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EXTENSIONS EXPLAIN THE  
EMERGENCE OF JOBLESS  
RECOVERIES?**

Kurt Mitman and Stanislav Rabinovich

**LABOUR ECONOMICS AND MONETARY  
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Countercyclical unemployment benefit extensions in the United States act as a propagation mechanism, contributing to both the high persistence of unemployment and its weak correlation with productivity. We show this by modifying an otherwise standard frictional model of the labor market to incorporate a stochastic and state-dependent process for unemployment insurance estimated on US data. Accounting for movements in both productivity and unemployment insurance, our calibrated model is consistent with unemployment dynamics of the past 50 years. In particular, it explains the emergence of jobless recoveries in the 1990's as well as their absence in previous recessions, the low correlation between unemployment and labor productivity, and the apparent shifts in the Beveridge curve following recessions. Next, we embed this mechanism into a medium-scale DSGE model, which we estimate using standard Bayesian methods. Both shocks to unemployment benefits and their systematic component are shown to be important for the sluggish recovery of employment following recessions, in particular the Great Recession, despite the fact that shocks to unemployment benefits account for little of the overall variance decomposition. If we also incorporate other social safety nets, such as food stamps (SNAP), the estimated model assigns an even bigger role to policy in explaining sluggish labor market recovery. We also find that unemployment benefit extensions prevented deflation in the last three recessions, thus acting similarly to a wage markup shock.

JEL Classification: E24, E32, J65

Keywords: Unemployment insurance, business cycles, jobless recoveries

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# Do Unemployment Benefit Extensions Explain the Emergence of Jobless Recoveries?\*

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May 20, 2019

## Abstract

Countercyclical unemployment benefit extensions in the United States act as a propagation mechanism, contributing to both the high persistence of unemployment and its weak correlation with productivity. We show this by modifying an otherwise standard frictional model of the labor market to incorporate a stochastic and state-dependent process for unemployment insurance estimated on US data. Accounting for movements in both productivity and unemployment insurance, our calibrated model is consistent with unemployment dynamics of the past 50 years. In particular, it explains the emergence of jobless recoveries in the 1990's as well as their absence in previous recessions, the low correlation between unemployment and labor productivity, and the apparent shifts in the Beveridge curve following recessions. Next, we embed this mechanism into a medium-scale DSGE model, which we estimate using standard Bayesian methods. Both shocks to unemployment benefits and their systematic component are shown to be important for the sluggish recovery of employment following recessions, in particular the Great Recession, despite the fact that shocks to unemployment benefits account for little of the overall variance decomposition. If we also incorporate other social safety nets, such as food stamps (SNAP), the estimated model assigns an even bigger role to policy in explaining sluggish labor market recovery. We also find that unemployment benefit extensions prevented deflation in the last three recessions, thus acting similarly to a wage markup shock.

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# 1 Introduction

Unemployment is volatile, persistent, and only weakly correlated with productivity; this correlation, moreover, has become weaker still over time. The jobless recoveries observed following the recessions of 1990-1991, 2001, and 2007-2009 exemplify these stylized facts. Explaining the first fact — the volatility of unemployment — has been a focus of the macro-labor literature since at least Andolfatto (1996) and Shimer (2005), which has met with arguably mixed success. It is especially difficult for productivity-driven models to match all three facts at once—for a clear reason: matching the high volatility of unemployment requires unemployment to be very sensitive to productivity, which implies a high correlation between unemployment and productivity. The data does not support these predictions and suggests the presence of a countercyclical and persistent labor wedge (Hall (1997), Chari et al. (2007), Shimer (2009), Ohanian (2010)). One interpretation of such a labor wedge is as a countercyclical tax (implicit or explicit) on labor. Most of the literature trying to explain jobless recoveries has, however, dismissed the literal interpretation of the labor wedge as a policy wedge, on the grounds that such countercyclical policy distortions are not observed in practice (or are small), and instead focused on wage rigidity, aggregate demand, or structural reasons. In this paper, we recognize that such a countercyclical policy wedge actually exists, namely countercyclical unemployment insurance. We assess quantitatively the importance of this wedge in explaining post-war labor-market dynamics in the US.

The mechanism we propose is simple and motivated by the now-standard equilibrium search model, in conjunction with the unemployment insurance (UI) system in the United States. The latter features automatic triggers that increase the duration of unemployment benefits during periods of high unemployment. Moreover, in all but one of the previous eight recessions, the government has enacted discretionary policies that extended UI benefit duration further. Crucially, because unemployment benefit duration is generally tied to the unemployment rate, high benefit durations persist long after labor productivity begins to recover following a recession. The standard search model predicts that unemployment insurance increases unemployment through both reduced worker search effort and reduced firm vacancy creation (the latter follows because unemployment benefits lower the surplus from forming a match between a worker and a firm). Thus, countercyclical unemployment benefit extensions that lag productivity would be theoretically expected to forestall the recovery in the labor market. In fact, existing quantitative analysis of unemployment benefit extensions, in particular Nakajima (2012), finds exactly this. The challenge is to quantify

the contribution of this mechanism, and in particular in the presence of competing ones, such as adverse productivity or aggregate demand shocks. The empirical literature on cross-sectional effects of unemployment benefits on unemployment does not address this, since it says nothing about either the aggregate effects or, most importantly, the timing. We address this first in a simple dynamic model, and then in an estimated medium-scale DSGE framework.

Introducing countercyclical unemployment insurance into the equilibrium search model requires taking a stand on expectations. While there is a systematic component to unemployment benefits written into law (that automatically extends benefits when unemployment is high), they by no means depend deterministically on unemployment. In fact, while unemployment benefits typically get extended in recessions, the size and duration of the extension has varied and became progressively higher over the last 50 years. Moreover, as evidenced by the latest recession, Congress may reauthorize unemployment benefit extensions in a discretionary manner when they are scheduled to expire. We incorporate these observations in a rational-expectations framework by assuming a stochastic state-dependent process for unemployment benefits, which we discipline from the data on actual unemployment benefit extensions, as detailed below.

We begin in Section 2 by quantitatively evaluating the importance of this channel in a simple calibrated search model by simulating the series of productivity shocks observed in the 1960-2014 period and sequentially introducing the unemployment benefit extensions enacted during this period.<sup>1</sup> We find that the model accounts well for the observed time series of unemployment, explaining 61% of unemployment fluctuations (as measured by the  $R^2$ ) over our sample. In particular, the model-generated recoveries were not jobless prior to 1990 and became jobless thereafter. The key to generating this result is the fact that the UI benefit extensions enacted after the recessions of 1990-1991, 2001, and 2007-2009 were large *relative* to the productivity recovery following these recessions (see figure 1). We also conduct counterfactual experiments to quantify the importance of the extensions: specifically, we examine how the cyclical behavior of unemployment would have been different had the extensions not occurred. The model predicts a much faster recovery of employment if the unemployment benefit extensions are not enacted. Without benefit extensions, the model only explains 30% of the fluctuations in unemployment (as measured by the  $R^2$ ), thus we attribute roughly 31% of the fluctuations in unemployment over this time period to

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<sup>1</sup>The model is calibrated by targeting, among other things, previously estimate cross-sectional elasticities of unemployment with respect to unemployment benefits. We will show in Section 4 that this estimate is stable over time, in particular it is quite similar in the 1970's and 1980's to the jobless recoveries period.

unemployment benefit extensions.

In addition to matching the unemployment dynamics, we find that the model accounts for the dynamics of the Beveridge curve during recessions, including the apparent shift in the Beveridge curve observed following the 2007-2009 recession. The Beveridge curve — the observed negative correlation between unemployment and vacancies — is a robust feature of the post-war labor market, but weakens in the aftermath of recessions, in particular the Great Recession. We show that our simulated model reproduces an unemployment-vacancy correlation very similar to the one observed in the data - including the 2007-2013 period, during which the model reproduces the perceived shift in the simulated Beveridge curve. In other words, the large unemployment benefit extensions implemented during this period acted as shocks that induced a substantial departure from the theoretical Beveridge curve, making it appear as if the curve itself shifted, although all the parameters of our model, including the matching function, have remained the same. Through the same mechanism, our model reproduces the perceived shifts in the Beveridge curve in the previous recessions as well.<sup>2</sup>

The analysis in the simple model elucidates the main mechanism through which unemployment benefit extensions shape the dynamics of unemployment, but raises several questions that require a richer framework to answer. How important are unemployment benefit shocks relative to other shocks? Moreover, how important are the *shocks* themselves, rather than the systematic component of unemployment insurance, which clearly depends on past unemployment rates? Finally, are unemployment benefit extensions also helpful for understanding the behavior of other aggregate variables, such as output and inflation? To answer these questions, in Section 3 we embed our mechanism in a medium-scale DSGE model with labor market frictions. Specifically, we extend the framework of Christiano et al. (2016) to include a state-dependent unemployment insurance policy rule. This policy rule includes both a stochastic shock and a feedback term that allows UI to depend on past unemployment. We estimate the model using standard Bayesian methods, as in Smets and Wouters (2007), and use it to quantify the role of both the systematic and the stochastic components. We find that unemployment benefit shocks account for relatively little of the overall variance decomposition; our mechanism can thus be easily embedded in a standard multi-shock DSGE framework without at all sacrificing plausible effects of other shocks. On the other hand, both shocks to unemployment benefits and their systematic component are very important

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<sup>2</sup>Such shifts, and in particular the fact that they are not unique to the Great Recession, are well documented; see e.g. Diamond and Şahin (2015).

for the recovery speed of employment following recessions. Consistent with our baseline model, we find that large positive shocks to unemployment benefits significantly slowed down the recovery of employment following the Great Recession. This is sharp contrast to the 1980’s, when negative shocks to unemployment benefits prevented unemployment benefits from rising as much as warranted by the severity of the recession, and thereby prevented unemployment from persisting. Finally, we find that unemployment benefit shocks matter for other economic variables, in particular inflation. The large unemployment benefit shocks in the Great Recession prevented strong deflation during that period, acting similarly to a ”wage markup” shock.

## 1.1 Related Literature

First, our analysis contributes broadly to the literature assessing the ability of productivity-driven business cycle models to explain observed labor market dynamics. The existence of jobless recoveries suggests that productivity-driven models struggle to do so; an important line of research therefore attempts to substantially modify existing models to account for the sluggish recovery of employment.<sup>3</sup> We argue that incorporating time-varying and state-dependent unemployment insurance remarkably improves the model’s ability to match observed dynamics; most notably this helps the model generate high unemployment persistence and low employment-productivity correlation without sacrificing on volatility.<sup>4</sup>

Second, we build on the DSGE literature with frictional labor markets, exemplified by Walsh (2003, 2005), Gertler et al. (2008), Trigari (2009), Furlanetto and Groshenny (2016), and Christiano et al. (2016), by incorporating our mechanism into an estimated multivariate DSGE framework. This contributes to a broader, more all-encompassing effort

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<sup>3</sup>There are a variety of approaches to explaining jobless recoveries. Bernanke (2003) attributes jobless recoveries to sluggish aggregate demand. Groshen and Potter (2003) propose structural change as an explanation, and Bachmann (2011) studies the role of labor hoarding. Berger (2011) has argued that countercyclical restructuring behavior of firms can generate jobless recoveries. Our paper is close in spirit to McGrattan and Prescott (2014), who likewise argue that small modifications to the benchmark model can be sufficient to explain the weak employment-productivity correlation, although their focus is not on policy. Our paper is also close in nature to the innovative work by Herkenhoff (2013), who argues that increased access to credit has led households to take on more debt and be pickier about finding jobs, leading to slower recoveries. Similar to that paper, we share the view that changes in the value of non-employment are important for generating observed unemployment patterns; our paper is distinct in emphasizing unemployment benefit extensions as the driving mechanism. This is by no means an exhaustive list.

<sup>4</sup>This sets our analysis apart from the large body of research that tries to explain the high volatility of unemployment, following the Shimer (2005) puzzle. In comparison, nearly all of the theories put forth by the literature to resolve the Shimer puzzle (e.g. wage rigidities in Hall (2005), small surplus in Hagedorn and Manovskii (2008), or marginal worker-firm matches in Menzio and Shi (2011)) feature a counterfactual correlation between labor productivity and unemployment close to unity. In contrast, our paper correctly predicts a much lower correlation between productivity and unemployment.



of understanding which shocks drive observed fluctuations in the US economy at different points in time. Our results suggest incorporating a state-dependent UI policy rule is a useful extension that matters significantly for explaining particular historical episodes - specifically, persistence during recessions - without generating unrealistic responses to other shocks. Closely related to Fratto and Uhlig (2014), we take a diagnostic approach to the Great Recession, as well as previous ones, by asking to which shocks the estimated model attributes the observed aggregate behavior. Since unemployment benefit extensions are both an additional shock and an additional propagation mechanism, the results of our exercise are correspondingly different, though the approach is the same in spirit. For example, with regard to unemployment, we find that positive unemployment benefit shocks contributed to the high unemployment persistence in the last three recessions, whereas negative unemployment benefit shocks were important for the lack thereof in the recession of 1981. With regard to inflation, we uncover that unemployment benefit shocks, were important for explaining the lack of deflation in the last three recessions - a role that was instead played by price markup shocks in Fratto and Uhlig (2014).

Finally, we view our analysis as complementary to the existing research on policy-induced labor market distortions: e.g. Mulligan (2002, 2010, 2012), Ohanian (2010), Herkenhoff and Ohanian (2011), and Krause and Uhlig (2012), among others. The closest paper is Nakajima (2012), which, to our knowledge, is the first quantitative model-based evaluation of the role of unemployment insurance in the Great Recession. We share with this paper the methodology of using a quantitative model, calibrated to match cross-sectional evidence on the effects of UI, to conduct policy experiments. Our results are also fully consistent with the results of Nakajima (2012) in that unemployment benefit extensions are, in fact, very important quantitatively. We hope to have pushed this line of research a step further, by arguing that this mechanism can and should be a component of more general frameworks, which account for the effects of other shocks on other aggregate variables. In this sense, this is less of a paper about the effects of unemployment insurance on unemployment, and more about the importance of accounting for state-dependent unemployment insurance in business cycle analysis in general.

