$$

$$v_t = (1 - \lambda_t^v)\tilde{v}_t. \tag{8}$$

Step 3: Production. Production takes place. Dividends and wages are paid.

Step 4: Consumption and saving. All capitalists and workers, both employed and unemployed, make their consumption-and-saving decisions.

3.3 Intermediate-good firms, vacancy creation and job separations

There is a continuum of intermediate-good firms producing a homogeneous good X_t sold in a competitive market, owned by the capitalists. The real price of the intermediate good is P_t^X and one unit of labor produces Z_t units of the intermediate good. The total production of intermediate goods is thus given by

$$X_t = Z_t(1 - u_t), \tag{9}$$

where the log of total factor productivity Z_t is subject to AR(1)-innovations ν_t^Z,

$$Z_t = Z_{ss}\nu_t^Z, \tag{10}$$

$$\log \nu_t^Z = \rho_A \log \nu_{t-1}^Z + \epsilon_t^Z, \tag{11}$$

where σ_Z is the standard deviation of ϵ_t^Z.

To hire labor the firms must post vacancies which are filled with probability λ_t^v, taken as given by each one-worker firm. We denote by V_t^v the value of a vacancy and by V_t^j the value of a match for the firm.

Separations. At the beginning of the period, a firm must pay a continuation cost $\chi_t \sim G$ or else the job match is destroyed.[14] There is no additional heterogeneity and consequently there exists a common cost cutoff $\chi_{c,t} = V_t^j$, such that for all $\chi_t > \chi_{c,t}$, the firm chooses to separate. Accordingly, the Bellman equation for the value of a job after the separation decision is

$$\begin{aligned} V_t^j &= P_t^X Z_t - W_t + \beta \mathbb{E}_t \left[\int^{\chi_{c,t+1}} (V_{t+1}^j - \chi_{t+1}) dG(\chi_{t+1}) \right] \\ &= M_t + \beta \mathbb{E}_t \left[(1 - \delta_{t+1}) V_{t+1}^j - \mu_{t+1} \right], \end{aligned} \tag{12}$$

where W_t is the real wage, δ_{t+1} is the endogenous separation probability given by $\delta_{t+1} = \int_{V_t^j}^{\infty} G(\chi_t) d(\chi_t)$, μ_{t+1} is the average cost paid, and $M_t = P_t^X Z_t - W_t$ is the gross fundamental surplus, following the terminology in Ljungqvist and Sargent (2017). In steady state we call $\tilde{M}_{ss} = M_{ss} - \beta\mu_{ss}$ the (net) fundamental surplus. Similarly, $m_t = (P_t^X Z_t - W_t)/(P_{ss}^X Z_{ss})$ and $\tilde{m}_{ss} = \tilde{M}_{ss}/(P_{ss}^X Z_{ss})$ are the gross and (net) fundamental surplus *ratios*.

The continuation-cost distribution G is a mixture of a point mass and a Pareto distri-

[14] Following Mortensen and Pissarides (1994), separation decisions are typically modeled as a result of idiosyncratic productivity shocks, such that low-productivity firms optimally decide to exit. Our simplified assumptions have similar material consequences, but avoid ex-post heterogeneity in firm outcomes.

bution with shape parameter ψ, location parameter Υ and mixture parameter p. We choose p and Υ so that in steady state, job separations are δ_{ss} and the continuation costs are approximately zero, $\mu_{ss} \approx 0$. See Appendix B for details. Out of steady state, the endogenous separation probability δ_t are then given by

$$\delta_t \quad = \quad \delta_{ss} \left(\frac{V_t^j}{V_{ss}^j} \right)^{-\psi}, \tag{13}$$

and the average continuation cost, μ_t, is a non-negative increasing function of the job value

$$\mu_t = \mu(V_t^j), \;\; \mu(\bullet) \geq 0, \mu'(\bullet) \geq 0. \tag{14}$$

The idiosyncratic continuation cost implies that the elasticity of job separations to the value of a job is ψ. In the special case where $\psi = 0$ separations occur exogenously at rate δ_{ss}.

Vacancy creation. The Bellman equation for the value of a vacancy is given by

$$V_t^v = -\kappa + \lambda_t^v V_t^j + (1 - \lambda_t^v)(1 - \delta_{ss})\beta \mathbb{E}_t[V_{t+1}^v], \tag{15}$$

where κ is the flow cost of the vacancy, to be paid every period. Vacancies are not subject to the stochastic continuation cost, and are instead destroyed with exogenous probability δ_{ss}. In contrast to the standard assumption of free entry to vacancy creation, we assume that there is a constant mass F of prospective firms drawing a stochastic idiosyncratic entry cost c following a distribution H.[15] The prospective firm posts a vacancy if and only if the value of a vacancy is larger than the entry cost. The total number of vacancies created is therefore $\iota_t = F \cdot H(V_t^v)$. Following Coles and Kelishomi (2018), the entry-cost distribution has a cumulative distribution function $H(c) = F \cdot (c/h)^{\xi}$ on $c \in [0, h]$. With the parameter h sufficiently large so that $h > V_t^v$, the resulting number of vacancies created is $\iota_t = F \cdot (V_t^v/h)^{\xi}$. Expressing

[15] An alternative assumption that would also result in sluggish vacancy dynamics is convex vacancy posting costs, as in Merz and Yashiv (2007).

vacancy creation in relation to steady state gives us

$$\iota_t = \iota_{ss} \left(\frac{V_t^v}{V_{ss}^v} \right)^{\xi}. \tag{16}$$

The stochastic-cost entry assumption implies that the elasticity of vacancy creation to the value of a vacancy is ξ. In the limit where $\xi \to \infty$, we must have $V_t^v = V_{ss}^v$ so that all entrants pay the same deterministic entry cost. We set $V_{ss}^v = \kappa_0$ and treat κ_0 as a free parameter. The free entry model is the double limit $\xi \to \infty$ and $\kappa_0 \to 0$, which implies $V_t^v = 0$. To facilitate comparisons with the free entry model we fix κ at a small positive value across all calibrations, $\kappa_0 = 0.1$. In Appendix D we show that changing κ_0 and ξ with the same factor leaves our results unaffected.

Wage setting. With search frictions, an additional condition is required to determine how the resulting match surplus is divided. In the baseline model, we follow Hall (2005) and assume that real wages are fixed

$$W_t = W_{ss}. \tag{17}$$

A recent body of research has documented that downward nominal wage rigidity is pervasive in the US labor market (Dupraz et al., 2021; Grigsby et al., 2021; Hazell and Taska, 2020). A fixed real wage is therefore likely a weak assumption in the context of studying contractionary shocks, as it implies more wage flexibility than a fully rigid nominal wage with pro-cyclical inflation. As we show in Section 4, inflation is pro-cyclical both in response to demand and supply shocks in our model.

3.4 The final-good sector and the wholesale sector

The representative final-good firm has the production function $Y_t = \left(\int_k Y_{kt}^{\frac{\epsilon_p - 1}{\epsilon_p}} dk \right)^{\frac{\epsilon_p}{\epsilon_p - 1}}$ where Y_{kt} is the quantity of the input of wholesale firm k's output used in production. The implied demand curve is $Y_{kt} = \left(\frac{P_{kt}}{P_t} \right)^{-\epsilon_p} Y_t$ where $P_t = \left(\int_k P_{kt}^{1-\epsilon_p} dk \right)^{\frac{1}{1-\epsilon_p}}$ is the aggregate price level. There is a continuum of wholesale firms indexed by $k \in [0, 1]$ producing differentiated goods using the production function $Y_{kt} = X_{kt}$ where X_{kt} is the amount of the intermediate good purchased by firm k at the intermediate-good price P_t^X. The wholesale firms face Rotemberg price adjustment costs, with scale factor ϕ. Since production is linear, the marginal cost of production is the input price P_t^X. In a symmetric equilibrium, optimal price setting implies a standard Rotemberg Phillips curve

$$1 - \epsilon_p + \epsilon_p \cdot P_t^X = \phi(\Pi_t - 1)\Pi_t - \beta\phi\mathbb{E}_t\left[(\Pi_{t+1} - \Pi_{ss})\Pi_{t+1}\frac{Y_{t+1}}{Y_t}\right], \tag{18}$$

where $\Pi_t = \frac{P_t}{P_{t-1}}$ is the gross inflation rate. Total output given by

$$Y_t = X_t D_t = (1 - u_t) Z_t D_t, \tag{19}$$

where $D_t = \int_k \left(\frac{P_{kt}}{P_t}\right)^{\epsilon_p} di$ is a measure of price dispersion.

3.5 Households

Households are of two types: workers and capitalists. Capitalists can buy and sell shares in an equity fund that owns all firms, but do not participate in the labor market.[16] All adjustment costs are assumed to be virtual, meaning that fluctuations in profits are the residual from fluctuations in output less of wage payments. Workers receive wage income W_t if employed and home production income ϑ if unemployed, but cannot buy and sell equity. All households can save in a zero-coupon one-period nominal bond, in zero net supply, which can be purchased at the price $1/(1 + i_t)$, where i_t is the nominal interest rate, and face a no-borrowing constraint.

Because of zero net supply of liquidity and no borrowing, the equilibrium interest rate clears the bond market only if all households decide not to save, and the borrowing constraint must bind for all but one type of household.[17] The model therefore admits analytical aggregation. Specifically, as in Ravn and Sterk (2021), under the assumption that aggregate shocks are small, the presence of idiosyncratic unemployment risk always gives the employed workers the strongest motive to save, and

[16] The assumption that workers but not capitalists participate in the labor market can be rationalized by means of a fixed labor-market participation cost, see Broer et al. (2020).

[17] Formally, any real interest rate low enough such that all three Euler equations are satisfied with weak inequality is consistent with the zero-borrowing limit. The natural interpretation is however to let liquidity approach zero, as in Krusell et al. (2011), then the real interest rate is such that one of the Euler equations holds with equality.

in equilibrium, the interest rate must be consistent with their Euler equation,

$$C_{n,t}^{-\sigma} = \beta_t \mathbb{E}_t \left[\frac{1+i_t}{\Pi_{t+1}} \left\{ (1 - \text{URISK}_t) C_{n,t+1}^{-\sigma} + \text{URISK}_t C_{u,t+1}^{-\sigma} \right\} \right],$$

where $C_{n,t}$ is the consumption of the employed, $C_{u,t}$ is the consumption of the unemployed, and $\text{URISK}_t = \delta_{t+1}(1 - \lambda_{t+1}^u)$ is the probability that an employed household is unemployed in the next period. β_t is the workers' discount factor, which we assume is subject to mean-one AR(1)-innovations ν_t^β,

$$\beta_t = \beta \nu_t^\beta, \tag{20}$$

$$\log \nu_t^\beta = \rho_\beta \log \nu_{t-1}^\beta + \epsilon_t^\beta, \tag{21}$$

where σ_β is the standard deviation of ϵ_t^β. Up to a first-order approximation, a positive shock to the discount factor is isomorphic to a positive shock to the monetary policy rule.

The no-borrowing constraint implies that all households consume their income in equilibrium. Together with the Euler equation for the employed households, this gives us the following asset-market clearing condition,

$$W_t^{-\sigma} = \beta_t \mathbb{E}_t \left[\frac{1+i_t}{\Pi_{t+1}} \left\{ (1 - \text{URISK}_t) W_{t+1}^{-\sigma} + \text{URISK}_t \vartheta^{-\sigma} \right\} \right] \tag{22}$$

where $R_t = \mathbb{E}_t \left[\frac{1+i_t}{\Pi_{t+1}} \right]$ is the gross real interest rate. In Appendix B, we formally specify the consumption problems of the capitalists and workers, and derive Equation (22). Higher unemployment risk results both in lower expected income (the first moment of the stochastic income process) and higher income uncertainty (the higher moments) for the household. The unemployment-risk channel includes both these effects.

3.6 Government

A government sets monetary policy according to the following Taylor rule,

$$1 + i_t = (1 + i_{ss}) \Pi_t^{\phi_\pi - 1} \mathbb{E}_t[\Pi_{t+1}]. \tag{23}$$

All our numerical results are robust to using a standard Taylor rule which only responds to current inflation, but the chosen rule allow us to prove a number of analytical results on the propagation mechanism in Section 4. Appendix Figure C.1 shows that the impulse responses are close to identical when the Taylor rule instead is $1 + i_t = (1 + i_{ss})\Pi_t^{\phi_\pi}$.

3.7 Solution algorithm

Equations (2)-(23) describe a closed system of 22 equations in 22 unknowns. In the background, there are equations describing the evolution of profits and consumption of the capitalist, which are determined as residuals from the goods-market clearing condition.

We solve for a log-linear approximation around the steady state. Technically, we solve for the perfect-foresight transition paths following unexpected MIT shocks to the household discount factor, β_t, (a "demand" shock) and TFP, Z_t, (a "supply shock"), assuming that the system eventually returns to steady state, exploiting that these transition paths, which are computed without treating aggregate risk, are first-order approximations to the full rational-expectations equilibrium for sufficiently small shocks (Boppart et al., 2018; Auclert et al., 2021). For the baseline parameterization described in Section 5, we have verified that the Blanchard-Kahn condition holds, meaning that the solution is unique.

4 The propagation mechanism

We now investigate the mechanism through which exogenous shocks propagate through the model, and in particular the feedback loop generated by the unemployment-risk channel. In Section 5, we quantitatively investigate this channel.

4.1 Impulse responses to supply and demand shocks

We consider a transitory shock to supply (TFP, Z_t) or to demand (the discount factor of the workers, β_t, or, equivalently, a monetary policy shock). For illustration, Figure 6 shows the impulse responses to these shocks, using the baseline calibration

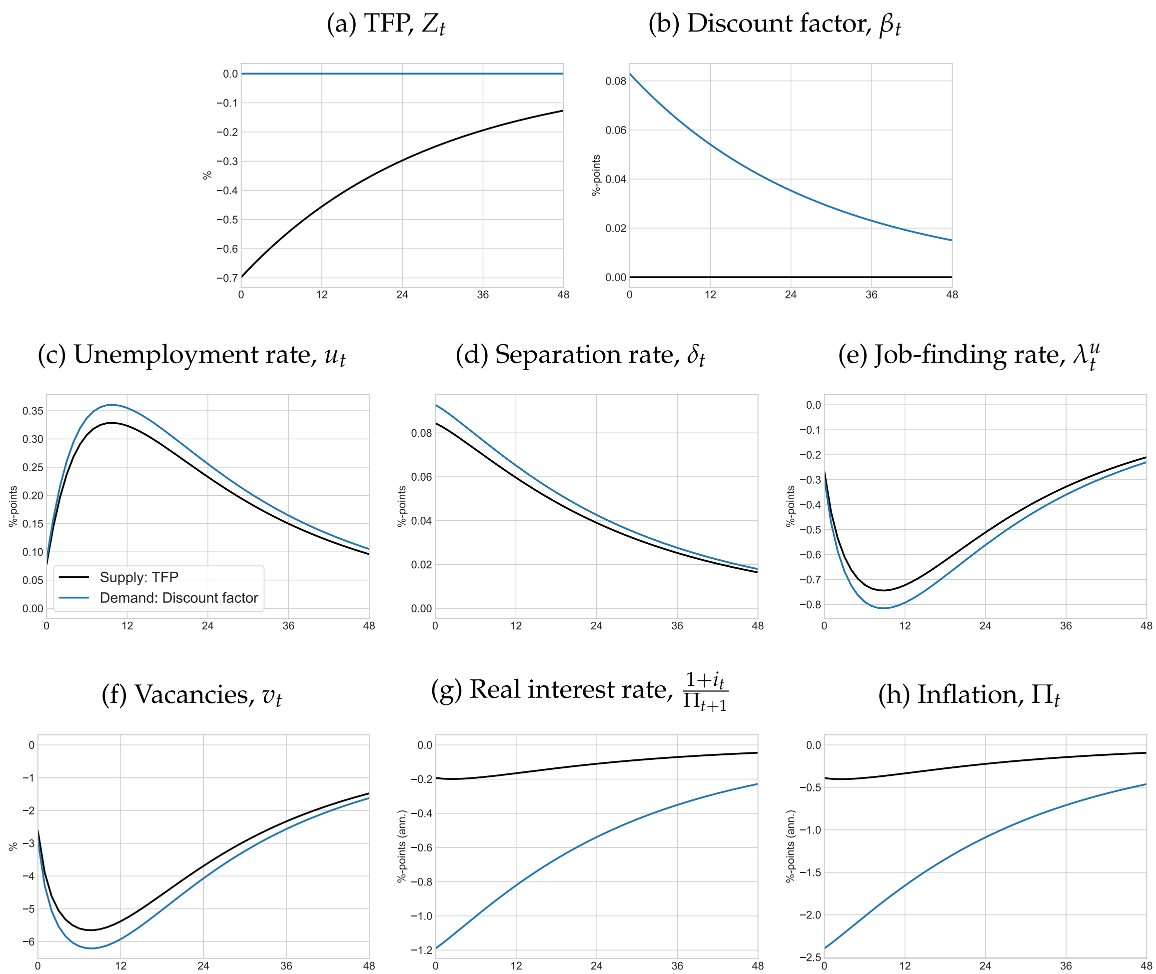


Figure 6: Impulse responses to 1-std. supply and demand shocks.