In Section 2 we describe the simple model environment with time-varying unemployment benefits, the calibration procedure and the results. The details of the simple model are described in Appendix A, with tables and figures in Appendix C. In Section 3 we formalize the medium-scale DSGE environment, the estimation procedure and the results and counterfactual analysis. The details of the DSGE model are described in Appendix B, with tables and

figures in Appendix D. In Section 4 we provide empirical evidence for the mechanism, in particular evidence that the estimated cross-sectional effect of unemployment insurance on unemployment is stable over time. Section 5 concludes.

## 2 Simple model

The model is a variant of the standard Mortensen-Pissarides model with aggregate productivity shocks, augmented to incorporate unemployment benefit expiration, and thereby accounting for the fact that the value of unemployment varies across unemployed workers. Specifically, workers in the model may lose UI eligibility when unemployed, and regain this eligibility when employed. The rate at which unemployment benefits expire may vary over time, and is the key policy variable that we focus on.

Time is discrete and the time horizon is infinite. The economy is populated by a unit measure of workers and a larger continuum of firms. In any given period, a worker can be either employed (matched with a firm) or unemployed. Workers are risk-neutral expected utility maximizers and have expected lifetime utility

$$U = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t (x_t - c(s_t)),$$

where  $\mathbb{E}_0$  is the period-0 expectation operator,  $\beta \in (0, 1)$  is the discount factor,  $x_t$  denotes consumption in period  $t$ , and  $s_t$  is search effort in period  $t$ , equal to zero if employed. An unemployed worker produces  $h$ , which stands for the combined value of leisure and home production. The cost of search function  $c(s)$  is strictly increasing and strictly concave. Firms are risk-neutral, maximize profits, and have the same discount factor  $\beta$ . A firm can be either matched to a worker or vacant. A firm posting a vacancy incurs a flow cost  $k$ .

Unemployed workers and vacancies match in pairs to produce output. The number of new matches in period  $t$  equals

$$M(S_t u_t, v_t),$$

where  $u_t$  is the unemployment level in period  $t$ ,  $S_t$  is the aggregate search intensity, and  $v_t$  is the measure of vacancies posted in period  $t$ . The matching function  $M$  exhibits constant returns to scale, and is strictly increasing and strictly concave in both arguments. Define  $\theta_t = v_t / (S_t u_t)$  to be the market tightness in period  $t$ . A worker supplying search effort  $s_t$  then finds a job with probability  $s_t f(\theta_t)$ , where  $f(\theta_t) = M(1, \theta_t)$ , and a firm fills its vacancy with probability  $q(\theta_t)$ , where  $q(\theta_t) = M(1/\theta_t, 1)$ . Existing matches are exogenously destroyed

with a constant job separation probability  $\delta$ . Thus, any of the  $1 - u_t$  workers employed in period  $t$  has a probability  $\delta$  of becoming unemployed in period  $t + 1$ .

All worker-firm matches are identical: the only shocks to labor productivity are aggregate shocks. Specifically, a matched worker-firm pair produces output  $z_t$  in period  $t$ , where  $z_t$  is aggregate labor productivity. We assume that  $\ln z_t$  follows an AR(1) process

$$\ln z_t = \rho \ln z_{t-1} + \sigma_\varepsilon \varepsilon_t, \quad (1)$$

where  $0 \leq \rho < 1$ ,  $\sigma_\varepsilon > 0$ , and  $\varepsilon_t$  are independent and identically distributed standard normal random variables.

Wages are determined by Nash bargaining. Define  $\Delta_t^i$  to be the surplus from being employed for a worker of eligibility type  $i$ , where  $i \in \{E, I\}$  can be either eligible ( $E$ ) or ineligible ( $I$ ). Similarly, define  $\Gamma_t^i$  to be the surplus for a firm from employing a worker of eligibility type  $i$ . The wage  $w_t^i$  is chosen to maximize the product

$$(\Delta_t^i)^\xi (\Gamma_t^i)^{1-\xi}, \quad (2)$$

where  $\xi \in [0, 1]$  is the worker's bargaining weight.

The government levies a constant lump sum tax  $\tau$  on firm profits and uses its tax revenues to finance unemployment benefits  $b$ . Every worker, at each point in time, can be either *eligible* or *ineligible* for unemployment benefits, and receives  $b$  only if unemployed and eligible. We assume stochastic benefit expiration, similarly to Fredriksson and Holmlund (2001) and Faig and Zhang (2012). Eligible workers may lose their eligibility if unemployed, and ineligible workers may regain eligibility when employed. Specifically, the eligibility status of a worker evolves as follows. A worker who is eligible for unemployment benefits retains his eligibility the following period with probability 1 if employed, and with probability  $1 - e_t$  if unemployed; with probability  $e_t$  he instead becomes ineligible. A worker who is ineligible for unemployment benefits remains ineligible the following period if unemployed, and becomes re-entitled to unemployment benefits with probability  $r$  if employed. This assumption is made to mimic the actual system of benefit expiration and re-entitlement in the US while ensuring the stationarity of the workers' and firms' decision problems. The key innovation is allowing  $e_t$  to be stochastic and state-dependent. The process for  $e_t$  will be described below. Note that we assume all agents have rational expectations about this process.

## 2.1 Calibration

We calibrate the model to match aggregate US data targets over the 1960-2005 period and then assess the model's fit with respect to the time series of unemployment. As explained below, we target aggregate moments of the key data series over this period. We also use, as calibration targets, the literature's estimates on the elasticity of unemployment with respect to UI benefits. We *do not* target the correlation between unemployment and productivity, nor any other moment that directly affects the timing of unemployment or the speed of the recovery. The success of the model can then be assessed by how well it matches the time series of unemployment and its correlation with productivity.

The model period is taken to be 1 week. We normalize mean weekly productivity to one. Following Shimer (2005), labor productivity  $z_t$  is taken to mean real output per worker in the non-farm business sector. This measure of productivity is taken from the quarterly data constructed by the BLS. We also use the seasonally adjusted unemployment series constructed by the BLS, and measure vacancies using the seasonally adjusted help-wanted index constructed by the Conference Board.

We set the discount factor  $\beta = 0.99^{1/12}$ , implying a yearly discount rate of 4%. The parameters for the productivity shock process are estimated, at the weekly level, to be  $\rho = 0.9895$  and  $\sigma_\varepsilon = 0.0034$ . The job separation parameter  $\delta$  is set to 0.0081 to match the average weekly job separation rate. We set  $k = 0.58$  following Hagedorn and Manovskii (2008), who estimate the combined capital and labor costs of vacancy creation to be 58% of weekly labor productivity.

Following den Haan et al. (2000), we assume the functional form of the matching function to be

$$M(Su, v) = \frac{Su \cdot v}{\left[ (Su)^\lambda + v^\lambda \right]^{1/\lambda}}$$

We assume the functional form of the cost of search to be

$$c(s) = A \frac{s^{1+\psi}}{1+\psi} \tag{3}$$

Following Hall and Milgrom (2008) we set  $b = 0.25$ . This is below the average replacement rate of unemployment insurance, and at the lower end of the range used in the literature, but we deliberately opt for this low number to account for the fact that UI take-up rates are less than 100%.<sup>5</sup> The tax rate is set so that the government balances its budget on average,

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<sup>5</sup>Note that a higher level of UI benefits would only increase the sensitivity of the worker's outside option

resulting in  $\tau = 0.023$ . We set the re-entitlement rate to  $r = 1/24$  to account for the fact that it takes 6 months of employment to gain eligibility for unemployment benefits.

Next, we turn to calibrating the stochastic process for  $e_t$ . Since  $e_t$  is the stochastic expiration rate of unemployment benefit eligibility, it is equal to the inverse of the expected unemployment benefit duration:

$$e_t = \frac{1}{\bar{D} + I_t^{EB} D^{EB} + I_t^{EUC} D_t^{EUC}} \quad (4)$$

The expected duration of unemployment benefits has three components. First, there is a baseline duration of unemployment insurance in normal times,  $\bar{D}$ , which is set to equal 26 weeks. Second, there are automatic triggers for extending unemployment benefits when unemployment is high. We denote these triggers “extended benefits” or *EB*.  $I_t^{EB}$  is an indicator variable, equal to 1 when the trigger is on, and 0 when it is off;  $D^{EB}$  denotes the added weeks of unemployment insurance when the trigger is on. To mimic the existing system, we set  $D^{EB}$  to 13 weeks, and

$$I_t^{EB} = \begin{cases} 1, & \text{if } u_t > 6.5\%, \\ 0, & \text{otherwise} \end{cases}$$

Third, there are discretionary extensions, which we call “emergency unemployment compensation,” or *EUC*.  $I_t^{EUC}$  is an indicator variable, equal to 1 when such an extension is in effect, and 0 when it is not;  $D^{EUC}$  denotes the added weeks of unemployment insurance when the discretionary extension is on. To account for the average size of such extensions in the data, we set

$$D_t^{EUC} = \begin{cases} 20, & \text{if } u_t > 8\%, \\ 13, & \text{otherwise} \end{cases}$$

In other words, either 20 or 13 weeks are added depending on the severity of the labor market conditions. Turning to  $I_t^{EUC}$ , we seek to account for the fact that, while these extensions and reauthorizations do not follow any pre-set rule (and are therefore not perfectly predictable, even given the unemployment rate), they are nevertheless persistent and correlated with unemployment. To this end, we estimate a transition probabilities for  $I_t^{EUC}$  by from the data on actual unemployment benefit extensions and reauthorizations, with transition probabilities between  $t$  and  $t + 1$  dependent on the unemployment rate in period  $t$ <sup>6</sup>.

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with respect to the duration of these UI benefits, which is the key policy variable of interest.

<sup>6</sup>Specifically, we estimate separate probit models for the probability that a discretionary extension is passed and for the probability that a discretionary extension is reauthorized conditional on being in placed, as a function of the unemployment rate. For the authorization regression, we find a constant of 10.99, and a

This leaves five parameters to be internally calibrated: the value  $h$  of non-market activity; the worker’s bargaining weight  $\xi$ ; the matching function parameter  $\lambda$ ; and the level and elasticity of the cost of search,  $A$  and  $\psi$ . We calibrate these five parameters jointly to match five data targets, chosen to capture relevant statistics from the US labor market. The first three of these statistics are aggregate targets: the average vacancy-unemployment ratio of 0.634, the average job-finding rate of 0.139, and the time-series elasticity of wages with respect to productivity, equal to 0.449.<sup>7</sup> The final two targets are the micro and macro elasticities of unemployment duration with respect to unemployment benefit generosity. The model counterpart of the latter is the percent change in average unemployment duration in response to a one-percent increase in unemployment benefit duration. The model counterpart of the former is holding fixed the value of  $\theta$ ; in other words, this captures the response that would be observed if only search intensity, not vacancy creation, responds to UI.

Research by Moffitt and Nicholson (1982), Moffitt (1985), and Katz and Meyer (1990), among others, reached consensus estimates that a one week increase in benefit duration increases the average duration of unemployment spells by 0.1 to 0.2 weeks. We target a macro elasticity of 0.1, the lower end of this range. In section 4, we further discuss the choice of this estimate, in particular its stability over time. With regard to the micro elasticity, we target the estimate obtained by Chetty (2008), indicating that a 10% increase in unemployment benefit level is associated with a 3-5% increase in unemployment duration. Table 1 reports the calibrated parameters.

## 2.2 Results

The simulated model is able to account for key features of the post-war labor market. In Figure 8, we plot the unemployment rate generated from the model and that observed in the data. The model with the implemented US unemployment benefit policy generates a time series of unemployment that closely matches what is seen in the data ( $R^2 = 0.93$ ). In addition, in Figure 9 we plot the log deviations from trend both in the data and in the model. Again, notice that the model does an excellent job of matching the data ( $R^2 = 0.61$ ). As shown in Figures 4-11, the model also does an excellent job of capturing the time-series of the vacancy rate, the vacancy-unemployment ration, the job-finding rate and employment. Next, we confirm the model’s ability to match key business cycle statistics. Tables 2 and 3

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coefficient on the unemployment rate of 0.99. For the re-authorization regression we find a constant of 8.89 and a coefficient on the unemployment rate of 1.47.

<sup>7</sup>Empirical estimates of the elasticity of wages with respect to productivity range from 0.45 to 0.7, depending on whether new hires only or all wages are used.

report the summary statistics from US data and from the model. The model slightly underpredicts the volatility of the labor market. This can also be seen in the time series plots: the model does not attain the same peaks in unemployment as in the data. In the model we have assumed a constant job separation rate, whereas layoffs typically spike at the beginning of recessions. Indeed, our estimates seem consistent with the finding that fluctuations in the job-finding rate (the source of variation in our model) account for roughly three-quarters of the fluctuations in unemployment Shimer (2012). We will confirm this in section 2.3.2, where we consider an extension with endogenous separations and show that this modification affects mostly the initial unemployment spikes at the start of each recession.

Table 4 reports the same summary statistics from the simulated model with no benefit extensions. In addition, we report in Table 5 the autocorrelation of unemployment and, in Table 6, the correlation of labor market variables with productivity lagged one quarter. These results show that the calibrated model performs well in matching the cyclical behavior of the labor market. Furthermore, shutting down time-varying unemployment benefit extensions would substantially worsen the model’s ability to match the observed dynamics, in particular the persistence of unemployment, the weak correlation between labor market variables and productivity, and the comparatively strong correlation between unemployment and lagged productivity.<sup>8</sup> The  $R^2$  between model and data falls to 0.30 in the model without extensions, thus we infer that unemployment benefit extensions explain roughly 31% of observed unemployment fluctuations.

We next investigate whether the model is consistent with the emergence of jobless recoveries. In Figure 12, we plot the change in employment - actual<sup>9</sup> and predicted by the model<sup>10</sup> - relative to the NBER peak before the 1973-1975, 1980 and 1981-1982 recessions. The model replicates the response of employment over those periods quite well. Next, in Figure 14, we similarly plot the change in employment for the 1990-1991, 2001 and 2007-2009 recessions. The model is able to replicate the observation that, unlike the previous three recessions, the recovery of productivity was not matched in this case by a rapid rise in employment. To understand the role of unemployment benefit extensions in generating jobless recoveries, we perform a counterfactual experiment in which we shut down all benefit extensions (i.e. fix the weeks of benefits at 26) and re-simulate the model. The result is shown

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<sup>8</sup>Note that the inclusion of time-varying unemployment benefit extensions was not guaranteed to improve the model’s fit, since what matters for the latter is the timing of the extensions relative to productivity, which was not targeted in the calibration.

<sup>9</sup>Measured in the Current Population Survey.

<sup>10</sup>In order to generate employment numbers we take the labor force from the data.

in Figure 15 for the 1990-1991, 2001 and 2007-2009 recessions. The figure illustrates that the model without the additional extensions does not generate jobless recoveries: employment recovers much faster in the model than it does in the data. Unemployment benefit extensions are thus quantitatively important for explaining the cyclical behavior of employment. In addition, in figure 32 we show that the model with extensions is able to match well the fall in the correlation between employment and labor productivity—the phenomenon that labor productivity has become more acyclical<sup>11</sup>. Whereas the when we shut down the extensions in the model the correlation between labor productivity and employment remains high post-1990.

As shown in Figures 25-31, the model is also consistent with apparent “shifts” in the Beveridge curve in recessions - not only in the Great Recession, but also in previous ones. Theoretically, the Beveridge curve is a steady-state relationship between vacancies and unemployment, and movements along it in the standard DMP model are generated by changing labor productivity. It is important to note that tightness (and vacancies) adjust immediately (they are jump variables), but unemployment takes time to adjust. Thus, at a weekly frequency, a drop in productivity would imply an immediate drop in tightness (and vacancies) but a fixed unemployment rate. This would be a downward departure from the theoretical Beveridge curve. But, the model would transit in the upward-right direction along a path of constant tightness until it returned to the Beveridge curve. This is inconsequential for small shocks: when aggregated to quarterly frequency, this movement would be masked and it would appear as if the economy remained on the theoretical Beveridge curve. However, for large shocks - such as unemployment benefit extensions in recessions - it would take the economy time to return to the Beveridge curve and what appear to be “departures” from the “true” Beveridge curve would emerge.

### 2.3 Robustness checks and extensions

Two of the important assumptions made in our baseline were exogenous separations and Nash-bargained wages, both of which are known to affect the model-implied cyclical behavior of the labor market. We therefore conduct exercises in which these assumptions are relaxed, recalibrating the model in each case.

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<sup>11</sup>Specifically, we compute the sixteen quarter rolling autocorrelation between log deviations from HP trend of employment and productivity in the data and model.



### 2.3.1 Wage rigidity

In the baseline model, there are two channels through which unemployment insurance affects unemployment - worker search effort and vacancy posting - the latter effect being operative due to Nash-bargained wages. In this section, we relax the assumption of Nash bargaining in our model. There are two reasons for doing so. First, despite the evidence in, e.g., Hagedorn et al. (2013) that we discuss below, the effect of UI on wages is a controversial topic.<sup>12</sup> Second, the main intuition for our argument hinges on the total effect of UI on unemployment combined with the timing of shocks and unemployment benefit extensions. We therefore consider the cyclical effects of UI in an environment where its only effect is through worker search effort. Specifically, we assume that the wage now is an exogenously specified function of productivity:  $w_t = \bar{w}z_t^{\epsilon_{wz}}$ , where  $\bar{w}$  and  $\epsilon_{wz}$  are parameters. We calibrate the level parameter  $\bar{w}$  to match average wages, and pick the elasticity parameter  $\epsilon_{wz}$  to match the elasticity of wages with respect to productivity of 0.449 in the data - the same moment that was used to calibrate the Nash bargaining parameter in the baseline model. We then recalibrate the model - in particular the parameters of the search cost function  $A$  and  $\psi$  - so as to still match the macro elasticity of unemployment duration with respect to unemployment benefit duration. In the absence of Nash bargaining, the model attributes the entire macro elasticity to search effort. Thus, under the new calibration the model still matches both the degree of wage rigidity in the time series and the observed elasticity of unemployment duration with respect to unemployment benefit duration in the cross-section, but through different channels. The results are displayed in Figures 16 and 17, which show the analogues of Figures 8 and 9 for the rigid wage model. While the model somewhat understates the persistence of unemployment in the last three recessions compared to the Nash-bargaining model, unemployment benefits still generate considerable persistence solely through worker search effort.

### 2.3.2 Endogenous separations

In the baseline model, we have assumed that the separation rate  $\delta$  is exogenous and fixed. In an extension, described in Appendix A.9, we endogenize the job separation rate by assuming that match productivity contains an idiosyncratic component. We re-calibrate the model, choosing the variance of the idiosyncratic productivity shock to target the cyclicity

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<sup>12</sup>As we discuss in our DSGE analysis below, the general equilibrium effect of UI on *unemployment* through Nash bargaining can be quite large even when its observed effect on wages is somewhat modest; this is because the effect of wages itself is mitigated by the falling job-finding rate, which in turn lowers the workers' outside option in general equilibrium.

of job separations in the data. The simulation results from the model with endogenous separations are shown in Figure 18. In the data, job separations are countercyclical and, moreover, layoffs typically spike at the beginning of a recession. In line with these facts, introducing endogenous separations improves the model’s ability to match the initial rise in unemployment at the beginning of recessions. It matters less quantitatively for the ability to match unemployment persistence along the recovery, which is driven - both in the model and in the data - by the slow recovery of the job finding rate.

### 3 Unemployment insurance in a DSGE framework

The previous analysis illustrated, in the context of a very simple search model, that countercyclical unemployment benefit extensions can be very important for unemployment persistence. This simple search model, however, cannot address the importance of unemployment insurance relative to other shocks. Moreover, it raises the question of whether this mechanism can be plausibly embedded in an aggregate model without generating unrealistic effects of other shocks. To address this, we show how to embed a stochastic UI policy rule in a medium-scale DSGE model with labor market frictions.

#### 3.1 Model description

We use a fairly standard DSGE model with labor market frictions.<sup>13</sup> Our own model is closest to the Christiano, Eichenbaum and Trabandt (2016) model, henceforth CET, with Nash bargaining.<sup>14</sup> Relative to CET, we introduce additional shocks and estimate the model using standard Bayesian techniques, similarly to Smets and Wouters (2007) (CET match impulse responses). The most important departure from CET is that we make UI follow a stochastic policy rule, while it is a fixed parameter in CET; one of the shocks in our model will therefore be to unemployment benefits. The other aspects of the model are very similar to CET.<sup>15</sup>

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<sup>13</sup>This builds on Walsh (2003, 2005), Gertler et al. (2008), and Trigari (2009), which in turn employ the large-household construct of Andolfatto (1996) and Merz (1995).

<sup>14</sup>CET emphasize the comparison between Nash bargaining and alternative wage determination mechanisms, in particular alternating offer bargaining. We opt for the conventional Nash bargaining solution, to preserve the similarity to the workhorse equilibrium search model as well as our own baseline model; but also to shift the emphasis to the role of unemployment insurance.

<sup>15</sup>See Appendix B.1 for the full description of the model.

There is a large representative household with preferences

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \ln (C_t - hC_{t-1}), \quad (5)$$

where  $h$  is the habit formation parameter. The household faces a budget constraint

$$P_t C_t + P_{I,t} I_t + B_{t+1} \leq (R_{K,t} u_t^K - \varpi (u_t^K) P_{I,t}) K_t + (1 - l_t) P_t D_t + W_t l_t + \zeta_t^B R_{t-1} B_t - T_t \quad (6)$$

where  $C_t$  and  $I_t$  are consumption and investment,  $K_t$  denotes capital services,  $B_t$  denotes bonds, and  $T_t$  denotes lump-sum transfers. All the prices are in nominal terms;  $P_t$  and  $P_{I,t}$  denote the price of consumption and investment goods, respectively;  $R_{K,t}$  denotes the rental rate on capital, and  $\varpi (u_t^K)$  is the cost of capital utilization  $u_t^K$ . The gross nominal interest rate in period  $t$  is  $R_t$ , and  $\zeta_t^B$  denotes the stochastic risk premium shock. A fraction  $l_t$  of the household is employed and earns nominal wage  $W_t$ . A fraction  $1 - l_t$  of the household is unemployed and earns unemployment benefits  $D_t$ , which will be the key object of interest in what follows. The capital stock  $K_t$  evolves according to

$$K_{t+1} = (1 - \delta_K) K_t + (1 - S_K (I_t/I_{t-1})) I_t \quad (7)$$

where  $S_K$  is a convex adjustment cost.

The final good,  $Y_t$ , can be used to produce either consumption or investment. Consumption is produced from output one-for-one, while the investment technology converts one unit of  $Y_t$  into  $\Psi_t^I$  units of  $I_t$ , where  $\Psi_t^I$  is the investment-specific technology process. The final good  $Y_t$ , in turn, is produced by aggregating specialized inputs  $Y_{jt}$  according to the technology

$$Y_t = \left( \int_0^1 (Y_{jt})^{\tau_t} dj \right)^{1/\tau_t}, \quad (8)$$

where  $\tau_t$  denotes the price markup. A representative final goods firm chooses the inputs  $Y_{jt}$  to maximize profits

$$P_t Y_t - \int_0^1 P_{jt} Y_{jt} dj \quad (9)$$

Specialized inputs  $Y_{jt}$  are produced by monopolistically competitive retailers according to the technology

$$Y_{jt} = k_{jt}^\alpha (z_t \iota_{jt})^{1-\alpha} - \Phi_t \quad (10)$$

where  $\Phi_t$  is a fixed cost of production (which grows at a rate that guarantees a balanced growth path),  $k_{jt}$  is capital,  $z_t$  is the neutral technology shock, and  $\iota_{jt}$  is an intermediate

good, purchased in a competitive market from wholesale firms. As in CET, we assume Calvo price stickiness: retailers can reoptimize their price every period with probability  $\vartheta_p$ , and with probability  $1 - \vartheta_p$  they keep their price unchanged from the previous period.

Wholesale firms hire labor in a frictional labor market and produce the intermediate good using labor one-for-one. Aggregate employment,  $l_t$ , evolves according to

$$l_t = (1 - \delta_L) l_{t-1} + M(1 - (1 - \delta_L) l_{t-1}, v_t) \quad (11)$$

where  $\delta_L$  is the job separation rate and  $M(1 - (1 - \delta_L) l_{t-1}, v_t)$  is the aggregate matching technology, with  $v_t$  the measure of vacancies and  $1 - (1 - \delta_L) l_{t-1}$  the measure of searching unemployed workers.<sup>16</sup> Firms face an ex ante cost  $\kappa_t^v$  of posting a vacancy and an ex post cost  $\kappa_t^e$  of hiring; both costs grow at the same rate as aggregate productivity to guarantee a balanced growth path.

As in the simple model, we assume that wages are determined by Nash bargaining, i.e. the wage is set to maximize

$$(\Delta_t^i)^{\xi_t} (\Gamma_t^i)^{1-\xi_t}, \quad (12)$$

where  $\xi_t$  is a stochastic bargaining weight. In this environment,  $\Gamma_t$  is the marginal value of an additional worker to the wholesale firm, and  $\Delta_t$  is the marginal value of an extra employed member to the large household.

Our specification of fiscal and monetary policy is standard. Government consumption as a share of GDP follows the process

$$\ln g_t = (1 - \rho_g) \ln g + \rho_g \ln g_{t-1} + \sigma_g \nu_t^g \quad (13)$$

Monetary policy follows the Taylor rule

$$\ln(R_t/R) = \rho_R \ln(R_{t-1}/R) + (1 - \rho_R) (r_\pi \ln(\pi_t/\bar{\pi}) + r_y \ln(y_t/\bar{y}_t)) + \sigma_R \nu_t^R, \quad (14)$$

where  $R$  is the steady-state interest rate,  $\pi_t/\bar{\pi}$  is the deviation of inflation from its target, and  $y_t/\bar{y}_t$  is the deviation of GDP from its non-stochastic growth path.

The novel part of the model lies in the specification of the unemployment insurance process,  $D_t$ . The motivation for our specification is two-fold. First, since the DSGE model will be log-linearized and estimated via maximum likelihood, we need to specify a smooth process for  $D_t$ . This rules out the exact modeling of the individual extensions

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<sup>16</sup>The time period is a quarter; to deal with time aggregation, we assume that workers laid off in period  $t$  can immediately search for a job in the same period.

that we employed with our simple model. Instead, we will assume that unemployment insurance follows a smooth stochastic process, which will be identified using data on dollars of unemployment insurance (which, as we will show, follows the observed extensions very closely). Second, we want to incorporate both a stochastic component (unexpected changes to unemployment insurance) and a systematic component (dependence on unemployment insurance on unemployment). The latter, in particular, usually specifies for unemployment insurance to rise when unemployment is unusually high. We capture this by assuming that unemployment insurance depends on the deviation of unemployment from its two-year moving average, consistent with existing legislation on the extended benefit program. Motivated by these two considerations, we assume the following specification for  $D_t$ :

$$\ln(D_t/\bar{D}) = \rho_D \ln(D_{t-1}/\bar{D}) + \rho_{D,U}(u_t - \tilde{u}_t) + \sigma_D \nu_t^{UI} \quad (15)$$

Here,  $\bar{D}$  is the steady-state value of unemployment benefits,  $u_t = 1 - l_t$  is unemployment,  $\tilde{u}_t$  is the two-year moving average of unemployment, and  $\nu_t^{UI}$  is the i.i.d. shock to unemployment insurance.