Notes: This figure shows the impulse responses to both a 1-std. TFP-shock and a 1-std. discount factor shock (with $\rho_\beta = 0.965$ and $\sigma_\beta = 1.01^{\frac{1}{12}} - 1.0$). All other parameters are set as in Table D.1.

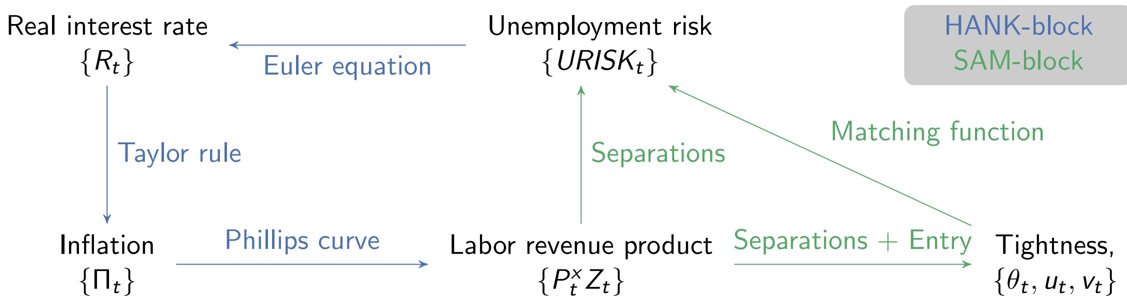


Figure 7: Graphical representation of the model equations.

discussed in Section 5 (the particular parameter values are not important here). We begin analyzing the TFP shock.

To guide the analysis of the propagation mechanism, consider the diagram in Figure 7, which shows the interaction between the key variables in a first-order approximation of the equilibrium. The model is composed of a *HANK block* (left-hand side) and a *SAM block* (right-hand side). Because the profits of intermediate-goods firms are consumed by capitalists every period, the two blocks communicate only through two variables: unemployment risk, URISK_t and the labor revenue product $P_t^X Z_t$, which in turn consists of *exogenous* TFP and the *endogenous* intermediate goods price. We now follow the unidirectional arrows through the diagram to describe the propagation mechanism.[18]

Starting in the SAM block, a reduction in TFP implies a lower net present value of match surpluses and therefore a spike in separations and a decline in entry. The increase in separations raises unemployment risk directly. The increase in separations, alongside the fall in entry, also leads to a decline in tightness, which leads to a decline in the job-finding rate through the matching function, further raising unemployment risk. In a model with infinitely elastic vacancy creation (as in the standard free-entry model), the effect of separations on tightness would be undone by a corresponding increase in entry. With finitely elastic vacancy creation, the offsetting entry effect is only partial, such that the newly separated households instead deplete the current vacancy stock, causing a persistent hump-shaped decline in tightness and

[18] Formally, each "arrow" just represents an equation linking the path of one variable to the other, and the choice of direction is therefore arbitrary, and here only made in terms of interpretation.

the job-finding rate, as seen in Figure 6.[19] The muted response of vacancy creation also implies that the vacancy stock is pro-cyclical, consistent with the notion of a Beveridge curve.

In the HANK block, an increase in unemployment risk causes desired savings to increase and goods demand to fall. To clear the asset market, the real interest rate must fall, as seen from Equation (22). To be consistent with the monetary policy rule (23), a path of lower real interest rates must be accompanied with a path of lower inflation rates. The Phillips curve (18) stipulates that a path of lower inflation rates must be accompanied by a path of lower real marginal cost, which in our setup equals the intermediate goods price.[20] A path of lower intermediate goods prices lowers the net present value of match surpluses, which sets in motion an additional cycle of separations and decline in entry. These generate an additional response of unemployment risk, which through the cycle generates yet another response of separations and entry.

In Figure 8, we unpack this multiplier process by solving the model iteratively in response to a TFP shock, again using our preferred calibration, explained in Section 5. Initially we keep the intermediary goods price fixed, P_t^X, and solve the model equations of the SAM block. This implies a path for unemployment risk, $URISK_t$. Next, we solve the equations of the HANK block given this path, which implies a new path for the intermediary goods price, P_t^X. We then repeat this process until the input and output intermediary goods price paths coincide.

4.2 The unemployment risk channel

In Proposition 1, we characterize the HANK block analytically and show how it is summarized by one single sufficient statistic, which is possible due to the zero-liquidity assumption underlying the Euler equation (22). In what follows, let x_t and $\hat{x}_t$ denote the log and the log deviation from steady state of any capital variable X_t.

[19] To get a hump shape in separations, a model with more "bells and whistles" such as habit formation or sticky expectations is needed, see, e.g., Auclert et al. (2020).

[20] In the Phillips curve (18), the growth path of output also enters and affects the determination of the intermediate goods price, but this effect is zero up to a first order approximation and quantitatively unimportant for our results.

(a) Intermediary goods price, P_t^X (b) Unemployment risk, $URISK_t$ (c) Unemployment, u_t

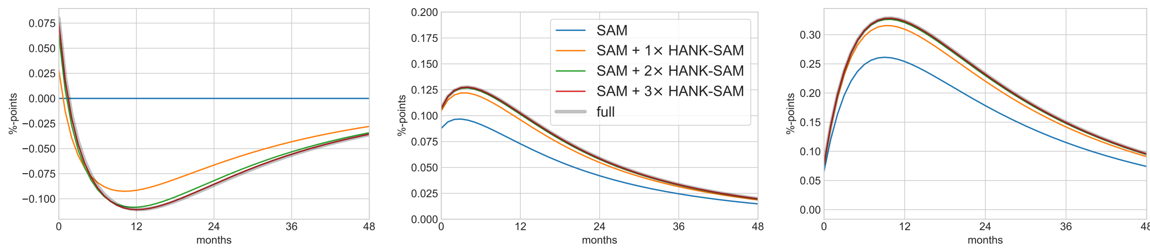


Figure 8: Multiplier process from 1-std. TFP.

Notes: This figure shows the multiplier process leading to the full impulse-response to a 1 std. TFP shock. All parameters are set as in Table D.1.

Proposition 1. *To a first-order approximation, the HANK block is explicitly described by*

$$\widehat{p_t^x} \quad = \quad -\Omega(\widehat{urisk}_t - \beta \mathbb{E}_t \widehat{urisk}_{t+1}), \tag{24}$$

where

$$\Omega = \frac{\underbrace{\frac{\text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta}\right)^{\sigma} - 1\right)}{1 + \text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta}\right)^{\sigma} - 1\right)}}_{\text{fear of unemployment}}}{\underbrace{(\epsilon^p - 1)\phi^{-1}}_{\text{pricing frictions}} \; \underbrace{(\phi_\pi - 1)}_{\text{monetary policy}}}. \tag{25}$$

Proof. See Appendix C. □

The sufficient statistic Ω encapsulates the unemployment channel that is determined by households' fear of unemployment (combining the risk-aversion parameter, the drop in consumption upon unemployment, and the unemployment risk), the conduct of monetary policy, and the pricing frictions. Changing any one of the parameters governing these has the same effect on the labor-market dynamics.

We can compare Equation (25) to an alternative version with complete markets, where all workers are part of a large family that pools all income, implying identical consumption equal to average worker income $W_t(1-u_t) + \vartheta u_t$. The real interest rate is proportional to the growth rate of average labor income, and, with $W_t = W_{ss}$, to a first order equal to $r_t = -\sigma \frac{u_{ss}(W_{ss}-\varphi)}{1-u_{ss}(W_{ss}-\varphi)} \Delta \widehat{u}_{t+1}$ where $\widehat{u}_t$ is the log deviation of the unemployment rate from steady state. Given the otherwise unchanged nature of the environment, in particular the identical labor market equilibrium for any given path of the intermediate-goods price, derivations identical to those above yield a condition for the intermediate-goods price,

$$\widehat{p_t^x} = -\Omega^{\mathrm{RA}}(\Delta\widehat{u}_{t+1} - \beta\Delta\widehat{u}_{t+2}) \tag{26}$$

with

$$\Omega^{\mathrm{RA}} = \frac{\underbrace{\sigma\frac{u_{ss}(W_{ss}-\varphi)}{1-u_{ss}(W_{ss}-\varphi)}}_{\text{intertemporal substitution}}}{\underbrace{(\epsilon^p-1)\phi^{-1}}_{\text{pricing frictions}}\underbrace{(\phi_\pi-1)}_{\text{monetary policy}}}. \tag{27}$$

The unemployment-risk channel is the difference between the equilibrium dynamics induced by Equations (24) and (26). In the model with incomplete markets, an increase in unemployment risk, either through an increase in separation or a decline in the job-finding rate, reduces the real interest rate, inflation, and the intermediate goods price by inducing precautionary savings among the households. The equilibrium fall in the intermediate goods price explains why the unemployment response is amplified to a contractionary TFP shock, as evident in Figure 3. With complete insurance markets, in contrast, separation and job-finding rates only play a role for the equilibrium response of interest rates and intermediate goods prices insofar as they affect the growth rate of unemployment. In such a model, the unemployment response is dampened to contractionary TFP shock. The initial increase in unemployment thereby instead causes the real interest rate to increase through intertemporal substitution, leading to an increased intermediate-goods price.

4.3 Equivalence of supply and demand shocks

So far, the discussion of the impulse responses in Figure 6 has focused on the supply shock to aggregate productivity Z_t (in black). The responses of key model variables to a demand shock (to the discount factor of the workers, β_t, in blue) are similar up to a scaling factor. This is no coincidence: a demand shock acts as a shock to $\widehat{p_t^x}$ in Equation (24) with the same effect on labor revenue product $\widehat{p_t^x} + \widehat{z}_t$ as a shock to productivity $\widehat{z}_t$. As a result, the labor market dynamics in response to supply and demand shocks are equivalent. This is summarized in Proposition 2.

Proposition 2. *To a first-order approximation, the impulse responses for labor-market variables to a shock to TFP (supply) and to the discount factor of workers (demand) are equivalent up to a scaling factor.*

Proof. See Appendix C. □

The fact that the dynamics of unemployment risk behave similarly in response to both supply and demand shocks in our model is reassuring since, in the data, the dynamics of unemployment risk looked similar both in response to identified supply and demand shocks. This feature contrasts with simple textbook versions of the new-Keynesian model, see, e.g., Galí (1999), which predicts that labor inputs fall in response to a negative demand shock, but *rise* in response to a negative technology shock. The latter feature of the textbook model is primarily an effect of having a frictionless labor market together with a particular choice of parameters. In the textbook model, to accommodate the initial fall and subsequent rise in consumption implied by a negative technology shock, the real interest rate has to rise. With a standard Taylor rule, inflation must increase. With nominal frictions, real marginal cost must be higher compared to the flexible-price equilibrium, implying an increase in wages, which, in the frictionless labor market, implies that labor supply increases relative to the flexible-price equilibrium. Combined with balanced-growth path preferences implying that hours worked is constant in response to technology shocks in the flexible-price equilibrium, the textbook model produces an increase in hours worked in response to a negative technology shock.

In models like ours, with a frictional labor market and where labor inputs are directly determined by firms' labor demand, hours worked fall in response to a negative productivity shock. This is also true without incomplete markets and pricing frictions, see, e.g., Balleer (2012). Moreover, in a model with incomplete markets, an increase in unemployment risk strengthens the precautionary-savings motive, which puts downward pressure on the market-clearing interest rate. In our model, where the ability of households to smooth unemployment risk is absent in equilibrium, this force is sufficiently strong such that the equilibrium real interest rate falls (in contrast to the textbook new-Keynesian model), which amplifies the contraction in hours worked.

5 Quantitative analysis

We first describe how the elasticities of separation and vacancy creation, alongside the steady-state wage level, are identified from the stylized facts about unemployment-risk dynamics in the data. Second, we study the implications of matching these facts for the contribution of the unemployment-risk channel to fluctuations in unemployment. Throughout this section, we calibrate to and study responses to a TFP shock that follows a standard $AR(1)$ process with persistence $\rho_A = 0.965$ and standard deviation, $\sigma_A = 0.007$.[21] Apart from the separation elasticity (ψ), entry elasticity (ξ), and the wage level (W_{ss}), we set all parameters to typical values found in the literature, or to capture standard long-run data moments in the model's steady state. See Table D.1 in Appendix D for details.

5.1 The role of endogenous separations and sluggish vacancy creation for matching unemployment-risk dynamics

To capture the stylized facts documented in Section 2, the contribution of separations to unemployment fluctuations and the lead-lag relation between separation and job-finding rates, our model features endogenous separations and sluggish vacancy posting. Quantitatively, these features are governed, respectively, by the separation elasticity (ψ) and entry elasticity (ξ). To understand how they together allow the model to capture the stylized facts, note that both amplify the response of unemployment to a contractionary productivity (or other) shock, but in fundamentally different ways. A higher separation elasticity trivially amplifies the increase in separations. With sluggish vacancy posting the resulting increase in unemployment also depresses the job-finding rate, as more workers search for vacancies that are replenished only slowly. In comparison, a lower entry elasticity hardly affects the separation rate. Vacancies fall by less in response to the shock, but also recover less quickly when an increasing number of unemployed workers in search for a job makes vacancy posting more attractive for firms. Taken together, this describes what Coles and Kelishomi (2018) have dubbed the *vacancy-depletion channel*. As a result, the re-

[21] We could just as well have worked with a demand shock: the facts regarding unemployment risk dynamics were very similar for identified supply and demand shocks in the data, and the responses to both shocks are identical up to a scaling factor in our model as per Proposition 2.

sponses of the job-finding rate and unemployment are more backloaded, increasing their lag with respect to the separation response. For a given values of the elasticities, we can choose the real wage W_{ss} and thus the gross fundamental surplus ratio, $m_{ss} = \frac{P^x_{ss} Z_{ss} - W_{ss}}{P^x_{ss} Z_{ss}}$ to target the overall size of the unemployment response. The gross fundamental surplus ratio is a key determinant of total unemployment volatility in this class of search-of-matching models (Ljungqvist and Sargent, 2017).

Panel a) and b) of Figure 9 illustrate the contrasting effects of the two elasticities on the dynamics of unemployment risk when recalibrating the wage level (W_{ss}) to match the standard deviation of the unconditional unemployment time series documented in Section 2, equal to 2.65 percentage point. The horizontal lines correspond to two calibration targets that capture the stylized facts in response to productivity shocks: a share of the unemployment variance accounted for by movements in the separation rate equal to 40 percent (in panel (a)); and a relative delay of the peak response of the job-finding rate of 9 months (in panel (b)). Across the different settings, we documented that separations account for 40-58 percent of fluctuations in unemployment and that the separation rate leads the job-finding rate by 6-16 months, meaning that these target numbers are conservatively selected. Trivially, the canonical free entry model with exogenous separations (corresponding to the parameter combination $\psi = 0.0$ and $\xi = 100.0$) misses these targets by a large margin.

When allowing for endogenous separations and sluggish vacancy posting, the two targets together identify the corresponding two elasticities: a higher separation elasticity increases the share of var(u_t) explained by separations in panel (a) of Figure 9. But for values of the separation elasticity ψ consistent with a substantial such share it leaves the lead-lag relation with the job-finding rate in panel (b) largely unaffected. That lead-lag relationship, in contrast, is strongly increased at lower values of the entry elasticity ξ. Because both a higher separation elasticity and a lower entry elasticity amplify the unemployment response in the vicinity of our preferred calibration, they imply a higher fundamental surplus share in panel (c) to match targeted unemployment volatility. Interestingly, this is not true for close-to-exogenous separations: because vacancy posting is the only transmission channel in that case, more sluggish vacancy posting dampens the unemployment response, implying a lower surplus ratio, as illustrated by the crossing of the lines in panel (c).

Given these contrasting effects of the three key parameters on labor-market dynamics, the stylized facts identify $\xi = 0.05$, $\psi = 1$ (indicated by the vertical line in panels

(a) to (c)) and a gross fundamental surplus ratio of approximately 14 percent, which, reflecting the additional sources of amplification in our model, is larger than in standard search-and-matching models (Ljungqvist and Sargent, 2017).

5.2 The effect of endogenous separations and sluggish vacancy creation on the unemployment-risk channel

We now turn to investigate how accounting for endogenous separations and sluggish vacancy posting affects the contribution of the URC to business-cycle fluctuations. Recall that we defined the URC as the difference in the response of unemployment between the baseline model and the corresponding model with complete asset markets (where all workers consume average labor income, see Section 4). The URC consequently captures all fluctuations in unemployment caused by the interaction of idiosyncratic unemployment risk and sticky prices. Figure 10 compares the dynamic response of unemployment to a productivity shock in these two models, and the shaded area captures the URC. In our model, the URC accounts for 35 percent of the unemployment variance. The share generated by the URC in our model does not depend specifically on the TFP shock since supply and demand shocks have equivalent effects on the labor market. In Appendix Figure 10, we verify that the URC also accounts for 35 percent of the unemployment variance in response to a demand shock to the discount factor, β_t.

Figure 11 shows how the quantitative importance of the URC for unemployment fluctuations varies with the choice of the separation elasticity (ψ) and the entry elasticity (ξ), when we re-calibrate the fundamental surplus ratio to keep the overall unemployment variance fixed. The figure presents a key result of our analysis: in a model with exogenous separations and free entry, the URC only accounts for 20 percent of unemployment fluctuations. When capturing the stylized facts of unemployment fluctuations through endogenous separations and sluggish vacancies, this contribution increases to 35 percent.

Figure 11 also shows that it is the endogeneity of separations that accounts for this result. Making vacancies more sluggish by reducing the elasticity of vacancy creation actually dampens the contribution of the URC, despite the fact that it amplifies the total response of unemployment, as shown above. Two forces pull in opposite direction in terms of shaping the dynamic path of unemployment risk that household

(a) Share of var(u_t) explained by separations

(b) Delay of job-finding through to separation peak

(c) Gross fundamental surplus ratio, $\frac{P^x_{ss} Z_{ss} - W_{ss}}{P^x_{ss} Z_{ss}}$

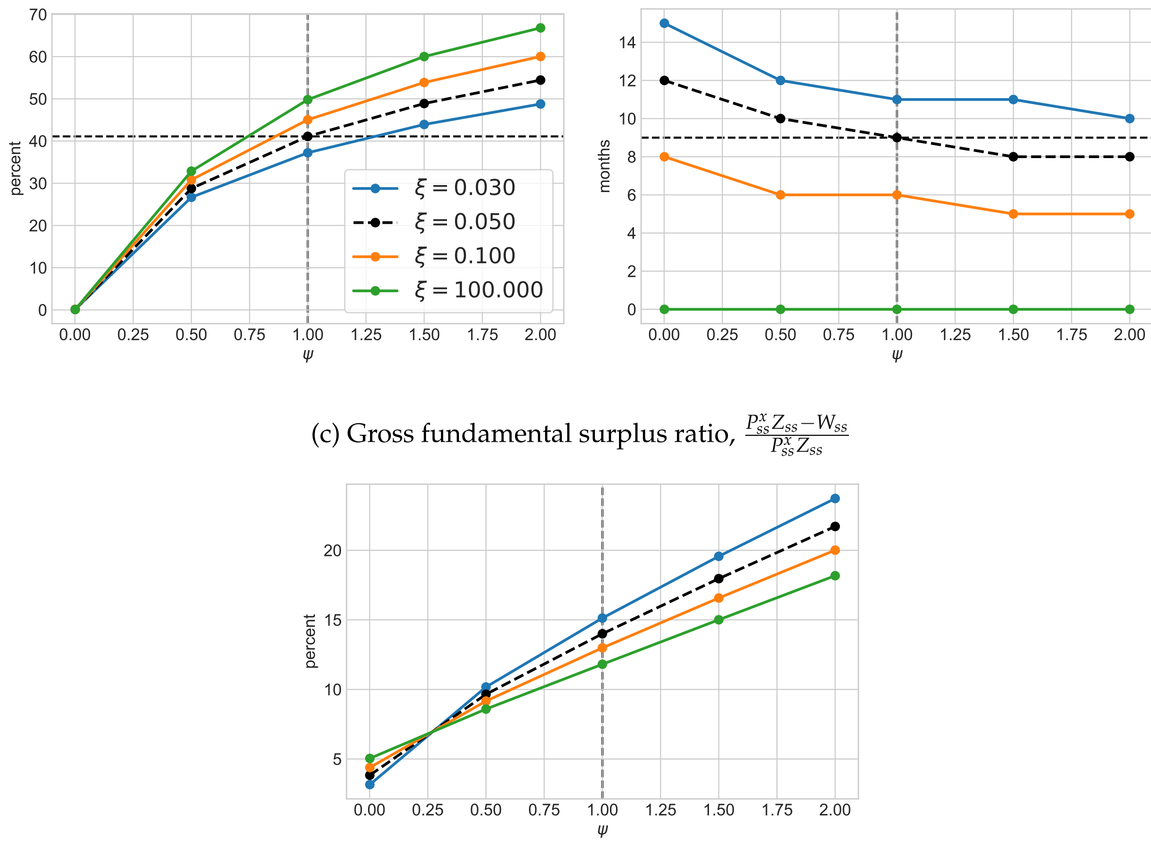


Figure 9: Identification of separation elasticity (ψ) and entry elasticity (ξ).

Notes: This figure shows model outcomes to identify the separation elasticity, ψ, and the entry elasticity, ξ, while re-calibrating the gross fundamental surplus ratio, $\tilde{m}_{ss}$, to fit a variance of unemployment of 2.65 (as found in Section 2). All other parameters are set as in Table D.1. Panel (a) shows the share of the variance of unemployment accounted for by separations using the static decomposition from Section 2. Panel (b) shows the delay from the separation rate peak to the job-finding rate trough to in months. The horizontal lines show the targeted moment values, and the vertical lines the chosen parameter values in our preferred calibration. Panel (c) shows the implied gross fundamental surplus ratio $\tilde{m}_{ss} = \frac{P^x_{ss} Z_{ss} - W_{ss}}{P^x_{ss} Z_{ss}}$.

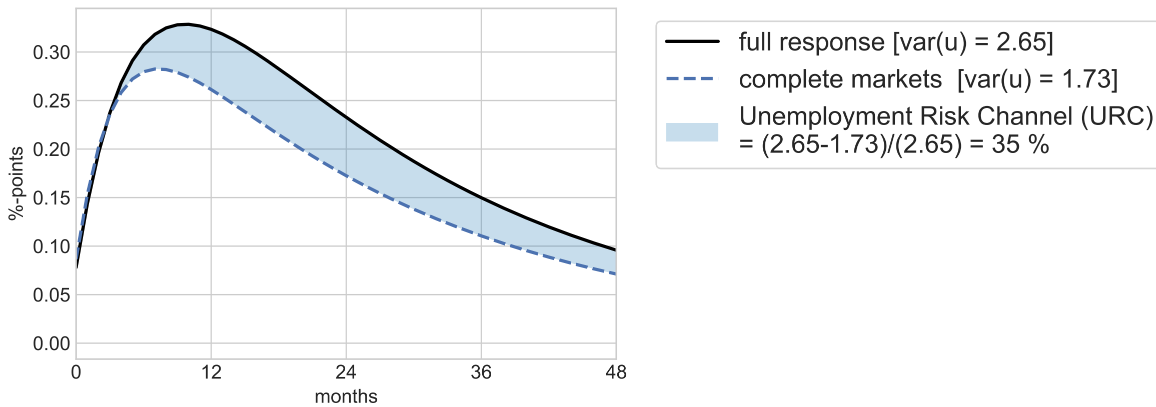


Figure 10: Decomposition of the unemployment response to a 1-std. TFP shock.

Notes: This figure shows a decomposition of the unemployment response in the baseline model to a 1-std. TFP shock. The Unemployment Risk Channel (URC) is the difference between the full response and the response with complete markets in percent of the full response.

face. With a larger share of the unemployment response generated by an increase in separations, households face more near-term income risk. With a larger share generated by a reduction in the job-finding rate, households face instead a higher risk of longer unemployment spells. Moreover, with vacancy creation being sluggish, this increase in duration risk becomes more back-loaded in time. With incomplete insurance against a potentially binding credit constraint, near-term income risk has a larger impact on employed households consumption-savings decisions relative to long-term income risk.

In our model, calibrated at a monthly frequency, the credit constraint is expected to bind for all employed households within one month, which is of course extreme. Typical calibrations of incomplete-markets model with positive liquidity will share the feature that the credit constraint eventually binds for most households, but also generate substantial heterogeneity in how long time that actually takes, and that it varies by households' current liquidity position, see, e.g., Kaplan and Violante (2018). Understanding how the distribution of households' liquidity position and its correlation with perceived unemployment risk matter for the strength of the URC is an important topic for future work.

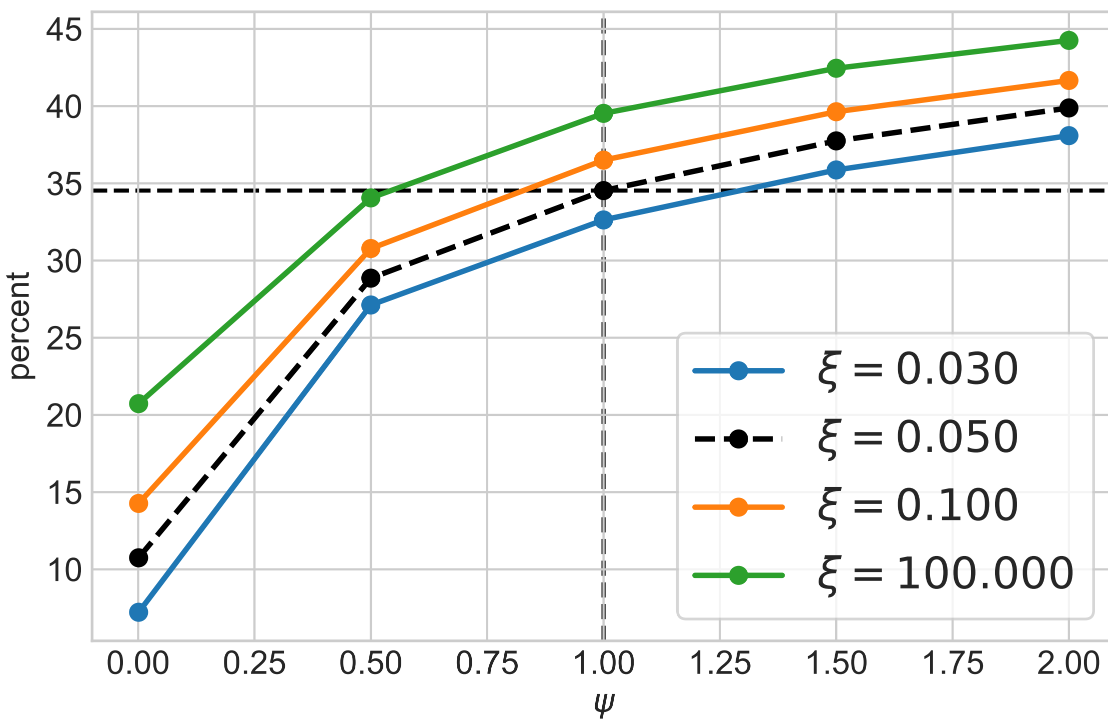


Figure 11: Unemployment Risk Channel

Notes: This figure shows the contribution of the Unemployment Risk Channel (URC) to the total response of unemployment across different values of the separation elasticity (ψ) and entry elasticity (ξ). The gross fundamental surplus ratio, $\tilde{m}_{ss}$, is re-estimated to fit the observed variance of unemployment, $\text{var}(u_t)$. The URC is the difference between the full response and the response with complete markets in percent of the full response. The dashed axes indicate the baseline calibration.

5.3 Robustness

In Appendix D we provide several robustness checks, documenting how the addition of endogenous separations and sluggish vacancy creations affects the contribution of the URC when varying other model parameters. On top of this, we explore two changes of the model here.

In the baseline model, we assumed that real wages are constant, in line with Hall (2005) and a large literature that has documented the rigidness of wage setting decisions. In the left panel of Figure 12, we show how the contribution of URC is affected when assuming that wages can respond to fluctuations instead. Specifically, we assume here that all wages respond to fluctuations in productivity with a unitary elasticity, in line with the estimates in Pissarides (2009). We recalibrate the wage level, the entry elasticity and the separations elasticity to match the same dynamic moments in response to the TFP shocks as with the baseline model. Just as in the baseline model, the contribution of the URC increases with the separation and the entry elasticity. When wages are flexible, however, the URC explains a larger share of the total response of unemployment. As shown in Equation (25), the size of the URC is determined by the ratio of consumption between the employed and unemployed. With wage flexibility, this ratio becomes larger in booms, and smaller in recessions, amplifying this channel.