The sources of fluctuations in the model are thus eight shocks: two technology shocks - neutral and investment-specific; monetary policy shocks; government spending shocks; risk premium shocks; shocks to price markups; shocks to bargaining power; and shocks to unemployment insurance.

## 3.2 Estimation

We estimate our model using standard Bayesian techniques, as in Smets and Wouters (2007). The estimation period is 1959Q1:2008Q3. The starting date of the sample is dictated by the availability of data on unemployment insurance. We end the estimation sample in 2008 to avoid the distortions from the zero lower bound (see Galí et al. (2012) and Furlanetto and Groshenny (2016) for a similar strategy). After estimating the model on this restricted sample, we will, however, simulate it until the end of 2013 and conduct counterfactuals over the 2008-2013 period, so as to discuss the effects of unemployment benefit extensions in the Great Recession.<sup>17</sup>

The model includes as many shocks as observables. We use quarterly data on the following 8 observables: real GDP per capita, real consumption per capita, real investment per capita, real wages, inflation, the nominal interest rate, the unemployment rate, and unemployment

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<sup>17</sup>We have also estimated the model on the full sample following the strategy of Fratto and Uhlig (2014). The results are not substantially different.

insurance. The first six series are standard and common in DSGE model estimation, and the use of the unemployment rate is standard in estimation of models with labor market frictions. Our unemployment insurance series is constructed as real unemployment benefit dollars per unemployed worker. The data construction is described in detail in Appendix B.2. Table 8 in Appendix D reports the priors and posteriors of the estimated parameters.

### 3.3 Results: the role of unemployment insurance

Figure 34 shows the impulse responses of key aggregate variables to the unemployment benefits shock (Appendix D also shows the impulse responses to all the other shocks). As expected, a shock to the stochastic component of unemployment insurance raises unemployment and lowers output. Interestingly, this shock does not have a radical effect on wages, despite the fact that its effect on unemployment clearly operates through wage bargaining. The reason for this is two-fold. First, because wages are much larger than profits, small effects on wages translate into large effects on profits and therefore unemployment. Second, the worker's outside option in wage bargaining depends not only on the contemporaneous unemployment benefit, but also on the probability of finding another job. The latter is an *endogenous* object that falls in response to an increase in unemployment benefits. As a consequence, the unemployment benefit shock itself and the endogenous response of the job-finding rate have offsetting effects on wages, as evidenced by the non-monotonic wage response. This mechanism plays a crucial role in understanding why unemployment benefits can have a significant effect on unemployment without generating unrealistically large wage movements.

We next ask whether including unemployment benefits in the model radically changes its predictions for the contributions of other shocks. Table 9 reports the infinite-horizon variance decomposition of several aggregate variables. The main drivers of output and unemployment fluctuations are the two technology shocks. Predictably, the unemployment benefit shock explains a large fraction of the fluctuations in unemployment benefits, though far from all, due to the presence of the systematic component. However, the unemployment benefit shock plays only a minor role in the variance decomposition of other aggregate variables. Thus, despite the addition of the stochastic unemployment benefit policy, the overall variance decomposition is quite standard and not extremely different from other studies. In spite of this, unemployment benefits play a key role in explaining individual historical episodes. This is illustrated in figure 33, which plots the historical decomposition of the unemployment rate over the 1959Q1-2013Q2 period. The neutral and investment-specific technology shocks play a major role in driving unemployment fluctuations over this period. Unemployment

benefits shocks, on the other hand, are particularly important for explaining persistently high unemployment in individual recessions: 1990-1991, 2001, and 2007-2009, as well as 1975. This is remarkably consistent with the narrative evidence: there were unprecedentedly large extensions of unemployment benefits in the 1970's, as well as in the three most recent recessions, while the extensions of the 1980's were somewhat smaller by the 1970's standards. Another important message from this figure is the significant role assigned by the estimated model to negative UI shocks, which are shown to be important for post-recession labor market recoveries. For example, the model implies that negative UI shocks in the 1980's recession dampened the unemployment response.

### 3.4 Counterfactual analysis

To assess the importance of unemployment insurance for unemployment dynamics, we perform counterfactual experiments in which fluctuations in unemployment insurance are shut down. Note that there are two parts to our estimated unemployment benefit policy: i.i.d. shocks to unemployment benefits and a systematic component that depends on unemployment. In what follows, we investigate the role of each of these elements.

We simulate the model for the 1959-2013 period. Figure 42 shows the simulated path of unemployment, along with the counterfactual path in which unemployment insurance is restricted to be constant. Comparison of the baseline with the constant UI case clearly shows that shutting down fluctuations in unemployment insurance significantly dampens fluctuations in unemployment. Moreover, UI is quantitatively more important in the jobless recoveries period. We computed an  $R^2$  value of 0.68 for the model with constant UI. However, this measure of fit is 0.81 for the pre-1985 period, and 0.51 for the post-1985 period, indicating that UI fluctuations account for more of unemployment fluctuations in the latter period.

The effect of UI on fluctuations, furthermore, stems from a combination of shocks and a systematic component that depends on current and past unemployment. To disentangle these two forces, figure 43 shows the simulated path of unemployment together with three counterfactuals. The first is the path of unemployment obtained when the systematic component is shut down, i.e. the feedback coefficient  $\rho_{D,U}$  on  $u_t - \tilde{u}_t$  is set to zero, but the shocks to unemployment benefits are still present. The second is the path of unemployment obtained when when shocks to unemployment benefits are absent, but the feedback component is present, so the variation in unemployment benefits is deterministic. Finally, in the third counterfactual we shut down both sources of variation, so unemployment insurance is constant (as in figure 42).

The two intermediate counterfactuals reveal important insights into the decomposition of the effect of UI. In particular, the systematic component and the i.i.d. shocks may have either dampening or amplifying effects, and are of various importance at different points in the sample. Consider the recession of the 1980's. Our model implies that there were negative shocks to UI during that period, which had a stabilizing effect. In other words, the rise in unemployment induced by other adverse shocks prescribed a larger systematic increase in unemployment insurance than was observed. Thus, shutting down the feedback effect but letting the shocks operate would have led to significantly lower unemployment. If only the systematic component had been operative, in the absence of the UI shocks, unemployment would have been even higher than it actually was in 1981. This contrasts sharply with the experience of the three recent jobless recoveries, in particular the Great Recession. In the latter, the systematic component prescribed only a mild rise in unemployment insurance; it was the unexpected shocks to unemployment benefits that dramatically increased unemployment, and its persistence, in 2007-2013.

Finally, we examine the effects of UI on variables other than unemployment. Figure 44, which plots the simulated and counterfactual GDP series, illustrates that shutting down fluctuations in unemployment insurance somewhat dampens fluctuations in GDP. More interestingly, figure 45 reveals that unemployment insurance extensions prevented deflation in the last three recessions. In other words, inflation would have fallen more in response to negative aggregate demand shocks had UI not been extended. Unemployment insurance, by putting upward pressure on wages, acts as a negative supply shock, akin to a shock to the disutility of labor. This confirms the claim that our model serves to endogenize the labor wedge, which is important not only to understanding unemployment per se, but also for other key variables: in this case, an endogenous labor wedge helps rationalize the missing disinflation in the Great Recession. It is useful to compare this result to Fratto and Uhlig (2014). Like that paper, we take a diagnostic approach to explaining the behavior of aggregate variables, in particular inflation, in the Great Recession. In Fratto and Uhlig (2014), it is price markup shocks that account for the lack of deflation. Here, UI shocks - whose estimation is disciplined by actual observed UI benefit extensions - act similarly to markup shocks; as a consequence, the model attributes correspondingly less explanatory power to actual price markup shocks.



### 3.5 The role of other policies

As pointed out by Mulligan (2012) among others, unemployment insurance was not the only social safety net that expanded during the Great Recession. In particular, eligibility for the Supplemental Nutrition Assistance Program (SNAP) likewise expanded over the 2007-2010 period, resulting in about 20% increase in spending per participant in real terms.<sup>18</sup> Such eligibility expansions included, e.g. the suspension of time limits for individuals not meeting work requirements (Eslami et al. (2011), 8). To the extent that this program increased the opportunity cost of work, looking at UI alone would understate the contribution of social insurance to unemployment persistence over this period. To account for this, we modify the Great Recession counterfactual for the 2008-2013 so that benefits accruing to the unemployed are a combination of UI and SNAP data. Not surprisingly, the estimated model then attributes an even larger role to social insurance in explaining unemployment persistence over this period. This is illustrated in figure 46, which compares the observed unemployment rate to two counterfactual scenarios. The unemployment rate would have over 1 percentage point lower in 2013 had the SNAP expansion not occurred, and smaller still had unemployment insurance been constant as well.

## 4 Evidence for the mechanism

In this section we aim to provide direct empirical evidence of the effect of unemployment benefit extensions on employment in the pre-jobless recovery time period and to show the empirical estimates have remained constant across the pre- and post-jobless recovery periods. Research starting with the seminal work of Moffitt and Nicholson (1982), Moffitt (1985), and Katz and Meyer (1990) reached consensus estimates that a ten-week increase in benefit duration increases the average duration of unemployment spells by 1 to 2 weeks. However, Katz (2014) and Rothstein (2011), among others, have argued that those estimates were driven by temporary layoffs, and may not be relevant for the experience during the Great Recession. Whether the difference in findings is due to a change in the nature of the labor market, or due to the fact that more recent studies rely on survey data and use a different identification strategy, is unclear.<sup>19</sup>

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<sup>18</sup>Source: data on Supplemental Nutrition Assistance Program Participation and Costs, and authors' calculations.

<sup>19</sup>Indeed, a recent study by Johnston and Mas (2018) using administrative data exploiting a natural experiment in Missouri in 2011 finds effects of similar magnitude to the earlier literature. See Hagedorn et al. (2016) for a review of recent quasi-experimental studies on the effects of unemployment benefit extensions.

To address this concern, we seek to provide a consistent estimate of the effect of unemployment benefits on employment using the same data and methodology in the pre- and post-jobless recovery period. To do so, we follow the empirical methodology of Hagedorn et al. (2013) who develop a semi-structural estimator that controls for expectations of future policy changes. That paper focuses on the experience during the Great Recession,<sup>20</sup> and finds effects of benefits on unemployment consistent with the earlier consensus estimates. We extend their methodology to: 1) provide additional direct empirical evidence on the mechanism and 2) show that the empirical estimates were stable in the pre-and post-jobless recoveries periods. Thus, we will be the first to provide estimates on the effect of benefits across the pre- and post-jobless recoveries period using consistent methodology and data sources.

As discussed in Hagedorn et al. (2013), there are two main challenges in estimating the effect of unemployment benefits on employment. First, benefits are extended in periods of high unemployment, creating a challenge for identification due to potential endogeneity problems. Second, since the decision to post a vacancy or exert search effort is a forward-looking decision, expectations about future policies affect labor market variables today. To overcome the first problem we perform the analysis by comparing the evolution of employment in counties that border each other but belong to different states (since the benefits extensions are a function of state level unemployment rate and federal law). To overcome the second problem, we use the quasi-difference estimator proposed by Hagedorn et al. (2013) that controls for expectations.<sup>21</sup>

We perform our analysis using data from the Quarterly Census of Employment and Wages from 1976-1984. Our empirical estimates are highly statistically significant and imply that extending benefits by 10 weeks permanently would decrease employment by 1.6 percent. This number is slightly larger than the effect found by Hagedorn et al. (2013) in the 2001 and 2007 recessions, but the implied magnitudes are not significantly different from each other in a statistical sense. Thus, applying a consistent methodology across time and using the same data sources, we conclude that the empirical estimate have remained stable across the pre-jobless and jobless recovery time periods, validating the mechanism in both the simple and DSGE model.

It is worth noting that our empirical estimates are consistent with the “consensus elasticities” estimated based on the 1970s and 1980s recessions that a 10 week extension leads to 1-2

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<sup>20</sup>The main specification in that paper covers the Great Recession period, 2005-2012, but also includes results for the 1991 and 2002 recessions.

<sup>21</sup>Since we are not innovating in terms of the estimator applied, we refer the interested reader to Hagedorn et al. (2013) for the full details.

week increase in unemployment duration. Although this elasticity might appear small, it is far from innocuous, for two reasons. First, an apparently small increase in unemployment duration can correspond to a large increase in the aggregate unemployment rate: a simple back-of-the-envelope calculation implies a 10-week increase in benefit duration leads to a 0.7 percentage point increase in the unemployment rate.<sup>22</sup> Second, the unemployment benefit extensions we consider are large, especially the extensions in the most recent recession, which increased potential benefit duration by up to 73 weeks (for a maximum of 99 weeks).

## 5 Conclusion

We have argued that unemployment benefit extensions act as an important propagation mechanism, contributing to both the persistence of unemployment and its weak correlation with productivity. More generally, our analysis implies that unemployment benefit extensions are a natural and compelling candidate for the endogenous labor wedge needed to reconcile an apparently weak productivity-labor market correlation with a theory of business cycles driven by “neoclassical” shocks. Further, unemployment benefit extensions explain a significant part of the volatility of GDP and can explain the “missing deflation” in the Great Recession.

Our analysis has been positive in nature. An important future direction for research is studying the optimal provision of unemployment benefits over the business cycle. Mitman and Rabinovich (2015) make progress in this dimension by solving the Ramsey problem in a model analogous to our simple model. A full quantitative evaluation would require performing this analysis in an extended model that incorporates more frictions and explicit heterogeneity and incomplete markets (e.g. Hagedorn et al. (2019)). We leave this for future research.