In the baseline model, we also assumed that profits are distributed to a hand-to-mouth capitalist, in line with with Ravn and Sterk (2021). In the right panel of Figure 12, we show how the contribution of URC is affected when assuming that profits are equally and lump-sum distributed to all the workers. Note that in this case, the URC not only depends on the consumption gap between the employed and unemployed, but also the intertemporal substitution induced by cyclical fluctations in profit income. We similarly recalibrate the wage level, the entry elasticity and the separations elasticity to match the same dynamic moments in response to the TFP shocks as with the baseline model. Just as in the baseline model, the contribution of the URC increases with the separation and the entry elasticity (except for very small values of the entry elasticity). When profits are equally distributed, however, the URC explains a larger share of the total response of unemployment. This is because full profit sharing dampen the output response with complete asset markets: procyclical fluctuations in profits increases the procyclicality of consumption, which, in turn, increases the countercyclical response of the interest rate and inflation, which,

(a) Flexible wages

(b) Equally distributed profits

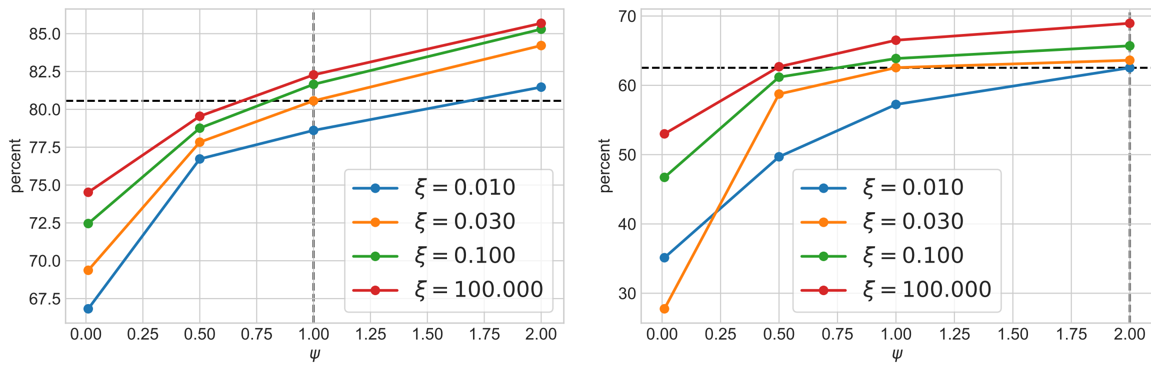


Figure 12: The unemployment-risk channel in two alternative models

Notes: This figure shows the contribution of the Unemployment Risk Channel (URC) to the total response of unemployment across different values of the separation elasticity (ψ) and entry elasticity (ξ). The gross fundamental surplus ratio, $\tilde{m}_{ss}$, is recalibrated to fit the observed variance of unemployment, $\text{var}(u_t)$, without recalibrating the separation and entry elasticities. The URC is the difference between the full response and the response with complete markets in percent of the full response. The dashed axes indicate the preferred calibration. In the case of flexible wages, the preferred calibration matches the target moments exactly. In the case of equally distributed profits, the preferred calibration slightly underestimates the share of unemployment variance explained by separations (36 percent, compared to a target of 40 percent).

in turn, dampen the response of the labor revenue product.

6 Conclusion

The unemployment-risk channel is quantitatively important for business-cycle fluctuations in unemployment, accounting for over a third of unemployment volatility. This quantitative assessment rests on an evaluation of two key labor-market elasticities: the sensitivity of job separations and vacancies to economic conditions. We identify these elasticities by jointly matching two stylized facts that we document: in response to both supply and demand shocks, (i) the job-separation rate and the job-finding rate account for substantial shares of unemployment fluctuations, and (ii) the job-finding rate responds with a lag relative to the job-separation rate. The implied job-separation and vacancy-creation elasticities needed to match these facts are strictly positive and finite. Further, the details of the labor-market dynamics matter for the assessment of the importance of the unemployment-risk channel. A correspondingly calibrated standard Diamond-Mortensen-Pissarides model, which implicitly sets the job-separation elasticity to zero and the vacancy-creation elasticity to infinity, only attributes 20 percent of unemployment volatility to the unemployment-risk channel.

Our analysis builds on a tractable framework, where we have purposefully kept some parts of the model simple and stylized. This enabled a transparent analysis of the role of endogenous separations and sluggish vacancy creation for the unemployment-risk channel. Some of the maintained assumptions are, however, restrictive and we believe it would be useful to investigate the effect of relaxing them in future work, especially for policy analysis.

First, the no-borrowing/zero-liquidity assumptions imply that workers have no ability to smooth income fluctuations in our framework. While the compressed asset distribution is in line with small liquid-asset holdings by most workers, and the consumption drop upon unemployment in the model matches that in the data, the relative role of separation risk vis-à-vis unemployment duration risk for fluctuations in consumption demand might be affected by this assumption.

Second, our modeling of the response of separations to macroeconomic conditions was intentionally simple, and thus does not capture the persistent heterogeneity in match productivity that likely drives separation decisions in the data. This means that our framework does not fully capture the costs and benefits of demand stabilization through its effect on the allocation of workers to firms. Future research should build, e.g., on the evidence in Haltiwanger et al. (2025) who document how labor-market cycles contribute to productivity-enhancing reallocation of workers, as separations in recessions are concentrated among low-productivity firms, while the job ladder reallocates workers to higher-productivity firms in booms. Similarly, the assumption of heterogenous costs of creating a vacancy follows previous work (Coles and Kelishomi, 2018; Haefke and Reiter, 2020), but does not allow us to quantitatively capture the heterogeneity of firm or job productivity, and their correlation with entry and exit decisions. An interesting avenue for future research includes enriching the labor market block with, e.g., recall unemployment, job-to-job transitions, endogenous search and recruitment intensities, and a distinction between separations and job destruction.

Third, we have assumed that all households are equally exposed to unemployment risk. To the extent that poorer individuals in terms of wealth (and thus self-insurance) are more exposed to unemployment risk (as documented in Clymo et al. (2022)), this heterogeneity could amplify the unemployment-risk channel. To the extent that poorer individuals (in terms of permanent income) are more exposed to unemployment risk (as documented in Broer et al. (2022)), this heterogeneity could, in contrast, dampen the channel, as they matter relatively less for aggregate consumption. Future research should investigate how incorporating heterogeneity in the exposure to unemployment risk affects the quantification of the unemployment-risk channel.

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A Appendix to Section 2

A.1 Accounting for time aggregation

To account for time aggregation, we analyze the data through the lens of a three state continuous time model, where workers are either employed (E), unemployed (U) or inactive (I), i.e. out of the labor force.

Let P_t denote the *discrete time transition probability matrix* from month t to month $t+1$. This can be calculated directly from the data. We use seasonally adjusted probabilities.

Let P_t^{AB} denote the transition probability from state $A \in \{E, U, I\}$ to state $B \in \{E, U, I\}$. The implied *transition rate matrix*, also known as the *infinitesimal generator matrix*, is given by[22]

$$
\begin{aligned}
Q_t &= \begin{bmatrix} -(\lambda_t^{EU} + \lambda_t^{EI}) & \lambda_t^{EU} & \lambda_t^{EI} \\ \lambda_t^{UE} & -(\lambda_t^{UE} + \lambda_t^{UI}) & \lambda_t^{UI} \\ \lambda_t^{IE} & \lambda_t^{IU} & -(\lambda_t^{IE} + \lambda_t^{IU}) \end{bmatrix} \\
&= p_t \begin{bmatrix} \ln(\mu_{t1}) & 0 & 0 \\ 0 & \ln(\mu_{t2}) & 0 \\ 0 & 0 & \ln(\mu_{t3}) \end{bmatrix} p_t^{-1},
\end{aligned}
$$

where μ_{t1}, μ_{t2} and μ_{t3} are the eigenvalues of P_t, and p_t is the associated eigenvector matrix. We can thus derive P_t^{AB}, and the underlying continuous time transition rates, from P_t alone.

We calculate the probability of at least one transition in a month from state A to state B, conditional on no transitions to the third state C, as $\Lambda_t^{AB} = 1 - e^{-\lambda_t^{AB}}$. For simplicity, we refer to this both as the *monthly transition probability*, and as the *monthly transition rate*.

A.2 Robustness of estimated impulse responses

Figure A.1 shows the estimated impulse responses to a technology shock, using the identified shocks from Francis et al. (2014) (retrieved from Valerie Ramey's website).

[22] We assume the eigenvalues of P_t are unique, real and positive. This is true in the data.

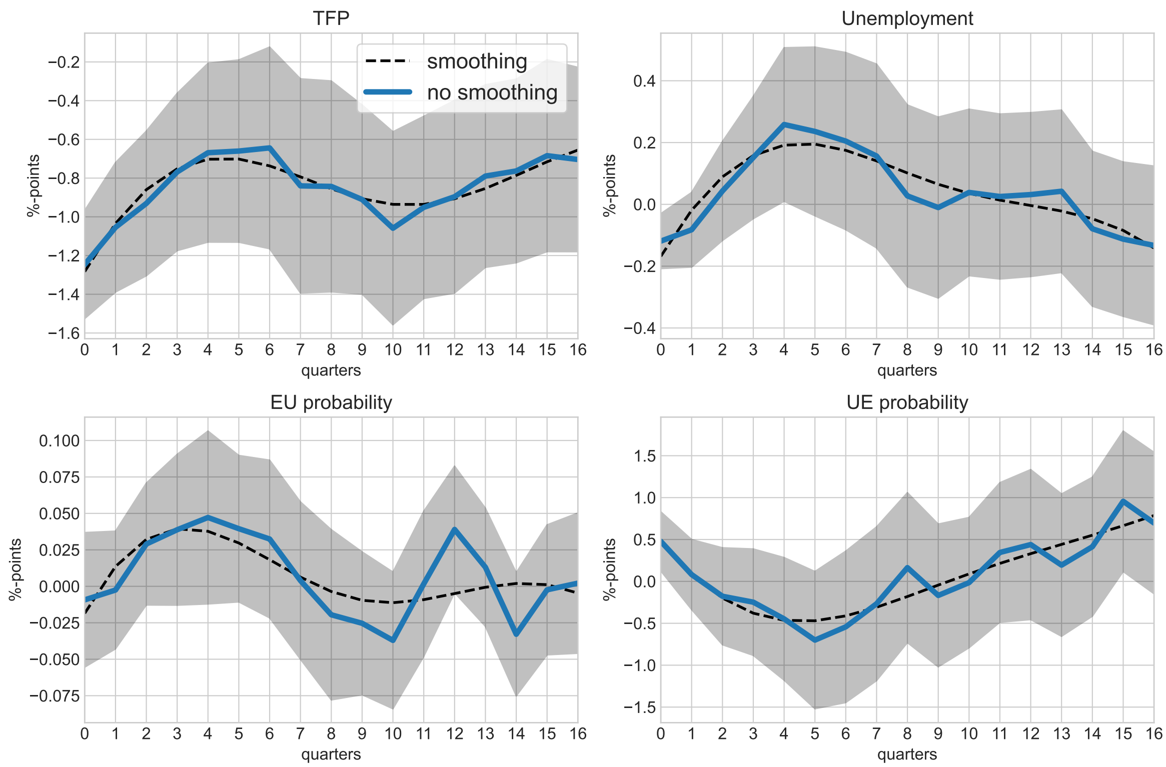


Figure A.1: Responses to a TFP shock using the shock series from Francis et al. (2014).

The specification is the same as for the IRFs in the main text. Figure A.2 shows the variance decomposition and lead-lag relationship between the separation rate and the job-finding rate based on these IRFs. With these shocks, we find that the separation rate accounts for 42 percent of fluctuations in unemployment, and leads the job-finding rate by 6 months.

Table A.1 shows how the results for the estimated TFP shock varies across specifications using different sets of control variables. Figures A.3-A.5 show the associated impulse-response functions. The control variables have overall a small effect on the share of the unemployment response explained by the separation rate as well as the lead-lag relationship between the separation rate and the job-finding rate.

Table A.2 shows how the results for the monetary policy shock vary across specifications using different sets of control variables. Figures A.6-A.9 show the associated impulse-response functions. The control variables have overall a small effect on the share of the unemployment response explained by the separation rate as well as the lead-lag relationship between the separation rate and the job-finding rate.

(a) Variance decomposition

(b) Lead-lag relationship

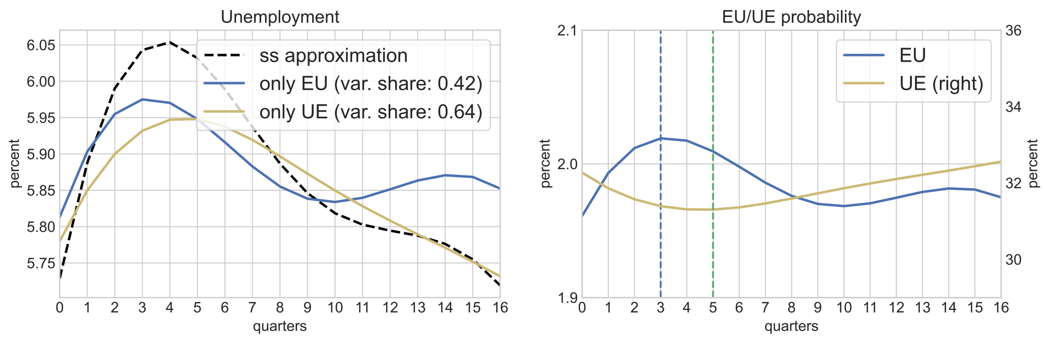


Figure A.2: Variance decomposition of unemployment and lead-lag of the transition rates to a TFP shock, using the shock series from Francis et al. (2014).

	Baseline	**Spec 1**	**Spec 2**	**Spec 3**
UE share (percent)	47	53	47	47
UE lead (months)	9	12	9	9
Controls				
Quad. time trend	x	x	x	x
Two lags of the shock	x	x	x	x
Two lags of log real GDP	x		x	x
Two lags of log real stock prices	x			x
Two lags of log real labor productivity	x			

Table A.1: Results for TFP shock across different specifications.

	Baseline	**Spec 1**	**Spec 2**	**Spec 3**	**Spec 4**
UE share (percent)	59	57	54	51	51
UE lead (months)	16	11	14	15	17
Controls					
Two lags of the shock	x	x	x	x	x
Two lags of the FFR	x	x	x	x	x
Contemp + two lags of log ind. prod.	x		x	x	x
Contemp + two lags of log PC deflator	x			x	x
Contemp + two lags of log comm. price index	x				x
Contemp + two lags of unemployment rate	x				

Table A.2: Results for monetary policy shock across different specifications.

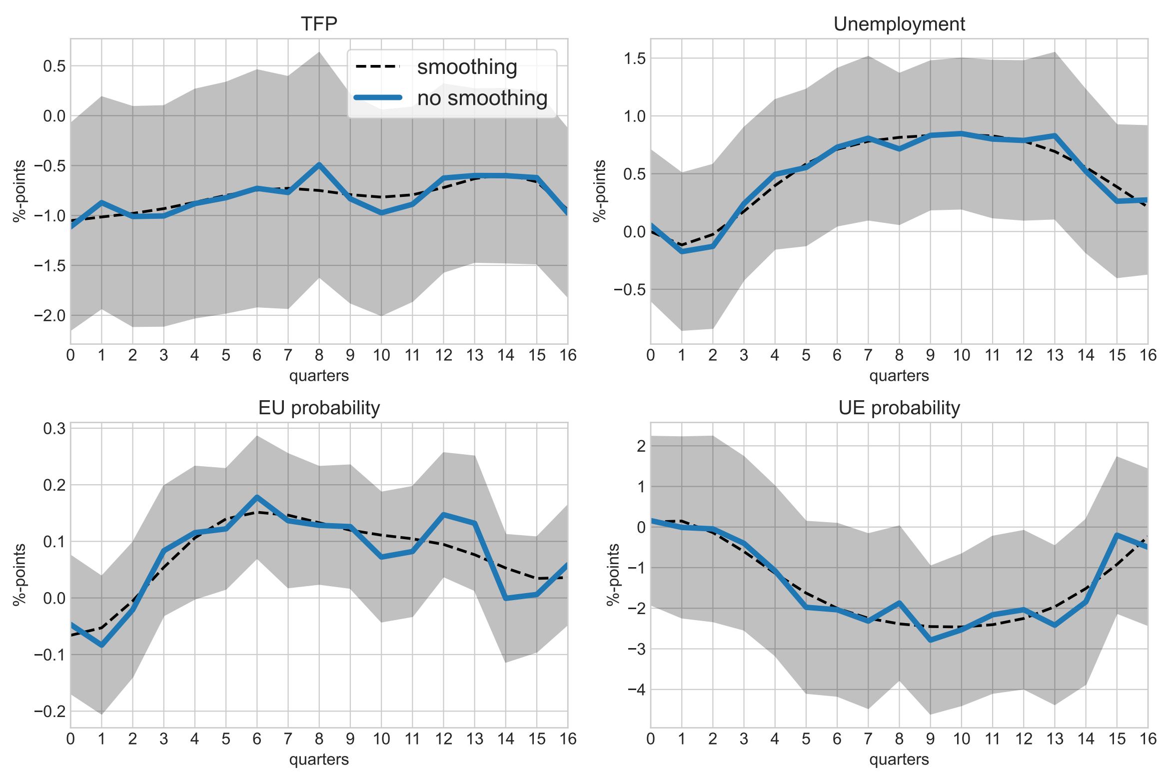


Figure A.3: Responses to a TFP shock controlling for a quadratic time trend and two lags the shock.