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<sup>22</sup>In particular, set the unemployment rate equal to its steady-state value,  $u = \frac{\delta}{\delta+f}$ , where  $\delta$  is the job separation rate and  $f$  is the job-finding rate, and use the fact that expected unemployment duration is equal to the reciprocal of the job-finding rate. At a weekly frequency,  $f \approx 0.14$ , and  $\delta$  is an order of magnitude smaller ( $\delta \approx 0.0081$ ). Then, a ten-week increase in unemployment duration is equivalent to slightly more than a 10% decrease in the job-finding rate, which, in turn, translates into a 0.7 percentage point increase in the unemployment rate.

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## A Details on the simple model analysis

In this section we describe in greater detail the policy, timing, value functions and definition of equilibrium for the simple model in Section 2.

### A.1 Law of motion for policy

A policy consists of an unemployment benefit level  $b$ , a re-entitlement rate  $r$ , and the expiration rate  $e_t$ . The level  $b$  and the re-entitlement rate  $r$  are assumed fixed. The expiration rate  $e_t$  is given by:

$$e_t^{-1} = \bar{D} + I_t^{EB} D^{EB} + I_t^{EUC} D^{EUC} \quad (16)$$

where:

- $e_t^{-1}$ , the inverse of the expiration rate, is the expected duration of benefits
- $\bar{D}$  is the baseline, equal to 26 weeks
- $I_t^{EB}$  and  $I_t^{EUC}$  are indicator functions (equal to 0 or 1) for whether the EB and EUC programs are active
- $D^{EB}$  and  $D^{EUC}$  are the additional weeks of benefits provided under EB and EUC; both are constant over time in the calibration. In the simulation,  $D^{EB}$  is constant, but  $D^{EUC}$  unexpectedly changes in each recession. Agents expect  $D^{EUC}$  to be whatever it was in the previous time it was turned on.

The EB program follows the law of motion:

$$I_t^{EB} = \begin{cases} 1 & \text{if } u_t \geq \hat{u} \\ 0 & \text{otherwise} \end{cases}$$

where  $\hat{u}$  is some pre-specified threshold.

The EUC program follows the law of motion  $Prob(I_t^{EUC} = 1 | I_{t-1}^{EUC} = i) = \Lambda_i(u_t)$ , where  $\Lambda_0$  is the (activation) probability that the EUC program gets turned on conditional on being off in the previous period, and  $\Lambda_1$  is the (renewal) probability that EUC continues being on conditional on being on in the previous period.

### A.2 Timing

1. The economy enters period  $t$  with some distribution of workers across employment and eligibility states:
  - $l_t^E$  = measure of eligible employed workers;
  - $l_t^I$  = measure of ineligible employed workers;
  - $u_t^E$  = measure of eligible unemployed workers;

- $u_t^I$  = measure of ineligible unemployed workers.

Note that  $l_t^E + l_t^I + u_t^E + u_t^I = 1$ .

2. The aggregate shock  $z_t$  then realizes and is publicly observed. The EUC policy shock realizes and is also publicly observed. Production and consumption then take place: employed workers get wage  $w_t^E$  if eligible for unemployment benefits and  $w_t^I$  if ineligible (see below for how wages are determined). Unemployed workers receive  $h + b$  if eligible for benefits and  $h$  if ineligible.
3. Firms decide how many vacancies  $v_t$  to post, at cost  $k$  per vacancy. Workers decide on search effort:  $S_t^E$  for UI-eligible workers, and  $S_t^I$  for UI-ineligible workers. This determines the market tightness

$$\theta_t = \frac{v_t}{S_t^E u_t^E + S_t^I u_t^I} \quad (17)$$

4. Job-finding outcomes are realized: in particular, each worker who supplied search effort  $s_t$  finds a job with probability  $s_t f(\theta_t)$ . At the same time, a fraction  $\delta$  of the existing  $l_t = l_t^E + l_t^I$  matches are exogenously destroyed.
5. UI eligibility is updated. We assume that an eligible employed person who loses his job may immediately lose eligibility with probability  $e_t$ , just like an eligible unemployed person who did not find a job. Similarly, an ineligible unemployed person who finds a job may immediately regain eligibility with re-entitlement probability  $r$ , just like an ineligible employed person who retains his job. The laws of motion for worker stocks are therefore:

$$l_{t+1}^E = (1 - \delta) l_t^E + S_t^E f(\theta_t) u_t^E + r [(1 - \delta) l_t^I + S_t^I f(\theta_t) u_t^I] \quad (18)$$

$$l_{t+1}^I = (1 - r) [(1 - \delta) l_t^I + S_t^I f(\theta_t) u_t^I] \quad (19)$$

$$u_{t+1}^E = (1 - e_t) [\delta l_t^E + (1 - S_t^E f(\theta_t)) u_t^E] \quad (20)$$

$$u_{t+1}^I = \delta l_t^I + (1 - S_t^I f(\theta_t)) u_t^I + e_t [\delta l_t^E + (1 - S_t^E f(\theta_t)) u_t^E] \quad (21)$$

Note that  $l_{t+1}^E + l_{t+1}^I + u_{t+1}^E + u_{t+1}^I = 1$ .

The aggregate state of the economy is  $\Omega_t = \{z_t, l_t^E, u_t^E, u_t^I, e_t, I_t^{EUC}\}$ .

### A.3 Worker value functions

The values functions for workers are given below. For ease of exposition, we suppress the explicit dependence of value functions on  $\Omega_t$  throughout. Denote by  $W_t^E$  and  $W_t^I$ , respectively, the value functions of UI-eligible and UI-ineligible employed workers. Similarly, denote by  $U_t^E$  and  $U_t^I$ , respectively, the value functions of UI-eligible and UI-ineligible unemployed workers. Then:



$$W_t^E = w_t^E + \beta(1-\delta)\mathbb{E}W_{t+1}^E + \beta\delta(1-e_t)\mathbb{E}U_{t+1}^E + \beta\delta e_t\mathbb{E}U_{t+1}^I \quad (22)$$

$$W_t^I = w_t^I + \beta(1-\delta)r\mathbb{E}W_{t+1}^E + \beta(1-\delta)(1-r)\mathbb{E}W_{t+1}^I + \beta\delta\mathbb{E}U_{t+1}^I \quad (23)$$

$$\begin{aligned} U_t^E &= \max_{s^E} h + b - c(s^E) + \beta s^E f(\theta_t)\mathbb{E}W_{t+1}^E \\ &\quad + \beta(1-s^E f(\theta_t))(1-e_t)\mathbb{E}U_{t+1}^E + \beta(1-s^E f(\theta_t))e_t\mathbb{E}U_{t+1}^I \end{aligned} \quad (24)$$

$$\begin{aligned} U_t^I &= \max_{s^I} h - c(s^I) + \beta s^I f(\theta_t)r\mathbb{E}W_{t+1}^E + \beta s^I f(\theta_t)(1-r)\mathbb{E}W_{t+1}^I \\ &\quad + \beta(1-s^I f(\theta_t))\mathbb{E}U_{t+1}^I \end{aligned} \quad (25)$$

We use the following notation:

- $\Delta_t^E = W_t^E - U_t^E =$  an eligible worker's surplus from being employed
- $\Delta_t^I = W_t^I - U_t^I =$  an ineligible worker's surplus from being employed
- $\Phi_t = U_t^E - U_t^I =$  an unemployed worker's surplus from being eligible

The first-order conditions for search intensity are then:

$$\begin{aligned} \frac{c'(S_t^E)}{f(\theta_t)} &= \beta(1-e_t)(\mathbb{E}W_{t+1}^E - \mathbb{E}U_{t+1}^E) + \beta e_t(\mathbb{E}W_{t+1}^E - \mathbb{E}U_{t+1}^I) \\ &= \beta\mathbb{E}\Delta_{t+1}^E + \beta e_t\mathbb{E}\Phi_{t+1} \end{aligned} \quad (26)$$

$$\begin{aligned} \frac{c'(S_t^I)}{f(\theta_t)} &= \beta r(\mathbb{E}W_{t+1}^E - \mathbb{E}U_{t+1}^I) + \beta(1-r)(\mathbb{E}W_{t+1}^I - \mathbb{E}U_{t+1}^I) \\ &= \beta r\mathbb{E}\Delta_{t+1}^E + \beta(1-r)\Delta_{t+1}^I + \beta r\mathbb{E}\Phi_{t+1} \end{aligned} \quad (27)$$

Next, combining equations (22)-(25) with equations (26)-(27), we get the following laws of motion:

$$\Delta_t^E = w_t^E - h - b + c(S_t^E) + (1-\delta - S_t^E f(\theta_t))\{\beta\mathbb{E}\Delta_{t+1}^E + \beta e_t\mathbb{E}\Phi_{t+1}\} \quad (28)$$

$$\begin{aligned} \Delta_t^I &= w_t^I - h + c(S_t^I) \\ &\quad + (1-\delta - S_t^I f(\theta_t))\{\beta r\mathbb{E}\Delta_{t+1}^E + \beta(1-r)\Delta_{t+1}^I + \beta r\mathbb{E}\Phi_{t+1}\} \end{aligned} \quad (29)$$

$$\Phi_t = b - c(S_t^E) + c(S_t^I) + S_t^E c'(S_t^E) - S_t^I c'(S_t^I) + \beta(1-e_t)\mathbb{E}\Phi_{t+1} \quad (30)$$

## A.4 Firm value functions

Denote by  $J_t^i$  the value of a firm employing a worker whose current UI eligibility status is  $i \in \{E, I\}$ . Then these values are given by:

$$J_t^E = z_t - w_t^E - \tau + \beta(1 - \delta) \mathbb{E}J_{t+1}^E \quad (31)$$

$$J_t^I = z_t - w_t^I - \tau + \beta(1 - \delta)(1 - r) \mathbb{E}J_{t+1}^I + \beta(1 - \delta)r \mathbb{E}J_{t+1}^E \quad (32)$$

Next, the value of a vacancy is

$$V_t = -k + \beta q(\theta_t) [\varpi_t \mathbb{E}J_{t+1}^E + (1 - \varpi_t) \mathbb{E}J_{t+1}^I] \quad (33)$$

where

$$\varpi_t = \frac{S_t^E u_t^E + r S_t^I u_t^I}{S_t^E u_t^E + S_t^I u_t^I} = \frac{\varsigma_t u_t^E + r u_t^I}{\varsigma_t u_t^E + u_t^I} \quad (34)$$

is the probability of hiring a UI-eligible worker conditional on hiring, and we define  $\varsigma_t = \frac{S_t^E}{S_t^I}$ .

In equilibrium, free entry of firms will imply that  $V_t = 0$  and hence the surplus from hiring a worker of eligibility status  $i$  is simply  $J_t^i$ .

## A.5 Wage bargaining

Worker bargaining power is denoted by  $\xi$ . Define the total eligible and ineligible surplus by  $Y_t^E = \Delta_t^E + J_t^E$  and  $Y_t^I = \Delta_t^I + J_t^I$ . Then, Nash bargaining implies that for the UI-eligible,

$$\Delta_t^E = \xi Y_t^E \quad (35)$$

and for the ineligible,

$$\Delta_t^I = \xi Y_t^I \quad (36)$$

## A.6 Equilibrium

We now define the recursive equilibrium of the model.

**Definition 1** *An equilibrium is a set of functions for wages  $w^E(\Omega_t)$ ,  $w^I(\Omega_t)$ , market tightness  $\theta(\Omega_t)$ , search intensity  $S^E(\Omega_t)$ ,  $S^I(\Omega_t)$  and value functions*

$$\{W^E(\Omega_t), W^I(\Omega_t), U^E(\Omega_t), U^I(\Omega_t), J^E(\Omega_t), J^I(\Omega_t), V(\Omega_t)\}$$

such that:

1. The value functions satisfy the worker and firm Bellman equations (22)-(25), (31)-(33)
2. Free entry: The value  $V(\Omega_t)$  of a vacant firm is zero for all  $\Omega_t$
3. Nash bargaining: The wage  $w^E(\Omega_t)$  satisfies (35), and  $w^I(\Omega_t)$  satisfies (36)
4. Laws of motion: The aggregate state  $\Omega_t$  evolves according to equations (1), (18)-(21).

## A.7 Equilibrium characterization

In this section we simplify the equilibrium conditions by rewriting them in terms of  $Y_t^E$ ,  $Y_t^I$  and  $\Phi_t$ , using the Nash bargaining conditions (35) and (36).

### A.7.1 Transforming the first-order conditions for search intensity

The optimal search conditions (26) and (27) for workers can be rewritten as

$$\begin{aligned} \frac{c'(S_t^E)}{f(\theta_t)} &= \beta \mathbb{E} \Delta_{t+1}^E + \beta e_t \mathbb{E} \Phi_{t+1} \\ &= \beta \xi \mathbb{E} Y_{t+1}^E + \beta e_t \mathbb{E} \Phi_{t+1} \end{aligned} \quad (37)$$

$$\begin{aligned} \frac{c'(S_t^I)}{f(\theta_t)} &= \beta r \mathbb{E} \Delta_{t+1}^E + \beta (1-r) \Delta_{t+1}^I + \beta r \mathbb{E} \Phi_{t+1} \\ &= \beta r \xi \mathbb{E} Y_{t+1}^E + \beta (1-r) \xi \mathbb{E} Y_{t+1}^I + \beta r \mathbb{E} \Phi_{t+1} \end{aligned} \quad (38)$$

### A.7.2 Laws of Motion for the Surplus

Adding (28) and (31) we get:

$$\begin{aligned} Y_t^E &= z_t - h - b - \tau + c(S_t^E) + \beta (1 - \delta - \xi S_t^E f(\theta_t)) \mathbb{E} Y_{t+1}^E \\ &\quad + \beta (1 - \delta - S_t^E f(\theta_t)) e_t \mathbb{E} \Phi_{t+1} \end{aligned} \quad (39)$$

Adding (29) and (32) we get:

$$\begin{aligned} Y_t^I &= z_t - h - \tau + c(S_t^I) + \beta r_t (1 - \delta - \xi S_t^I f(\theta_t)) \mathbb{E} Y_{t+1}^E \\ &\quad + \beta (1-r) (1 - \delta - \xi S_t^I f(\theta_t)) \mathbb{E} Y_{t+1}^I \\ &\quad + \beta r (1 - \delta - S_t^I f(\theta_t)) \mathbb{E} \Phi_{t+1} \end{aligned} \quad (40)$$

The third law of motion, for  $\Phi_t$ , is given by (30).