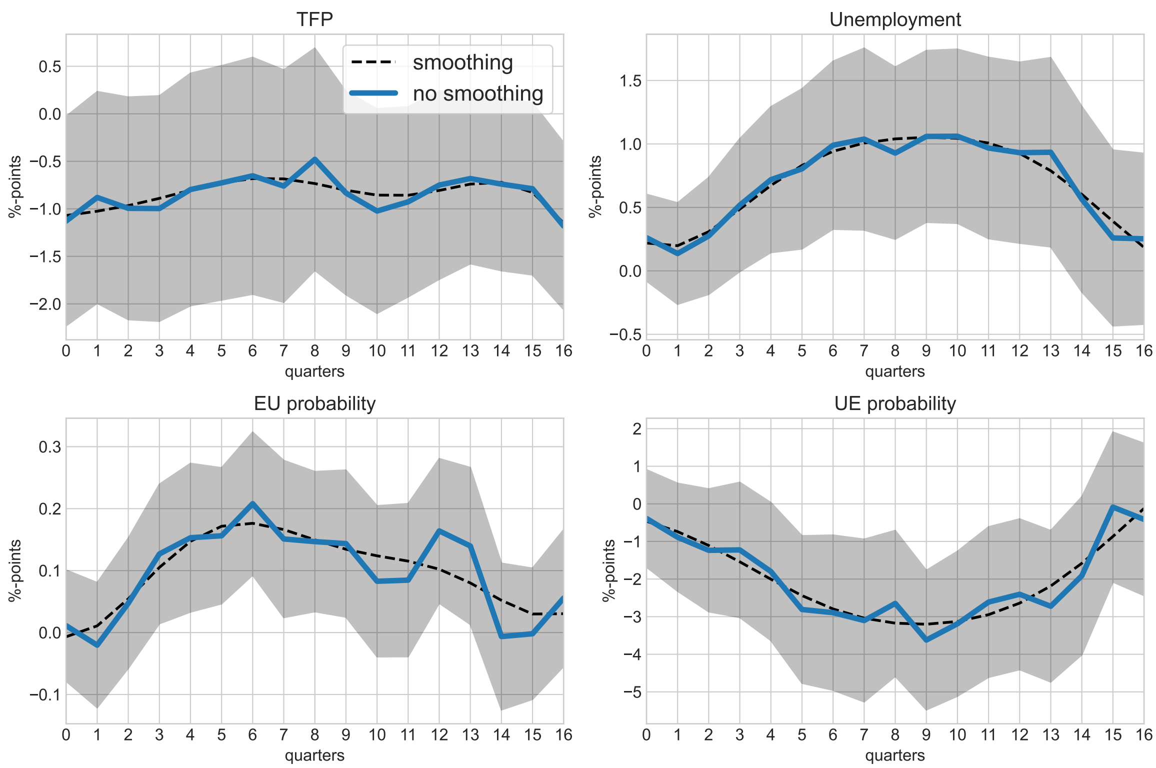


Figure A.4: Responses to a TFP shock controlling for a quadratic time trend, two lags the shock and two lags of log real GDP.

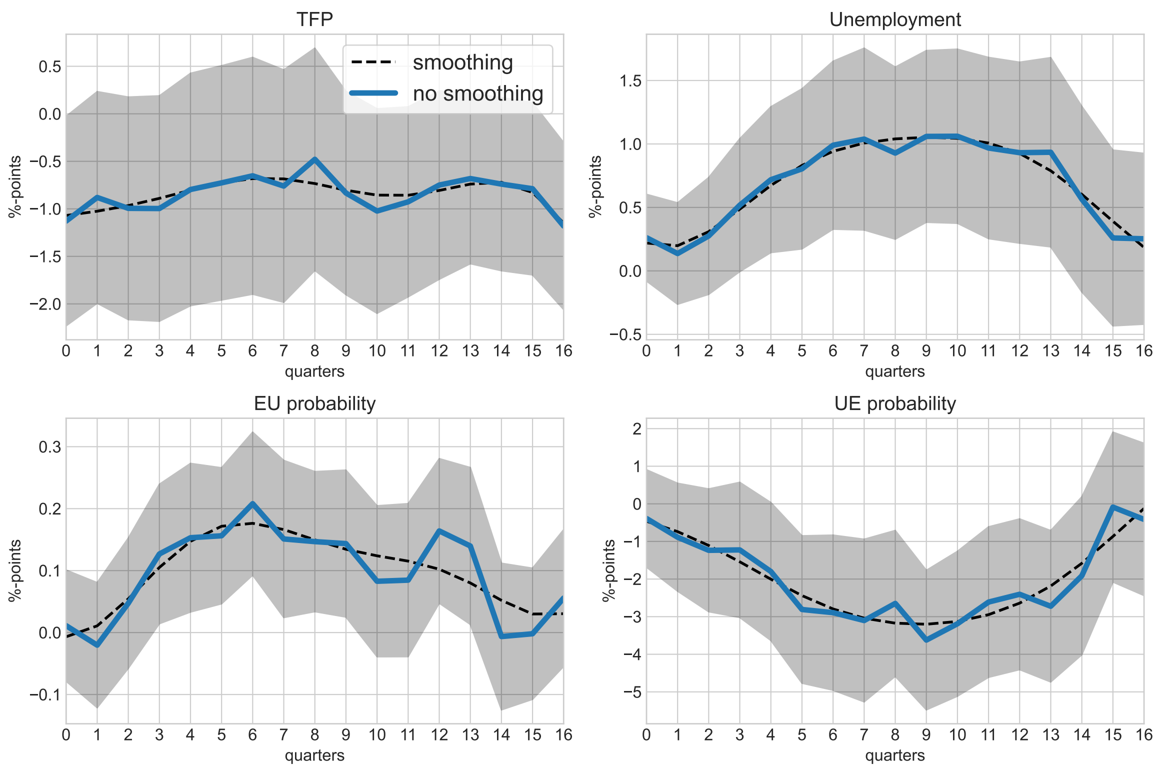


Figure A.5: Responses to a TFP shock controlling for a quadratic time trend, two lags the shock, two lags of log real GDP and and two lags of real stock prices.

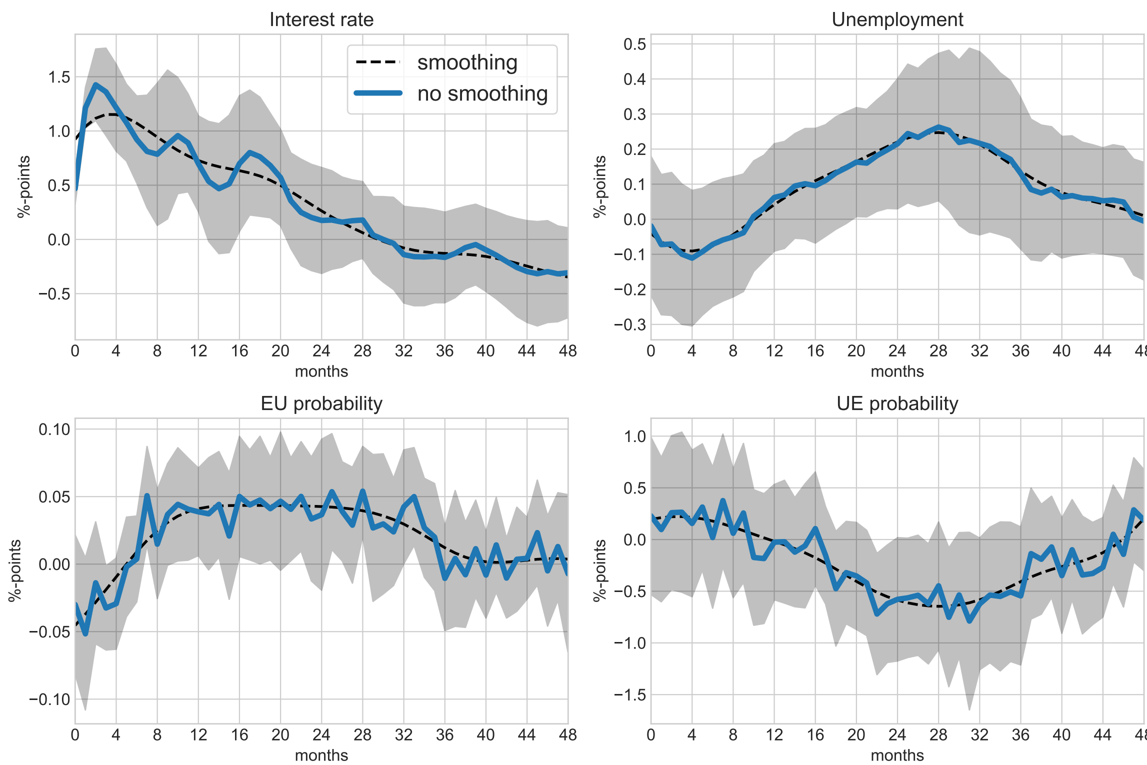


Figure A.6: Responses to a monetary policy shock controlling for two lags of the shock, and two lags of the FFR.

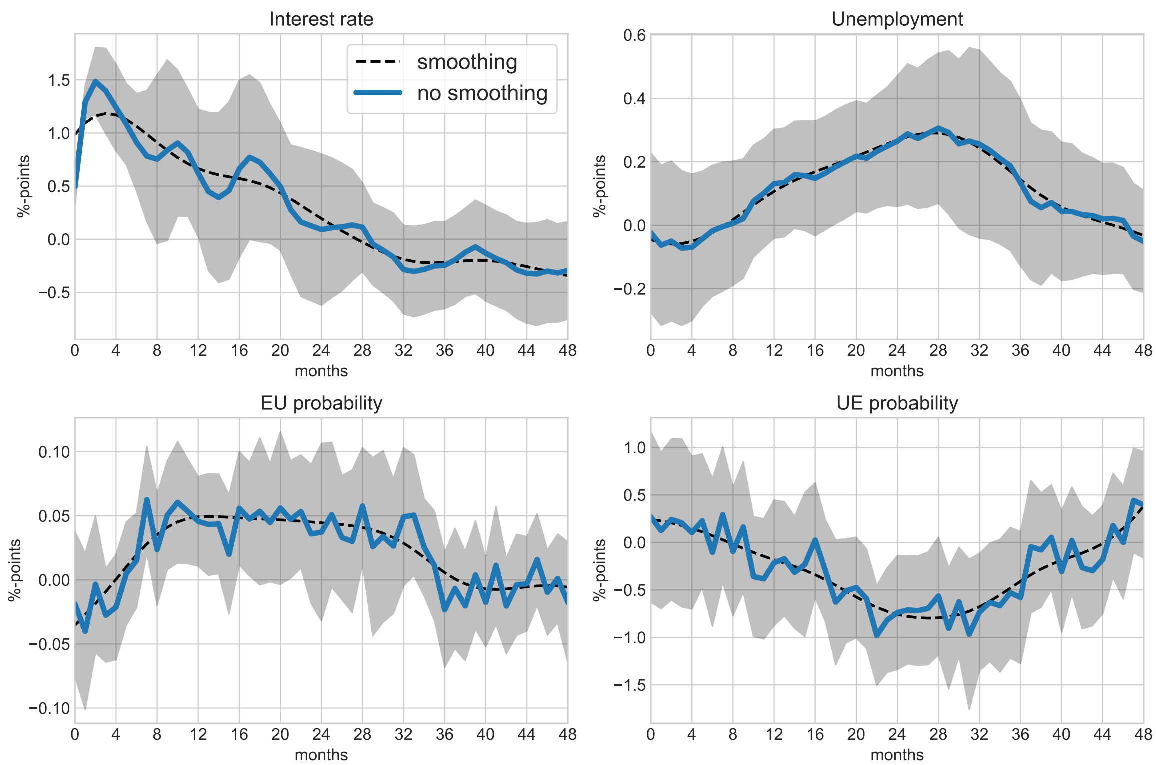


Figure A.7: Responses to a monetary policy shock controlling for two lags of the shock, two lags of the FFR and the contemporaneous value as well as two lags of log ind. production.

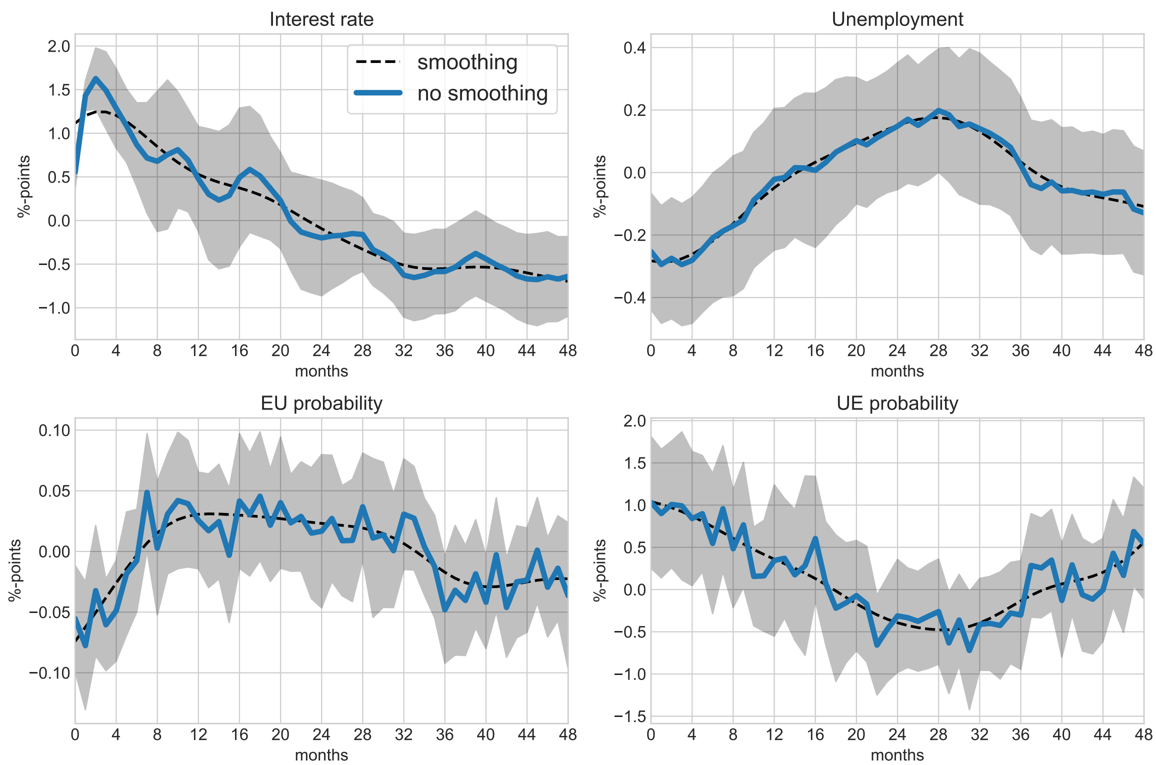


Figure A.8: Responses to a monetary policy shock controlling for two lags of the shock, two lags of the FFR and the contemporaneous value as well as two lags of log ind. production, log PC deflator and log comm. price index.