### A.7.3 Free Entry Condition

The free entry condition for firms implies that

$$k = \beta q(\theta_t) (1 - \xi) [\varpi_t \mathbb{E} Y_{t+1}^E + (1 - \varpi_t) \mathbb{E} Y_{t+1}^I] \quad (41)$$

where  $\varpi_t$  is still given by (34).

## A.8 Computation

The equilibrium is computed as follows. The aggregate state is  $\Omega_t = \{z_t, l_t^E, u_t^E, u_t^I, I_t^{EUC}\}$ . We discretize the productivity process using Tauchen's method. We discretize the endogenous aggregate states (unemployment, fraction of eligible employed and fraction of eligible unemployed). We then solve the model non-linearly by iterating on the surplus equations:

1. Guess  $Y_t^E(\Omega_t)$ ,  $Y_t^I(\Omega_t)$ ,  $\Phi_t(\Omega_t)$ ,  $l_{t+1}^E(\Omega_t)$ ,  $u_{t+1}^E(\Omega_t)$ ,  $u_{t+1}^I(\Omega_t)$ .
2. Get  $\varsigma_t = \frac{S_t^E}{S_t^I}$  by using the ratio of (37) and (38). Specifically, using the functional form  $c(s) = A \frac{s^{1+\psi}}{1+\psi}$ , we can derive

$$\varsigma_t^\psi = \frac{\beta \xi \mathbb{E} Y_{t+1}^E + \beta e_t \mathbb{E} \Phi_{t+1}}{\beta r \xi \mathbb{E} Y_{t+1}^E + \beta (1-r) \xi \mathbb{E} Y_{t+1}^I + \beta r \mathbb{E} \Phi_{t+1}} \quad (42)$$

3. Get  $\theta_t$  using the free entry condition (41) and (34).
4. Get  $S_t^E$ ,  $S_t^I$  using the optimal search conditions (37) and (38).
5. Update using (18)-(21), (39), (40), (30).

In steady state we keep  $D^{EB}$  and  $D^{EUC}$  constant. When conducting the main experiment of simulating the time series of productivity and extensions, the extension functions,  $D^{EB}$  and  $D^{EUC}$ , are changing over time (e.g. in 1960 the EB program did not yet exist). We need to take a stand on what agents' expectations about the path of future  $D^{EB}$  and  $D^{EUC}$  will be. We assume that households believe that the extensions of the most recent recession will be the extensions enacted in all future recessions. For example, in the 1975 recession the government provided up to 26 weeks of benefits during the recession as part of the discretionary extensions. Going into the 1982 recession, agents' expectations were for discretionary extensions up to 26 weeks (that occur stochastically with the estimated transition probabilities that are kept constant). In September 1982 agents are surprised when the government instead only enacts a up to 10 weeks of extensions (i.e. it is a probability 0 event). But going forward, they assume that this is the expected discretionary response of the government until they are "surprised again." We found this to be a parsimonious and plausible way to handle the beliefs about future discretionary actions. To be clear, throughout the all time periods agents beliefs about the probability that an extension will occur or expire are constant functions of the unemployment rate and current extension status, with the actual realization taken from the data. Thus, the simulation forward of the model is by a sequence of MIT shocks whenever the  $D^{EB}$  and  $D^{EUC}$  policies change, but agents always have full rational expectations over  $z_t$ ,  $I_t^{EB}$ , and  $I_t^{EUC}$ .

## A.9 Model with Endogenous Separations

Here we describe the extension with endogenous separations discussed in Section 2.3.2. We assume match productivity is  $z_t a_t$ , where  $z_t$  is aggregate productivity, whose logarithm follows an AR(1) process, and  $a_t$  is match-specific idiosyncratic productivity, drawn i.i.d. each period from a cumulative distribution  $G$ . If  $a_t$  is above an endogenous threshold  $\bar{a}_t$ , it is decided to continue the match. This decision applies both to existing matches and to newly formed matches. In addition, there is an exogenous job separation rate  $\delta^x$ .

Every period consists of the following stages: search, matching, separations, and production. Having observed the aggregate shock  $z_t$ , firms decide on vacancy posting, and workers make job search decisions. This determines, as in the baseline model, the aggregate market

tightness  $\theta_t$ . Workers and firms are then matched. Both new and existing matches draw idiosyncratic productivity  $a_t$  from the distribution  $G$ . New matches decide whether or not to continue, and existing matches decide whether or not to separate. Matches that remain then produce, and wages and unemployment benefits get paid. As before, unemployment benefits for eligible unemployed workers expire with probability  $e_t$ , and ineligible employed workers become re-entitled with probability  $r$ .

Note that the threshold  $\bar{a}_t$  for continuing a match, in addition to depending on the aggregate state, will also depend on the worker's UI eligibility status. Let  $\bar{a}_t^E = \bar{a}^E(\Omega_t)$ ,  $\bar{a}_t^I = \bar{a}^I(\Omega_t)$  be the reservation values for continuing an eligible and ineligible match, respectively. Define the continuation probabilities

$$A_t^i = A^i(\Omega_t) = 1 - G(\bar{a}^i(\Omega_t)), \quad i = E, I$$

Then the destruction rate is

$$\delta_t^i = \delta^i(\Omega_t) = \delta^x + (1 - \delta^x)(1 - A^i(\Omega_t))$$

The laws of motion for this model (suppressing dependence on  $\Omega_t$  for notational convenience) are:

$$l_t^E = (1 - \delta_t^E) l_{t-1}^E + S_t^E f(\theta_t) A_t^E u_{t-1}^E + r [(1 - \delta_t^I) l_{t-1}^I + S_t^I f(\theta_t) A_t^I u_{t-1}^I] \quad (43)$$

$$l_t^I = (1 - r) [(1 - \delta_t^I) l_{t-1}^I + S_t^I f(\theta_t) A_t^I u_{t-1}^I] \quad (44)$$

$$u_t^E = (1 - e_t) [\delta_t^E l_{t-1}^E + (1 - S_t^E f(\theta_t) A_t^E) u_{t-1}^E] \quad (45)$$

$$u_t^I = \delta_t^I l_{t-1}^I + (1 - S_t^I f(\theta_t) A_t^I) u_{t-1}^I + e_t [\delta_t^E l_{t-1}^E + (1 - S_t^E f(\theta_t) A_t^E) u_{t-1}^E] \quad (46)$$

Value functions for workers and firms are easily derived similarly to the baseline model.

## B Details on the DSGE analysis

In this section we describe the model, data and estimation employed in section 3.

### B.1 Model

#### B.1.1 Households

There is a large representative household with preferences

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \ln(C_t - hC_{t-1}), \quad (47)$$

where  $h$  is the habit formation parameter. The household faces a budget constraint

$$P_t C_t + P_{I,t} I_t + B_{t+1} \leq (R_{K,t} u_t^K - \varpi(u_t^K) P_{I,t}) K_t + (1 - l_t) P_t D_t + W_t l_t + \zeta_t^B R_{t-1} B_t - T_t \quad (48)$$

where  $C_t$  and  $I_t$  are consumption and investment,  $K_t$  denotes capital services,  $B_t$  denotes bonds, and  $T_t$  denotes lump-sum transfers. The gross nominal interest rate in period  $t$  is  $R_t$ , and  $\zeta_t^B$  denotes the risk premium shock, which evolves according to

$$\ln \zeta_t^B = \rho_\zeta \ln \zeta_{t-1}^B + \sigma_\zeta \nu_t^B, \quad (49)$$

where  $\nu_t^B$  is an i.i.d. standard normal random variable.  $P_t$  and  $P_{I,t}$  denote the nominal price of consumption and investment goods, respectively. A fraction  $l_t$  of the household is employed and earns nominal wage  $W_t$ . A fraction  $1 - l_t$  of the household is unemployed and earns unemployment benefits  $D_t$ . The evolution of  $l_t$  will be described below.  $R_{K,t}$  denotes the nominal rental rate on capital, and  $\varpi(u_t^K)$  is the cost of capital utilization  $u_t^K$ . The capital utilization cost takes the functional form<sup>23</sup>

$$\varpi(u_t^K) = \omega_0 \omega_1 (u_t^K)^2 / 2 + \omega_1 (1 - \omega_0) u_t^K + \omega_1 (\omega_0 / 2 - 1) \quad (50)$$

The capital stock  $K_t$  evolves according to

$$K_{t+1} = (1 - \delta_K) K_t + (1 - S_K(I_t/I_{t-1})) I_t \quad (51)$$

where  $S_K$  is a convex adjustment cost, taking the functional form

$$S_K(I_t/I_{t-1}) = \frac{1}{2} \left[ \exp(\sqrt{S''}(I_t/I_{t-1} - \gamma_I)) + \exp(-\sqrt{S''}(I_t/I_{t-1} - \gamma_I)) \right] - 1, \quad (52)$$

where  $\gamma_I$  is the growth rate of investment in the non-stochastic steady state.

### B.1.2 Firms and production

The final good,  $Y_t$ , can be used to produce either consumption or investment. Consumption is produced from output one-for-one, while the investment technology converts one unit of  $Y_t$  into  $\Psi_t^I$  units of  $I_t$ ; the investment-specific technology process  $\Psi_t^I$  is assumed to follow

$$\ln(\Psi_t^I/\Psi_{t-1}^I) = \ln \gamma_\Psi + \sigma_\Psi \nu_t^I, \quad (53)$$

with  $\nu_t^I$  is an i.i.d. standard normal random variable.

The final good  $Y_t$ , in turn, is produced by aggregating specialized inputs  $Y_{jt}$  according to the technology

$$Y_t = \left( \int_0^1 (Y_{jt})^{\tau_t} dj \right)^{1/\tau_t} \quad (54)$$

The price markup  $\tau_t$  evolves according to

$$\ln \tau_t = (1 - \rho_\tau) \ln \bar{\tau} + \rho_\tau \ln \tau_{t-1} + \sigma_\tau \nu_t^\tau, \quad (55)$$

---

<sup>23</sup>As in CET,  $\omega_1$  is picked given  $\omega_0$  so that  $u_t^K$  is 1 in steady state (a normalization), and  $\omega_0$  is a parameter to be estimated.

where  $\nu_t^r$  is an i.i.d. standard normal random variable.

A representative final goods firm chooses the inputs  $Y_{jt}$  to maximize profits

$$P_t Y_t - \int_0^1 P_{jt} Y_{jt} dj \quad (56)$$

Specialized inputs  $Y_{jt}$  are produced by monopolistically competitive retailers according to the technology

$$Y_{jt} = k_{jt}^\alpha (z_t l_{jt})^{1-\alpha} - \Phi_t \quad (57)$$

where  $\Phi_t$  is a fixed cost of production (which grows at a rate that guarantees a balanced growth path),  $k_{jt}$  is capital,  $z_t$  is the neutral technology shock, and  $l_{jt}$  is an intermediate good. We assume Calvo price stickiness: each retailer can reoptimize its price  $P_{jt}$  every period with probability  $1 - \vartheta_p$ , and with probability  $\vartheta_p$  it keeps its price unchanged from the previous period. The retailers rent capital in a competitive market from households and purchase the intermediate good in a competitive market from wholesale firms. The neutral technology shock evolves according to

$$\ln(z_t/z_{t-1}) = \ln \gamma + \sigma_z \nu_t^z, \quad (58)$$

where  $\nu_t^z$  is an i.i.d. standard normal random variable.

### B.1.3 Labor market frictions

Wholesale firms hire labor in a frictional labor market and produce the intermediate good using labor one-for-one. Aggregate employment,  $l_t$ , evolves according to

$$l_t = (1 - \delta_L) l_{t-1} + M(1 - (1 - \delta_L) l_{t-1}, v_t) \quad (59)$$

where  $\delta_L$  is the job separation rate and

$$M(1 - (1 - \delta_L) l_{t-1}, v_t) = \mu_m (1 - (1 - \delta_L) l_{t-1})^{1-\sigma_m} v_t^{\sigma_m} \quad (60)$$

is the aggregate matching technology.  $\mu_m$  denotes aggregate matching efficiency and  $\sigma_m$  is the elasticity of the matching function. Vacancies,  $v_t$ , are posted at a cost  $\kappa_t^v$ . In addition, a firm hiring a worker incurs a fixed ex post recruiting cost  $\kappa_t^e$ . Both  $\kappa_t^v$  and  $\kappa_t^e$  grow at a rate proportional to aggregate productivity so as to guarantee a balanced growth path. Denote by  $\kappa^v$  and  $\kappa^e$  the steady-state ratio of the vacancy cost to output and the steady state ratio of the recruiting cost to output, respectively;  $\kappa^v$  and  $\kappa^e$  are parameters to be estimated.

### B.1.4 Wages

Wages are determined by Nash bargaining, i.e. the wage is set to maximize

$$(\Delta_t^i)^{\xi_t} (\Gamma_t^i)^{1-\xi_t} \quad (61)$$

In this environment,  $\Gamma_t$  is the marginal value of an additional worker to the wholesale firm, and  $\Delta_t$  is the marginal value of an extra employed member to the large household. The

bargaining weight  $\xi_t$  follows the process

$$\ln \xi_t = (1 - \rho_\xi) \bar{\xi} + \rho_\xi \ln \xi_{t-1} + \sigma_\xi \nu_t^\xi, \quad (62)$$

where  $\nu_t^\xi$  is an i.i.d. standard normal random variable.