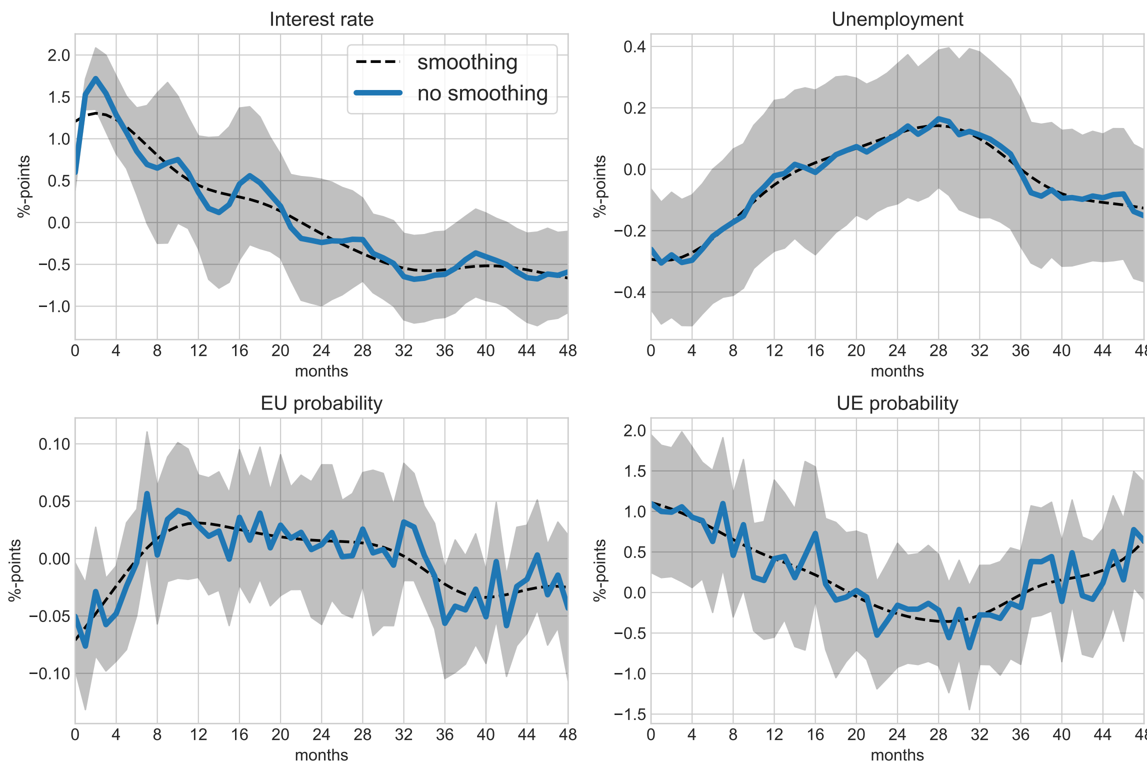


Figure A.9: Responses to a monetary policy shock controlling for two lags of the shock, two lags of the FFR and the contemporaneous value as well as two lags of log ind. production and log PC deflator.

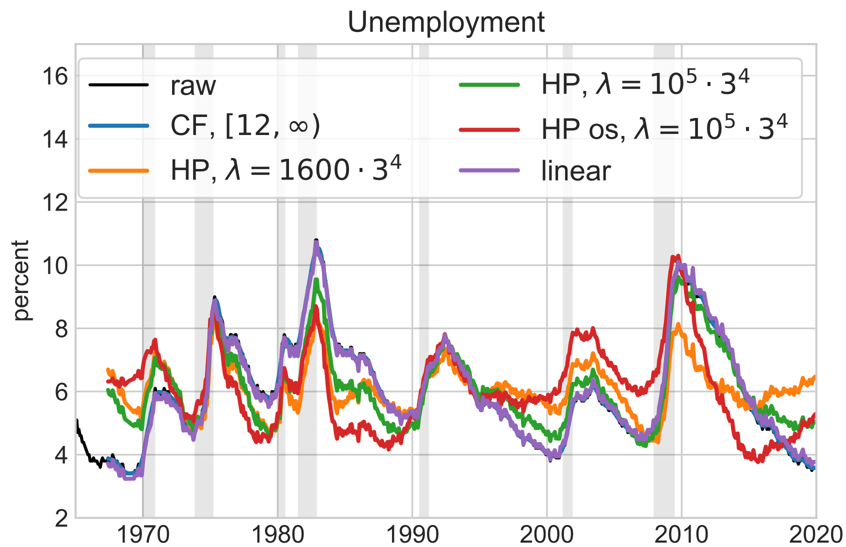


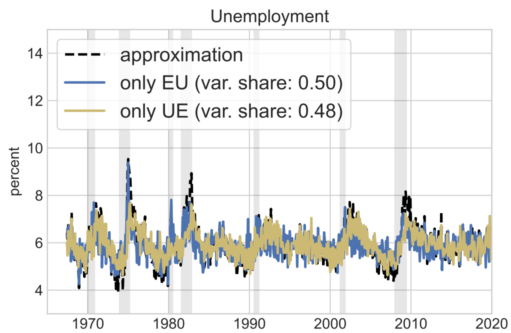
Figure A.10: Detrended unemployment using different filters

A.3 Filtering methods and sample periods

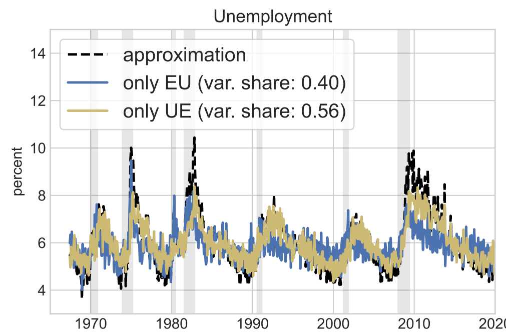
Figure A.10 shows the time series of unemployment using different filtering methods. Fujita and Ramey (2009) use a two-sided Hodrick-Prescott filter with $\lambda = 1600$; Shimer (2012) uses a two-sided Hodrick-Prescott filter with $\lambda = 10^5$ (here, we adjust these values to monthly data by multiplying by 3^4). As seen from Figure A.10, two-sided Hodrick-Prescott filters tend to attribute a larger share of the Great Recession to the trend rather than the cycle component, and also do not filter out erratic short-term movements in the unemployment rate. The one-sided filter attributes a larger share of the slow recovery after the Great Recession to the trend. A linear filter closely tracks the Christiano-Fitzgerald bandpass filter used for the specification in the main text.

Figure A.11 shows the variance decomposition of the time series of unemployment using different filtering methods. With all the alternative filters, the resulting time series are more erratic, as high-frequency fluctuations are not filtered out. The variance explained by the separation rate varies from 38 to 50 percent. Figure A.12 shows the correlation structure of the time series of unemployment using different filtering methods. With all the alternative filters, the resulting time series are more erratic, as high-frequency fluctuations are not filtered out. The peak in the correlation between the job-finding rate at time t and the separation rate at time t-h varies between 4 and

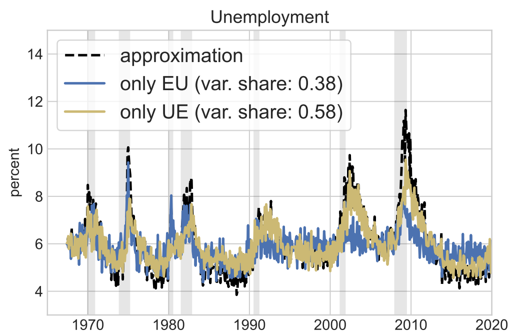
(a) Two-sided HP-filter, $\lambda = 1600 \cdot 3^4$



(b) Two-sided HP-filter, $\lambda = 10^5 * 3^4$



(c) One-sided HP-filter, $\lambda = 1600 * 3^4$



(d) Linear filter

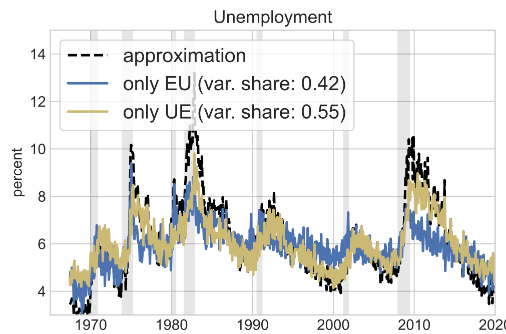


Figure A.11: Variance decomposition of unemployment with different filtering methods.

6 months.

Figure A.12 shows the variance decomposition and the correlation structure when restricting to the sample starting 1987-01 and ending 2019-12. The variance share explained by the separation rate is here 28 percent, and the peak correlation between the job-finding and the separation rate happens when the former leads the latter with 9 months.

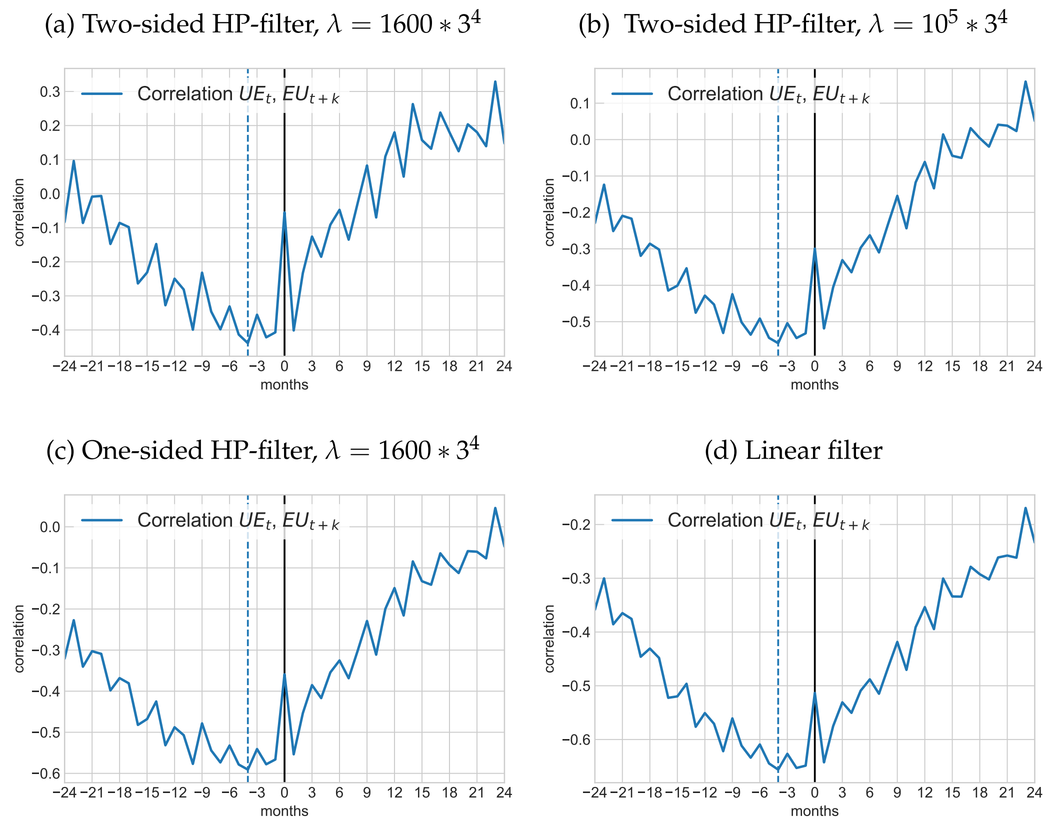


Figure A.12: Correlation structure of the EU and UE rate with different filtering methods.

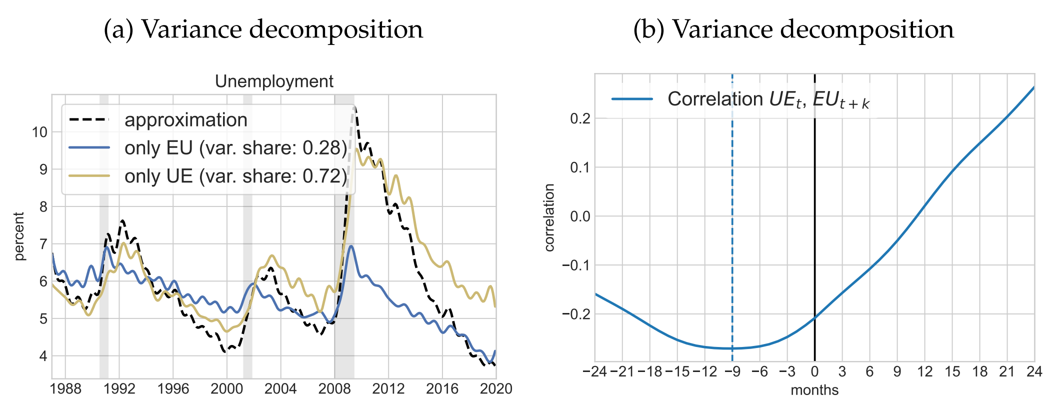


Figure A.13: Variance decomposition of unemployment and lead-lag of the transition rates in the post-1987 sample period.

B Appendix to Section 3

B.1 Separation decision

In Equation 12, we assume that G is a mixture of a point mass at 0 and a Pareto distribution with location parameter $\Upsilon > 0$ and shape parameter ψ,

$$G(\chi_t) = \begin{cases} 0 & \chi_t < 0, \\ 1-p & 0 \leq \chi_t < \Upsilon, \\ (1-p) + p(1-(\chi_t/\Upsilon)^{-\psi}) & \chi_t \geq \Upsilon, \end{cases} \tag{28}$$

This implies

$$\begin{aligned} \delta_t &= \int_{V_t^j}^{\infty} G(\chi_t) d(\chi_t) \\ &= \begin{cases} p & \text{if } V_t^j \leq \Upsilon \\ p\left(\frac{V_t^j}{\Upsilon}\right)^{-\psi} & \text{else} \end{cases} \end{aligned} \tag{29}$$

and

$$\begin{aligned} \mu_t &= \int_0^{V_t^j} \chi_t dG(\chi_t) \\ &= \frac{\mathbb{E}[\chi_t] - \text{Prob.}[\chi_t > V_t^j]\mathbb{E}[\chi_t|\chi_t > V_t^j]}{1-\text{Prob.}[\chi_t > V_t^j]} \\ &= \begin{cases} 0 & \text{if } V_t^k \leq \Upsilon \\ \frac{p\frac{\psi\Upsilon}{\psi-1} - p\left(\frac{V_t^j}{\Upsilon}\right)^{-\psi}\frac{\psi V_t^j}{\psi-1}}{(1-p)+p(1-(\chi_t/\Upsilon)^{-\psi})} & \text{else} \end{cases} \\ &= \begin{cases} 0 & \text{if } V_t^k \leq \Upsilon \\ \frac{p\frac{\psi}{\psi-1}\Upsilon\left[1-\left(\frac{V_t^j}{\Upsilon}\right)^{1-\psi}\right]}{1-p\left(\frac{V_t^j}{\Upsilon}\right)^{-\psi}} & \text{else} \end{cases} \\ &= \mu(V_t^j) \end{aligned} \tag{30}$$

We always choose $\Upsilon = \left(\frac{\delta_{ss}}{p}\right)^{\frac{1}{\psi}} V_{ss}^j$ which implies Equation (13) in the main text. Furthermore, with $p = \delta_{ss}$ we have $\Upsilon = V_{ss}^j$ which implies $\delta_t = \delta_{ss}$ when $V_t^j \leq V_{ss}^j$. Instead we set $p = (1 + \Delta_\delta)\delta_{ss}$ where $\Delta_\delta > 0$ is a small positive number. This implies that δ_t can rise above δ_{ss} when V_t^j falls below V_{ss}^j. It also implies that μ_{ss} is a small positive number.

B.2 Asset market equilibrium

Workers' optimization problem The post-decision value function for the employed worker is

$$\mathcal{W}_t^n = \mathbb{E}_t \left[(1 - \text{URISK}_t) V_{t+1}^n + \text{URISK}_t V_{t+1}^u \right]$$

where $\text{URISK}_t = \delta_{t+1}(1 - \lambda_{t+1}^u)$ is the probability of an employed worker becoming unemployed. The Bellman equation for an employed worker is

$$\begin{aligned} V_t^n = & \max_{C_{n,t}, B_{n,t+1}} \frac{C_{n,t}^{1-\sigma}}{1-\sigma} + \beta \mathcal{W}_t^n \\ & \text{s.t.} \\ & C_{n,t} + \frac{B_{n,t+1}}{1+i_t} \leq W_t + \frac{B_{n,t}}{\Pi_t}, \\ & B_{n,t+1} \geq 0. \end{aligned} \tag{31}$$

where $B_{n,t}$ are bond holdings. In the zero-liquidity equilibrium, the sum of all agents' asset holdings is zero. Together with assumption that no agent is allowed to borrow, it follows that all individual agents' asseting holdings must be zero. Hence, $B_{n,t} = B_{n,t+1} = 0$, and all employed workers are symmetrical such that $C_{n,t} = W_t$.

The post-decision value function for the unemployed worker is

$$\mathcal{W}_t^u = \mathbb{E}_t \left[\lambda_{t+1}^u V_{t+1}^n + (1 - \lambda_{t+1}^u) V_{t+1}^u \right].$$

The Bellman equation for an unemployed worker is

$$V_t^u = \max_{C_{n,t}, B_{n,t+1}} \frac{C_{u,t}^{1-\sigma}}{1-\sigma} + \beta \mathcal{W}_t^u \tag{32}$$
$$\text{s.t.}$$
$$C_{u,t} + \frac{B_{u,t+1}}{1+i_t} \leq \vartheta + \frac{B_{u,t}}{\Pi_t},$$
$$B_{u,t+1} \geq 0.$$

In the zero-liquidity equilibrium, $B_{u,t} = B_{u,t+1} = 0$, and all unemployed workers are symmetrical such that $C_{u,t} = \vartheta$.

Capitalists' optimization problem The Bellman equation for the capitalists, who do not participate in the labor market, is

$$V_t^c = \max_{C_{n,t}, B_{n,t+1}} C_{c,t} + \beta \mathbb{E}_t[V_{t+1}^c] \tag{33}$$
$$\text{s.t.}$$
$$C_{c,t} + \frac{B_{c,t+1}}{1+i_t} + P_t^S S_t \leq \vartheta + \frac{B_{c,t}}{\Pi_t} + (P_t^s + D_t) S_{t-1},$$
$$C_{c,t} \geq 0, \tag{34}$$
$$B_{c,t+1} \geq 0, \tag{35}$$
$$S_t \geq 0,$$

where $B_{c,t}$ are bonds, S_t are equity fund shares. The equity fund owns all firms in the economy, and pays out the firm profits as D_t.

In the zero liquidity equilibrium, $B_{c,t} = B_{c,t+1} = 0$, and with all capitalists symmetrical, $S_t = S_{t+1} = \frac{1}{\text{pop}_c}$. Consumption of the capitalists is given by

$$C_{c,t} = \frac{D_t}{\text{pop}_c} + \vartheta.$$

Since capitalists have linear utility, the discount factor that enter the firm problems is simply β.

Asset market equilibrium Optimality requires that the three Euler equations of the three types of agents are satisfied with weak inequality,

$$W_t^{-\sigma} \geq \beta \mathbb{E}_t \left[\frac{1+i_t}{\Pi_{t+1}} \left((1-\text{URISK}_t) W_{t+1}^{-\sigma} + \text{URISK}_{u,t} \vartheta^{-\sigma} \right) \right], \tag{36}$$

$$\vartheta^{-\sigma} \geq \beta \mathbb{E}_t \left[\frac{1+i_t}{\Pi_{t+1}} \left(\lambda_{t+1}^u W_{t+1}^{-\sigma} + (1-\lambda_{t+1}^u) \vartheta^{-\sigma} \right) \right], \tag{37}$$

$$1 \geq \beta \mathbb{E}_t \left[\frac{1+i_t}{\Pi_{t+1}} \right]. \tag{38}$$

Formally, any real interest rate $(1+i_t)/\Pi_{t+1}$ low enough such that all three Euler equations are satisfied with weak inequality is consistent with the zero-liquidity equilibrium. The natural interpretation is however to let liquidity approach zero, as in Krusell et al. (2011), then the real interest rate is such that one of the Euler equations holds with equality.

At a zero-inflation steady state, the three Euler equations amount to

$$1 \geq \beta(1+i_{ss}), \tag{39}$$

$$1 \geq \beta(1+i_{ss}) \left(1 + \text{URISK}_{ss}((W_{ss}/\vartheta)^{\sigma} - 1)\right), \tag{40}$$

$$1 \geq \beta(1+i_{ss}) \left(1 - \lambda_{ss}^u (1 - (W_{ss}/\vartheta)^{-\sigma})\right). \tag{41}$$

With the transition rates strictly positive, and the wage of the employed larger than the home production of the unemployed, $W_{ss} > \vartheta$, we get the inequalities $1 + \text{URISK}_t((W_{ss}/\vartheta)^{\sigma} - 1) > 1 > 1 - \lambda_{ss}^u(1 - (W_{ss}/\vartheta)^{-\sigma})$ and the marginal saver is the employed worker. For small enough aggregate shocks, around the zero-inflation steady state, the employed worker remains the marginal saver and Equation (22) is the asset-marking clearing condition.

B.3 Solution algorithm

First, we solve for the **steady state** in 3 steps:

1. **Normalizations:** We use $Z_{ss} = 1.0$ and $\Pi_{ss} = 1.0$
2. **Targets:** We choose δ_{ss}, λ_{ss}^u, θ_{ss},$\tilde{M}_{ss}$ and V_{ss}^v, as calibration targets
3. **Solution**: The steady state for the remaining variable can then be found in closed form. See details in Appendix D.3.

Second, we solve for the **impulse-response to MIT shocks** around the steady using the following 5 step approach:

1. **Exogenous:** We choose paths for $\{Z_t\}_0^T$ and $\{\beta_t\}_0^T$ where for $t \in [\underline{T}, T]$ with $\underline{T} \ll T$ we have $Z_t = Z_{ss}$ and $\beta_t = \beta_{ss}$.
2. **Inputs:** Guess on 4 inputs paths.

   Intermediary goods price, $\{P_t^X\}_0^T$

   Job value, $\{V_t^j\}_0^T$

   Vacancy value, $\{V_t^v\}_0^T$

   Inflation, $\{\Pi_t\}_0^T$
3. **Evaluation:** Evaluate paths for all remaining variables.
4. **Errors:** Check errors of the 4 target equations.

   Intermediary goods price, $\{P_t^X\}$

   Job value, $\{V_t^j\}$

   Vacancy value, $\{V_t^v\}$

   Inflation, $\{\Pi_t\}$
5. **Convergence:** Loop through step 2-4 until errors are below chosen tolerance.

To speed up the solution, we compute the Jacobian of the equation system using numerical differentiation and solve the problem with a Broyden solver. The code is mostly written in Python, but the evaluation of the equation system is written in C++, and the computation of the Jacobian is parallelized.

In practice, the system is close to linear for small aggregate shocks, and we could have computed the transition paths under a linear approximation directly. We opt for computing the non-linear transition paths as this method was seemingly more stable when considering parameter changes to the model.

C Appendix to Section 4

C.1 Proof of Proposition 1 and Proposition 2

The log-linearized equations for the HANK block are the asset-marking clearing condition,

$$i_t - \mathbb{E}_t \pi_{t+1} = -\frac{\text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)}{1 + \text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)} urisk_t - \log \nu_t^{\beta},$$

the Taylor rule,

$$i_t = (\phi_\pi - 1)\pi_t + \mathbb{E}_t[\pi_{t+1}],$$

and the Phillips curve,

$$\pi_t = \beta \mathbb{E}_t \pi_{t+1} + (\epsilon^p - 1)\phi^{-1} p_t^x.$$

Solving for $i_t - \mathbb{E}_t[\pi_{t+1}]$ in the Taylor rule and substituting in the expression for $i_t - \mathbb{E}_t[\pi_{t+1}]$ from the asset-marking clearing condition gives

$$\pi_t = -\frac{1}{\phi_\pi - 1} \left(\frac{\text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)}{1 + \text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)} urisk_t + \log \nu_t^{\beta} \right).$$

Substituting into the Phillips curve gives

$$\begin{aligned} p_t^x = &- \frac{\frac{\text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)}{1 + \text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)}}{(\phi_\pi - 1)(\epsilon^p - 1)\phi^{-1}} (urisk_t - \beta \mathbb{E}_t urisk_{t+1}) \\ &- \frac{1}{(\phi_\pi - 1)(\epsilon^p - 1)\phi^{-1}} (\log \nu_t^{\beta} - \beta \mathbb{E}_t \log \nu_{t+1}^{\beta}) \end{aligned}$$

which, by invoking that $\log \nu_{t+1}^{\beta}$ follows an $AR(1)$ with persistence ρ^{β}, gives

$$p_t^x + z_t = -\frac{\frac{\text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)}{1 + \text{URISK}_{ss} \times \left(\left(\frac{W_{ss}}{\vartheta} \right)^{\sigma} - 1 \right)}}{(\phi_\pi - 1)(\epsilon^p - 1)\phi^{-1}} (urisk_t - \beta \mathbb{E}_t urisk_{t+1}) - \frac{1 - \beta\rho^{\beta}}{(\phi_\pi - 1)(\epsilon^p - 1)\phi^{-1}} \log \nu_t^{\beta} + z_t,$$

(a) Unemployment rate, u_t (b) Separation rate, δ_t (c) Job-finding rate, λ_t^u

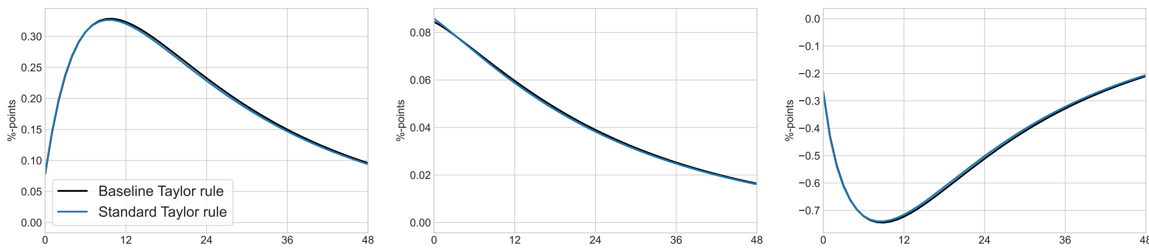


Figure C.1: Impulse-response to a 1-std. TFP shock - varying the Taylor Rule .

Notes: This figure shows the impulse-response to a TFP-shock varying the Taylor rule. The baseline Taylor rule is Equation 23. The standard Taylor rule is $1 + i_t = (1 + i_{ss})\Pi_t^{\phi_\pi}$. All other parameters are set as in Table D.1.

Therefore, labor revenue product, $p_t^x + z_t$, responds identically to a TFP shock and a demand shock, up to the proportionality factor $\frac{1-\beta\rho^\beta}{(\phi_\pi-1)(\epsilon^p-1)\phi^{-1}}$. This proves Proposition 2.

In the absence of demand shocks, we have

$$p_t^x = \frac{\frac{\text{URISK}_{ss}\times\left(\left(\frac{W_{ss}}{\vartheta}\right)^\sigma-1\right)}{1+\text{URISK}_{ss}\times\left(\left(\frac{W_{ss}}{\vartheta}\right)^\sigma-1\right)}}{(\phi_\pi-1)(\epsilon^p-1)\phi^{-1}}(urisk_t - \beta\mathbb{E}_t urisk_{t+1}),$$

proving Proposition 1.

C.2 Standard Taylor Rule

Figure C.1 compares the impulse response to a TFP shock in the baseline model to that with a standard Taylor rule, where Equation 23 is replaced with $1 + i_t = (1 + i_{ss})\Pi_t^{\phi_\pi}$.

D Appendix to Section 5

D.1 Externally calibrated parameters

Panel A of Table D.1 displays the externally calibrated parameters. We set the level of home production ϑ to be 90 percent of the wage level, such that consumption drops by 10 percent upon unemployment. This is in between the target values of 5 and 20 percent considered in Ravn and Sterk (2021), and roughly in line with estimates from micro-data of the consumption drop after unemployment shocks.[23] In addition, the model contains a number of scale parameters in the matching function and idiosyncratic cost functions. We choose these to satisfy three steady state targets for the separation rate, the job-finding rate, and tightness. The targeted values are shown in Panel B of Table D.1.

D.2 Identification of fundamental surplus ratio, separation and entry elasticities

Panel I in Figure D.1 shows that the separation elasticity, ψ, mainly scales the magnitude of the impulse responses with a particularly large effect on the separation rate. Panel II shows that the entry elasticity hardly affects the separation rates, but a lowered entry elasticity implies larger and more persistent fluctuations in unemployment, through a more pronounced and delayed hump in the job-finding rate. In panel III, we see that the fundamental surplus ratio, $\tilde{m}$, affects all impulse responses proportionally. As discussed in Ljungqvist and Sargent (2017), for a broad class of SAM models, the steady-state level of the fundamental surplus ratio is a key determinant of unemployment volatility since a lower fundamental surplus ratio increases the elasticity of match profits with respect to labor productivity, and therefore also increases the response of separations and vacancy creation to changes in labor productivity. A given surplus ratio pins down the steady state wage, W_{ss}. It also determines the value of the flow vacancy cost, κ, because the fundamental sur-

[23] Gruber (1997) find a 6.8 percent consumption drop upon unemployment using the PSID, Browning and Crossley (2001) find a 14 percent consumption in Canadian survey data and Kolsrud et al. (2018) find a consumption drop between 4.4-9.1 percent in Swedish register data. We target a 10 percent consumption drop in the middle of these estimates and set ϑ to be 90 percent of the wage level.

Parameter	Value	Source
Panel A: Externally calibrated		
Discount factor, β	$0.96^{1/12}$	Standard
CRRA coefficient, σ	2	Standard
Home production, ϑ	$0.90 \cdot W_{ss}$	See text
Substitution elasticity, ϵ_p	6	Standard
Rotemberg cost, ϕ	600.0	Standard
Taylor rule parameter, ϕ_π	1.5	Standard
Matching function elasticity, α	0.6	Petrongolo and Pissarides (2001)
Panel B: Steady state targets		
Separation rate, δ_{ss}	0.027	Data
Job-finding rate, λ^u_{ss}	0.31	Data
Tightness, θ_{ss}	0.6	Hagedorn and Manovskii (2008)
Panel C: TFP process		
Persistence, ρ_Z	0.965	Coles and Kelishomi (2018)
Standard deviation, σ_Z	0.007	
Panel D: Internally calibrated parameters		
Separation elasticity, ψ	1.000	See Figure 9
Entry elasticity, ξ	0.050	See Figure 9
Fundamental surplus ratio, M_{ss}	0.128	See Figure 9

Table D.1: Calibration.

plus ratio determines the value of a job, which implies the flow vacancy cost must be adjusted to meet the target value of vacancy values in steady state, κ_0. We also note that Figure D.1 shows that the model generates a fall in vacancies together with a rise in unemployment, i.e., a downward sloping Beveridge curve.