### B.1.5 Balanced growth path

Long-run growth is driven by neutral and investment-specific technological progress. Along the non-stochastic balanced growth path,  $z_t/z_{t-1} = \gamma$  and  $\Psi_t/\Psi_{t-1} = \gamma_\Psi$ , so that output grows at the rate  $Y_t/Y_{t-1} = \gamma_Y = \gamma \cdot \gamma_\Psi^{\alpha/(1-\alpha)}$ , and investment grows at the rate  $I_t/I_{t-1} = \gamma_I = \gamma \cdot \gamma_\Psi^{1/(1-\alpha)} = \gamma_Y \cdot \gamma_\Psi$ .

### B.1.6 Fiscal and monetary policy

Government consumption as a share of GDP follows the process

$$\ln g_t = (1 - \rho_g) \ln g + \rho_g \ln g_{t-1} + \sigma_g \nu_t^g, \quad (63)$$

where  $\nu_t^g$  is an i.i.d. standard normal random variable. Monetary policy follows the Taylor rule

$$\ln (R_t/R) = \rho_R \ln (R_{t-1}/R) + (1 - \rho_R) (r_\pi \ln (\pi_t/\bar{\pi}) + r_y \ln (y_t/\bar{y}_t)) + \sigma_R \nu_t^R, \quad (64)$$

where  $R$  is the steady-state interest rate,  $\pi_t/\bar{\pi}$  is the deviation of inflation from its target,  $y_t/\bar{y}_t$  is the deviation of GDP from its non-stochastic growth path, and  $\nu_t^R$  is an i.i.d. standard normal random variable.

### B.1.7 Unemployment insurance

Unemployment benefits  $D_t$  follow the process

$$\ln (D_t/\bar{D}) = \rho_D \ln (D_{t-1}/\bar{D}) + \rho_{D,U} (u_t - \tilde{u}_t) + \sigma_D \nu_t^{UI} \quad (65)$$

Here,  $\bar{D}$  is the steady-state value of unemployment benefits,  $u_t = 1 - l_t$  is unemployment,  $\tilde{u}_t$  is the two-year moving average of unemployment, and  $\nu_t^{UI}$  is an i.i.d. standard normal random variable.

## B.2 Data and estimation

The estimation period is 1959Q1:2008Q3. The model includes 8 shocks and is estimated using quarterly data on 8 observables: output, consumption, investment, wages, inflation, the nominal interest rate, the unemployment rate, and unemployment insurance.

These variables are constructed as follows. Nominal output is taken to be nominal GDP. Nominal consumption is measured as nominal consumption expenditures of nondurables and services. Nominal investment is measured as the sum of gross private domestic investment and nominal consumption of durables. The real per capita variables are constructed by dividing the nominal variable by the GDP deflator and by the population. Real wages are



taken to be nominal compensation per hour, divided by the GDP deflator. The price level is also measured by the GDP deflator. The nominal interest rate is measured by the gross effective federal funds rate. The unemployment rate is the number of unemployed persons 16 and older divided by the labor force. Finally, unemployment benefits data is obtained from NIPA table 2.6, line 21. This data is aggregated to quarterly frequency and divided by the GDP deflator and the number of unemployed persons to obtain the series of real unemployment benefits per unemployed person.

These variables are then used to construct the 8 observables used in the estimation, namely: the quarterly growth rate of real GDP per capita, the quarterly growth rate of real consumption per capita, the quarterly growth rate of real investment per capita, the quarterly growth rate of real wages, the quarterly inflation rate, the quarterly nominal interest rate, the unemployment rate, and unemployment benefits per unemployed worker. The first six are expressed in log deviations from the respective sample mean. The unemployment rate and the unemployment benefit series are detrended using the Hodrick-Prescott filter with a smoothing parameter of  $10^5$ .

We estimate the model using Bayesian maximum likelihood (Smets and Wouters, 2007). Table 7 reports the values for parameters fixed a priori, and table 8 reports the priors and posteriors for the estimated parameters.

## C Tables and figures

### C.1 Tables and figures for section 2

Table 1: Internally Calibrated Parameters

Parameter	Value	Target	Value
$h$ Value of non-market activity	0.80	Average $v/u$	0.634
$\xi$ Bargaining power	0.15	Wage elasticity w.r.t. productivity	0.449
$\lambda$ Matching parameter	0.57	Job-finding rate	0.139
$A$ Level disutility of search	0.90	Micro elasticity of unemp. duration w.r.t. $b$	0.3
$\psi$ Curvature of disutility of search	1.38	Macro elasticity of unemp. duration w.r.t. $1/e$	0.1

Table 2: Summary Statistics, Quarterly US Data, 1960:I to 2014:IV

	$u$	$v$	$v/u$	$f$	$w$	$z$	
Standard Deviation	0.1191	0.1353	0.2556	0.0864	0.0087	0.0125	
Correlation Matrix	$u$	1	-0.9236	-0.9587	-0.9064	-0.0188	-0.2124
	$v$		1	0.9846	0.8900	-0.0039	0.3872
	$v/u$			1	0.9176	0.0130	0.3253
	$f$				1	-0.0079	0.2120
	$w$					1	0.1797
	$z$						1

Table 3: Results from the Calibrated Model

	$u$	$v$	$v/u$	$f$	$w$	$z$	
Standard Deviation	0.0976	0.1145	0.2048	0.1140	0.0121	0.0125	
Correlation Matrix	$u$	1	-0.7776	-0.9194	-0.9256	0.0235	-0.3004
	$v$		1	0.9509	0.9533	0.1857	0.5135
	$v/u$			1	0.9981	0.0834	0.4325
	$f$				1	0.0963	0.4450
	$w$					1	0.5299
	$z$						1

Table 4: Results from the Model with No Benefit Extensions

	$u$	$v$	$v/u$	$f$	$w$	$z$	
Standard Deviation	0.0794	0.0877	0.1610	0.0896	0.0091	0.0125	
Correlation Matrix	$u$	1	-0.8139	-0.9436	-0.9449	-0.7503	-0.7562
	$v$		1	0.9561	0.9575	0.8960	0.8876
	$v/u$			1	0.9994	0.8639	0.8661
	$f$				1	0.8632	0.8634
	$w$					1	0.9860
	$z$						1

Table 5: Autocorrelation of Unemployment

Quarter Lag	Data	Model	Model w/o Extensions
0	1	1	1
1	0.9182	0.8765	0.8576
2	0.7536	0.6391	0.5598
3	0.5485	0.4072	0.2408
4	0.3336	0.1973	-0.0336
5	0.1413	0.0183	-0.2302
6	-0.0207	-0.1115	-0.3484
7	-0.1643	-0.1885	-0.3919

Table 6: Correlation with lagged productivity,  $z_{t-1}$

Variable	Data	Model	Model w/o Extensions
$u_t$	-0.3998	-0.4348	-0.8150
$v_t$	0.5369	0.3854	0.7309
$v_t/u_t$	0.4950	0.4265	0.8236
$f_t$	0.4110	0.4396	0.8219
$w_t$	0.1791	0.3591	0.7339

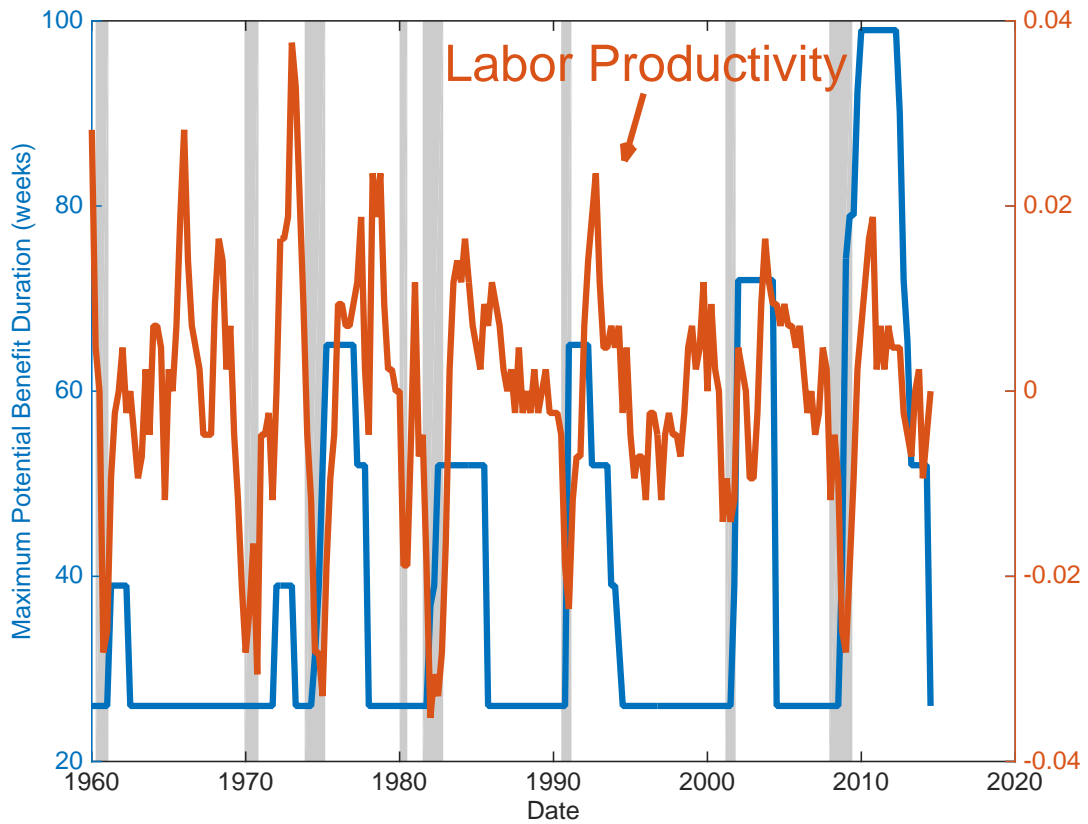


Figure 1: Labor productivity (in log-deviations from trend), left axis and maximum potential unemployment benefit duration, right axis, January 1960 through September 2014. NBER dated recessions are shaded.

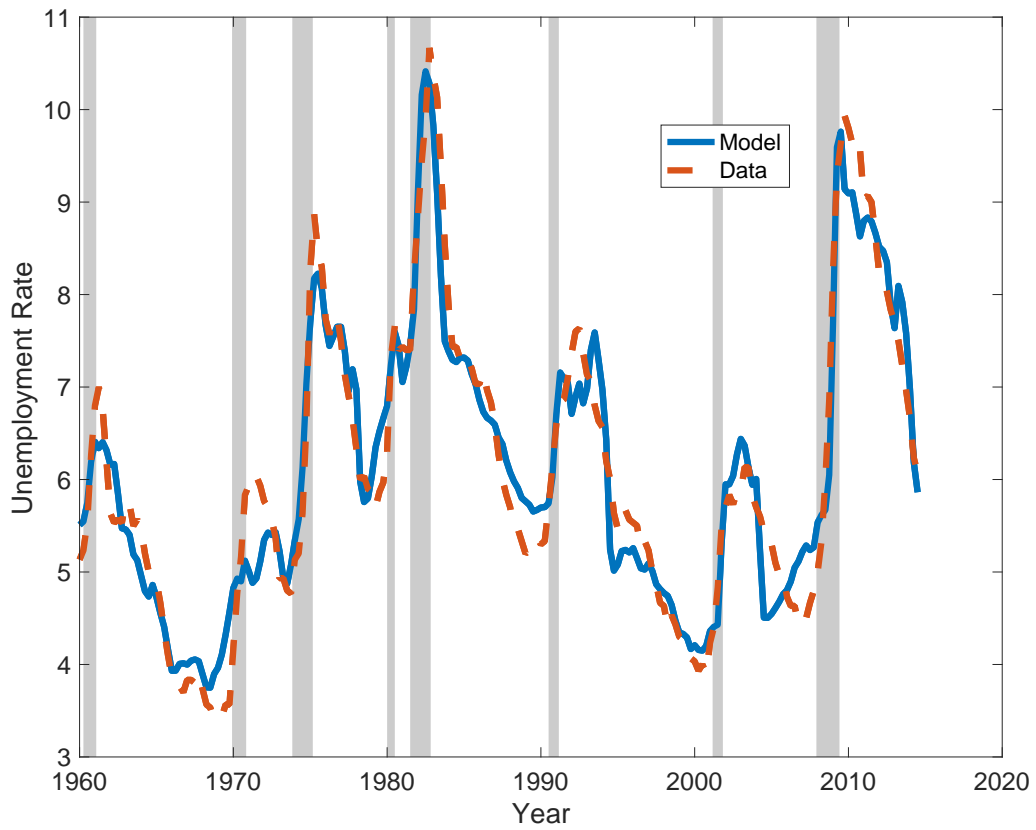


Figure 2: Simulated and actual unemployment from January 1960 through September 2014. NBER dated recessions are shaded.