D.3 Remaining parameters

From Table D.1, we have the externally calibrated parameters (β, ρ, ϑ,ϵ_p, ϕ, δ_π, α), the steady targets (δ_{ss}, λ^u_{ss}, θ_{ss}), and the internally calibrated parameters ($\tilde{m}_{ss}$, ψ, ξ). Together with the two auxiliary parameters ($\kappa_0 = 0.1 \approx 0$, $\Delta_\delta = 0.1 \approx 0$), the remaining model parameters can be deduced. From the matching function, we directly have

$$A = \frac{\lambda^u_{ss}}{\theta^\alpha_{ss}}.$$

This implies that the steady states of labor markets stocks and flows can be found by,

$$\begin{aligned}
\lambda^v_{ss} &= A\theta^{-\alpha}_{ss}, \\
u_{ss} &= \frac{\delta_{ss}(1-\lambda^u_{ss})}{\lambda^u_{ss} + \delta_{ss}(1-\lambda^u_{ss})}, \\
\tilde{u}_{ss} &= \frac{u_{ss}}{1-\lambda^u_{ss}}, \\
\tilde{v}_{ss} &= \tilde{u}_{ss}\theta_{ss}, \\
v_{ss} &= (1-\lambda^v_{ss})\tilde{v}_{ss}, \\
\iota_{ss} &= \tilde{v}_{ss} - (1-\delta_{ss})v_{ss}.
\end{aligned}$$

We can now also calculate both the value of a job and the value of a vacancy,

$$\begin{aligned}
V^j_{ss} &= \frac{\tilde{m}_{ss}}{1-\beta(1-\delta_{ss})}, \\
V^v_{ss} &= \kappa_0.
\end{aligned}$$

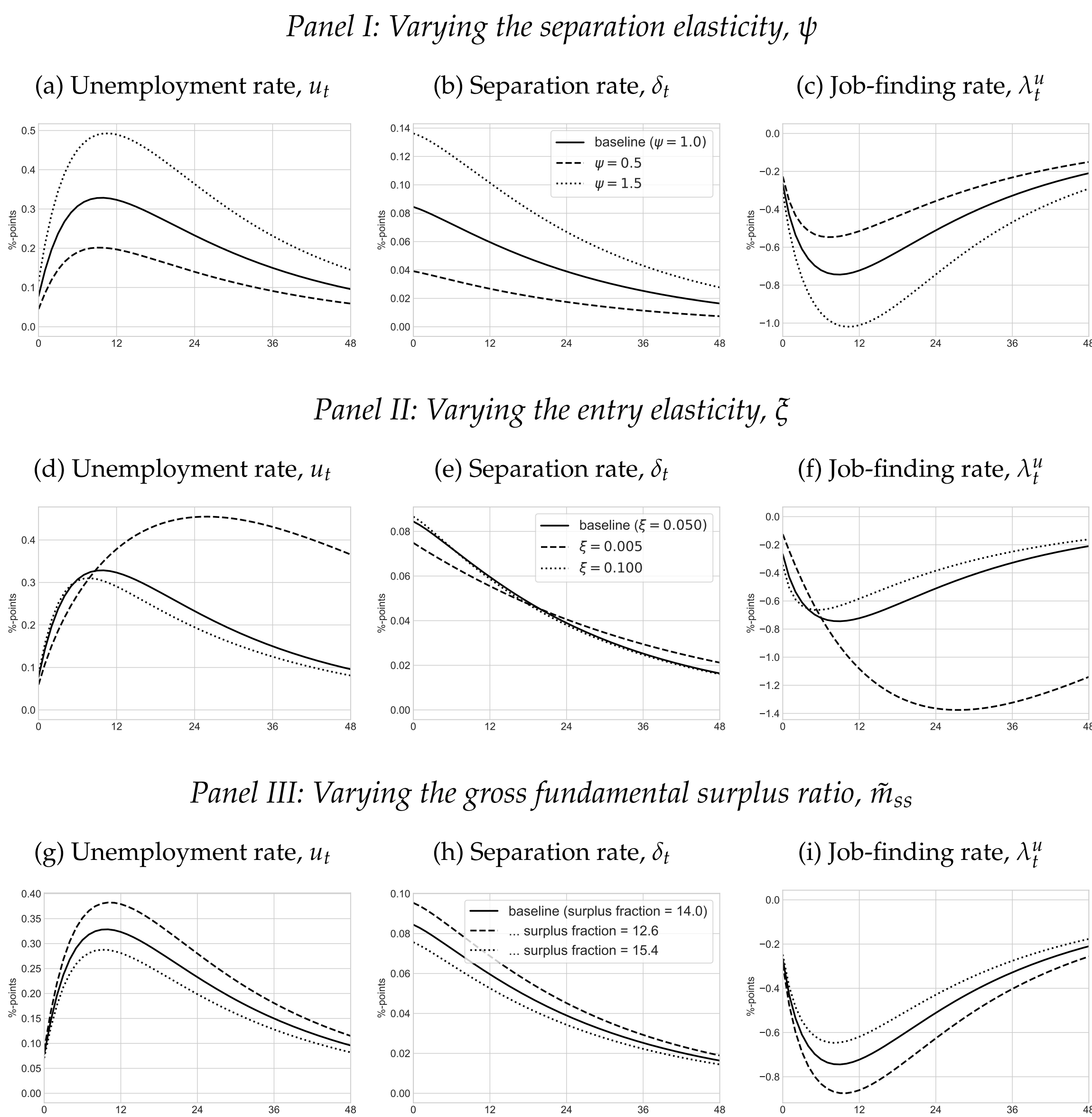


Figure D.1: Impulse response to a 1-std. TFP shock - varying parameters.

Notes: This figure shows the impulse response to a TFP shock varying the separation elasticity, ψ, the entry elasticity, ξ, and the gross fundamental surplus ratio, $\tilde{m}_{ss}$. All other parameters are set as in Table D.1.

Hereby, we can infer p, F, κ, Y and W_{ss} by

$$
\begin{aligned}
p &= (1+\Delta_\delta)\delta_{ss} \\
F &= \iota_{ss}(V_{ss}^v)^{-\xi} \\
\kappa &= \lambda_{ss}^v V_{ss}^j - (1-\beta(1-\lambda_{ss}^u)(1-\delta_{ss}))V_{ss}^v \\
\mathrm{Y} &= \left(\frac{\delta_{ss}}{p}\right)^{\frac{1}{\psi}} V_j^{ss} \\
\mu_{ss} &= \frac{p\frac{\psi}{\psi-1}\mathrm{Y}\left[1-\left(\frac{V_{ss}^j}{\mathrm{Y}}\right)^{1-\psi}\right]}{1-p\left(\frac{V_{ss}^j}{\mathrm{Y}}\right)^{-\psi}} \\
M_{ss} &= \tilde{m}_{ss}P_{ss}^x Z_{ss} + \beta\mu_{ss} \\
W_{ss} &= P_{ss}^x Z_{ss} - M_{ss}
\end{aligned}
$$

Hereafter the steady state values of all other variables can be found as well.

D.4 The URC to a demand shock

Figure D.2 shows the impulse response of unemployment to a 1-std. β-shock. As seen from the figure, the contribution of the URC is the same as in response to a TFP shock, and explains 35 percent of the total unemployment response.

D.5 Additional robustness analysis

Figures D.3-D.5 show how the URC changes with each of the calibrated parameters starting from both the baseline model and a counterfactual model with a standard DMP labor market (exogenous separations and free entry). The fundamental surplus ratio, $\tilde{m}_{ss}$, is re-estimated to fit the observed variance of unemployment, $\mathrm{var}(u_t)$. The URC in the baseline model is always substantially larger compared to the model with a standard DMP labor market.

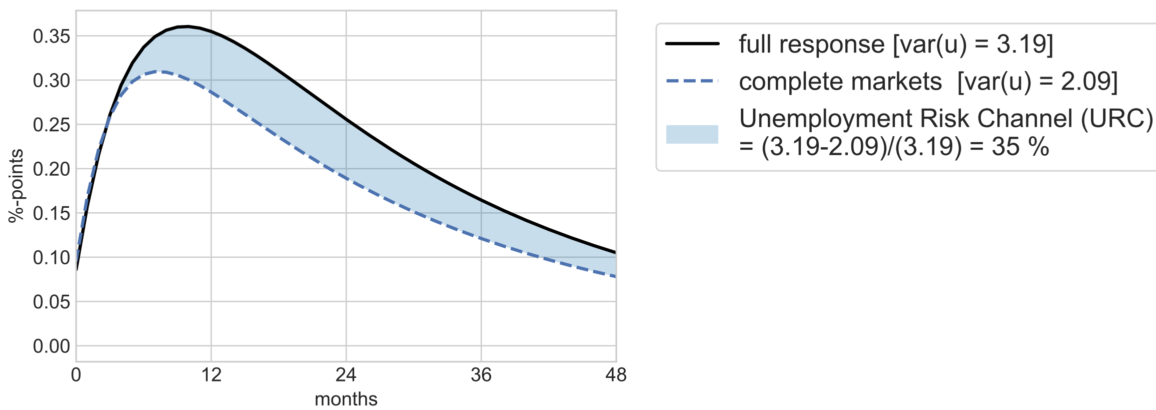


Figure D.2: Decomposition of the unemployment response to a 1-std. β-shock.

Notes: This figure shows a decomposition of the unemployment response to a 1-std. β-shock in the baseline model. The Unemployment Risk Channel (URC) is the difference between the full response and the response with complete markets in percent of the full response.

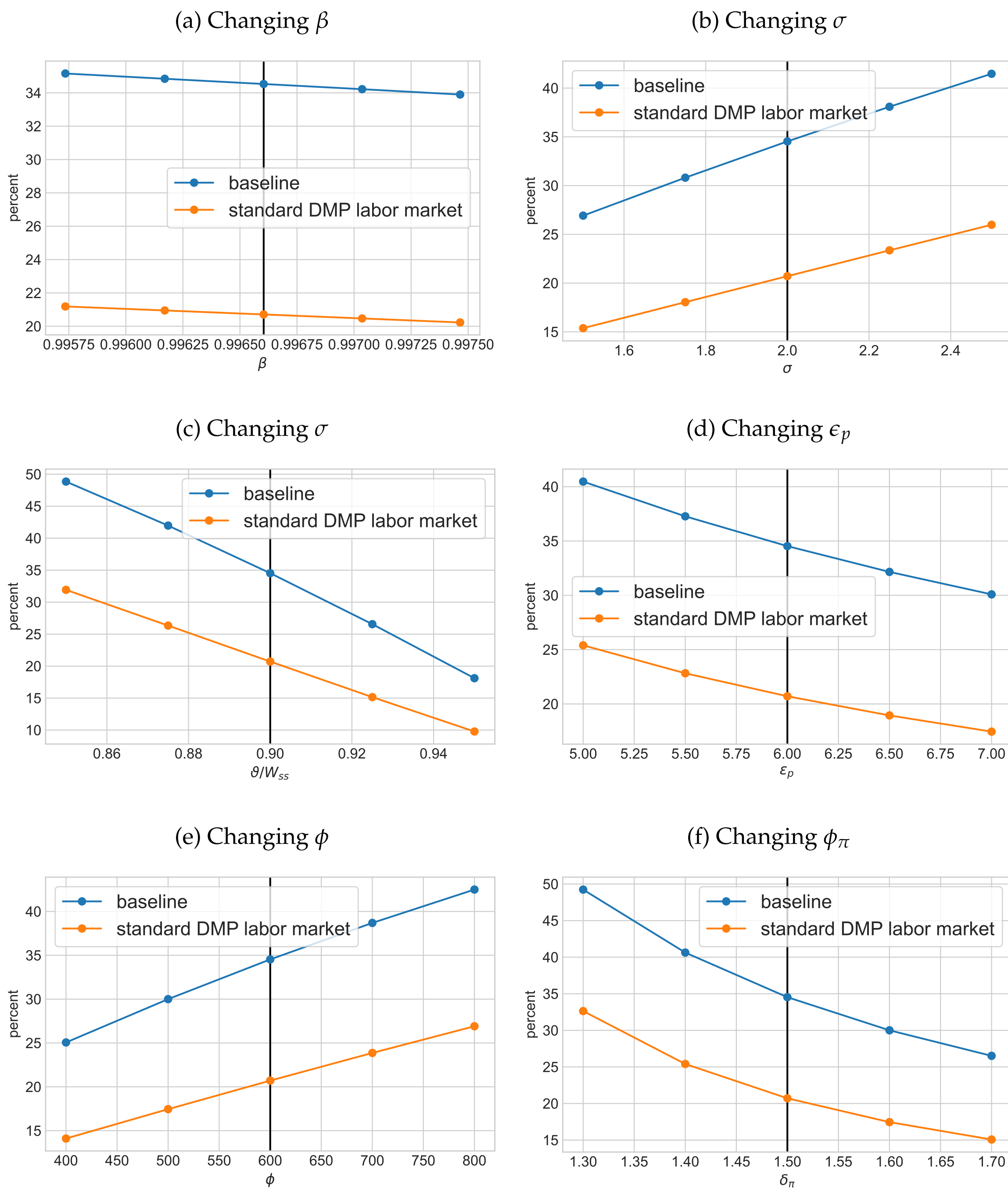


Figure D.3: Robustness I: The contribution of the URC to the total unemployment response with alternative calibration choices

Notes: This figure shows how the URC changes with alternative calibration choices. The standard DMP labor market specification is the baseline model, but with exogenous separations and free entry. The vertical line indicates the baseline calibration value. The gross fundamental surplus ratio, $\tilde{m}_{ss}$, is re-estimated to fit the observed variance of unemployment, $\text{var}(u_t)$. All other parameters are as in Table D.1. The Unemployment Risk Channel (URC) is the difference between the full response and the response with complete markets in percent of the full response.

(a) Changing α (b) Changing θ_{ss}

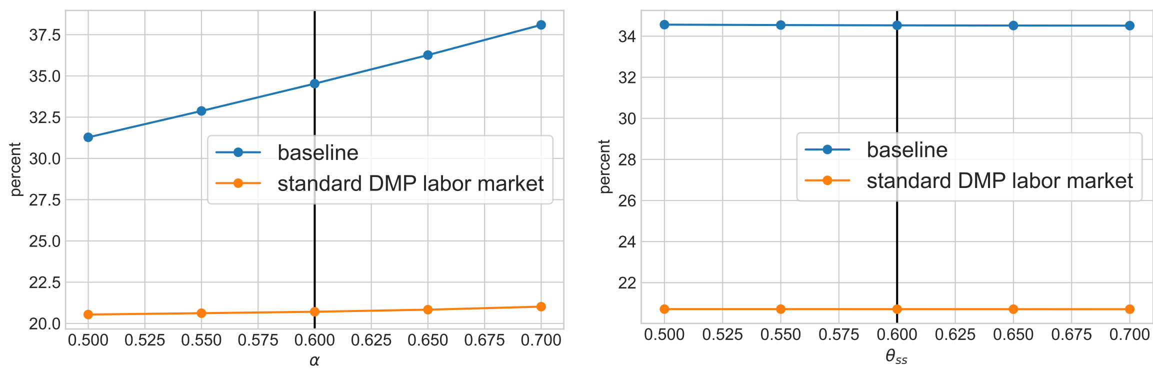


Figure D.4: Robustness II: The contribution of the URC to the total unemployment response with alternative calibration choices

Notes: See Figure D.3

(a) Changing p (b) Changing κ_0 and ξ

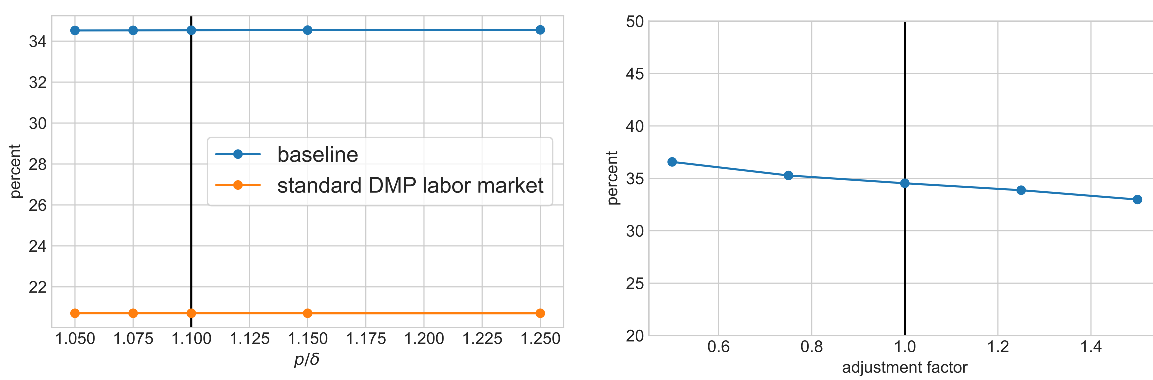


Figure D.5: Robustness III: The contribution of the URC to the total unemployment response with alternative calibration choices

Notes: See Figure D.3