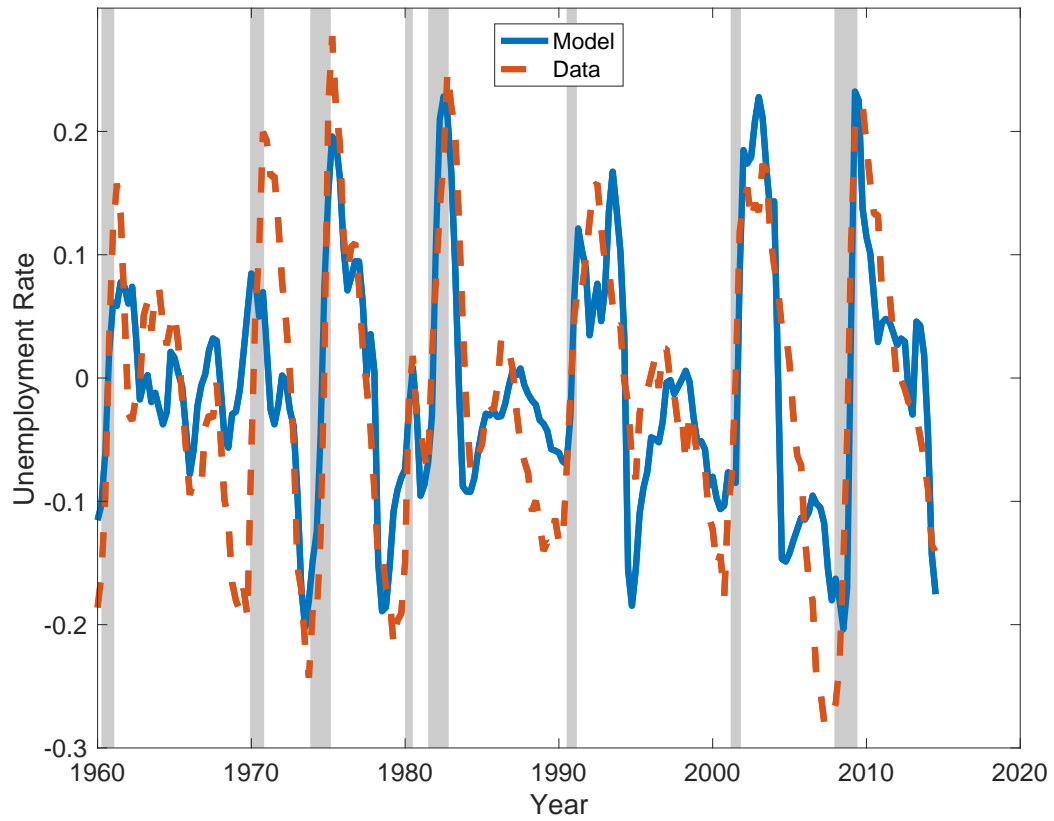


Figure 3: Log deviations from HP filtered trend for simulated and actual unemployment from January 1960 through September 2014. NBER dated recessions are shaded.

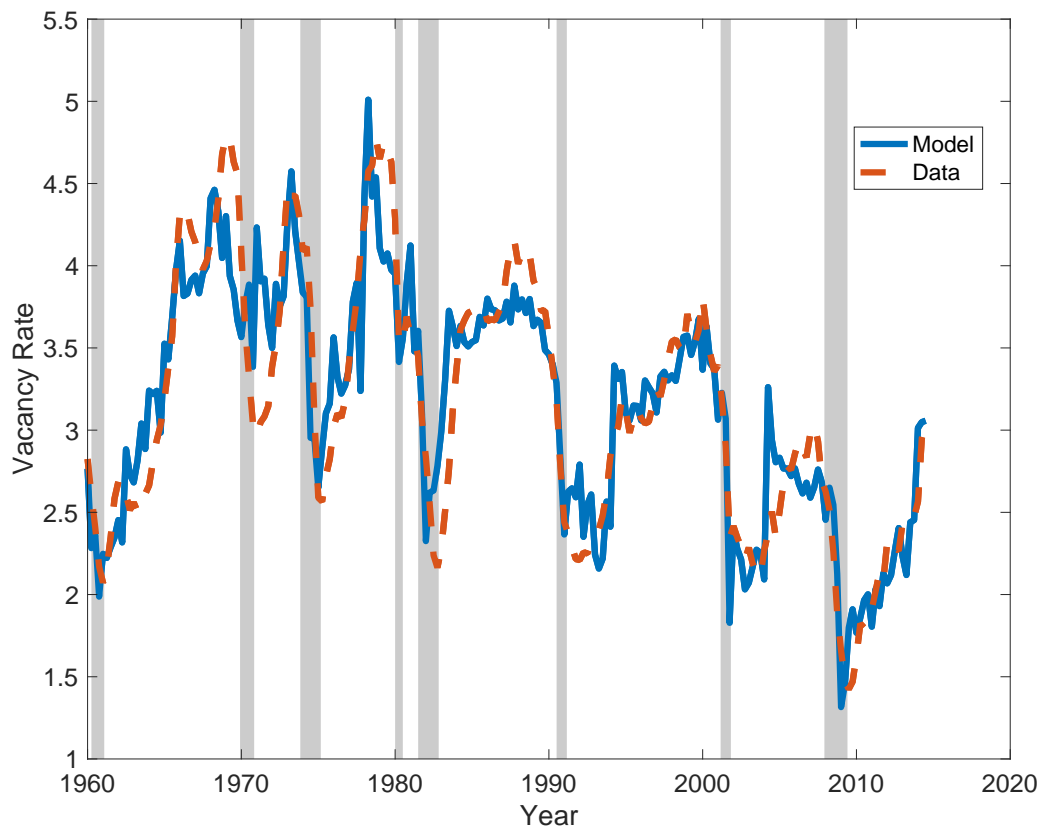


Figure 4: Simulated and actual vacancy rate from January 1960 through September 2014. NBER dated recessions are shaded.



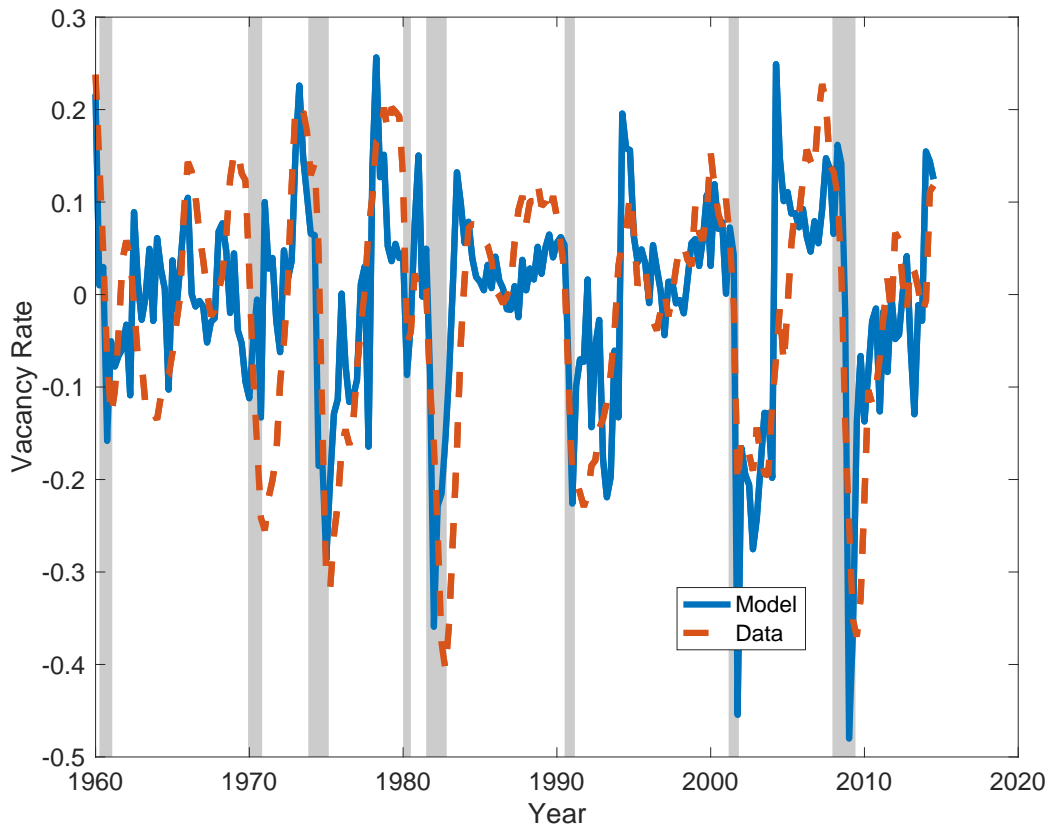


Figure 5: Log deviations from HP filtered trend for simulated and actual vacancy rate from January 1960 through September 2014. NBER dated recessions are shaded.

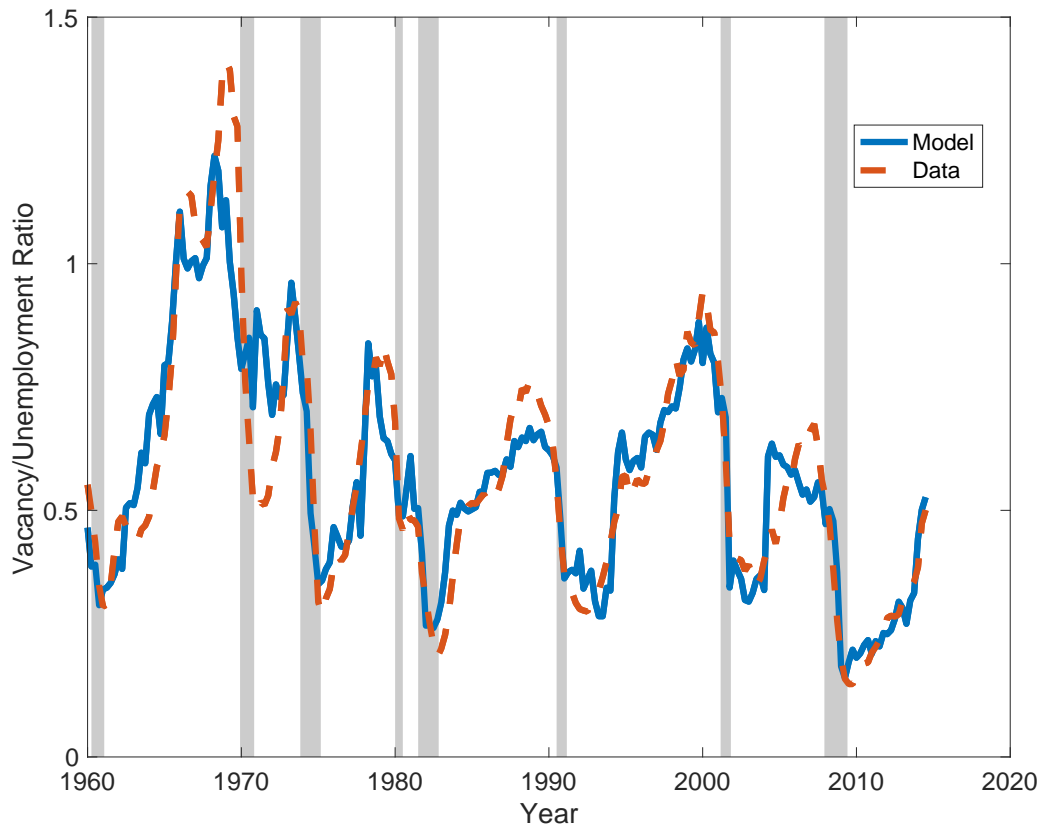


Figure 6: Simulated and actual vacancy/unemployment ratio from January 1960 through September 2014. NBER dated recessions are shaded.

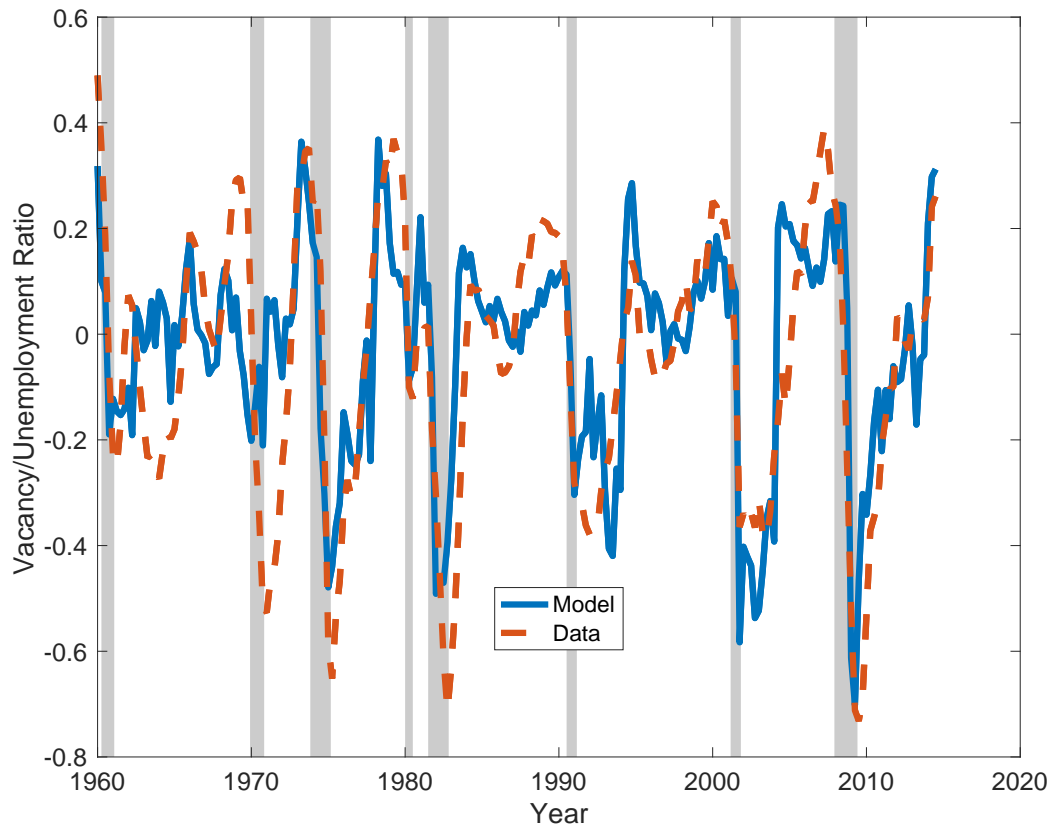


Figure 7: Log deviations from HP filtered trend for simulated and actual vacancy/unemployment ratio from January 1960 through September 2014. NBER dated recessions are shaded.

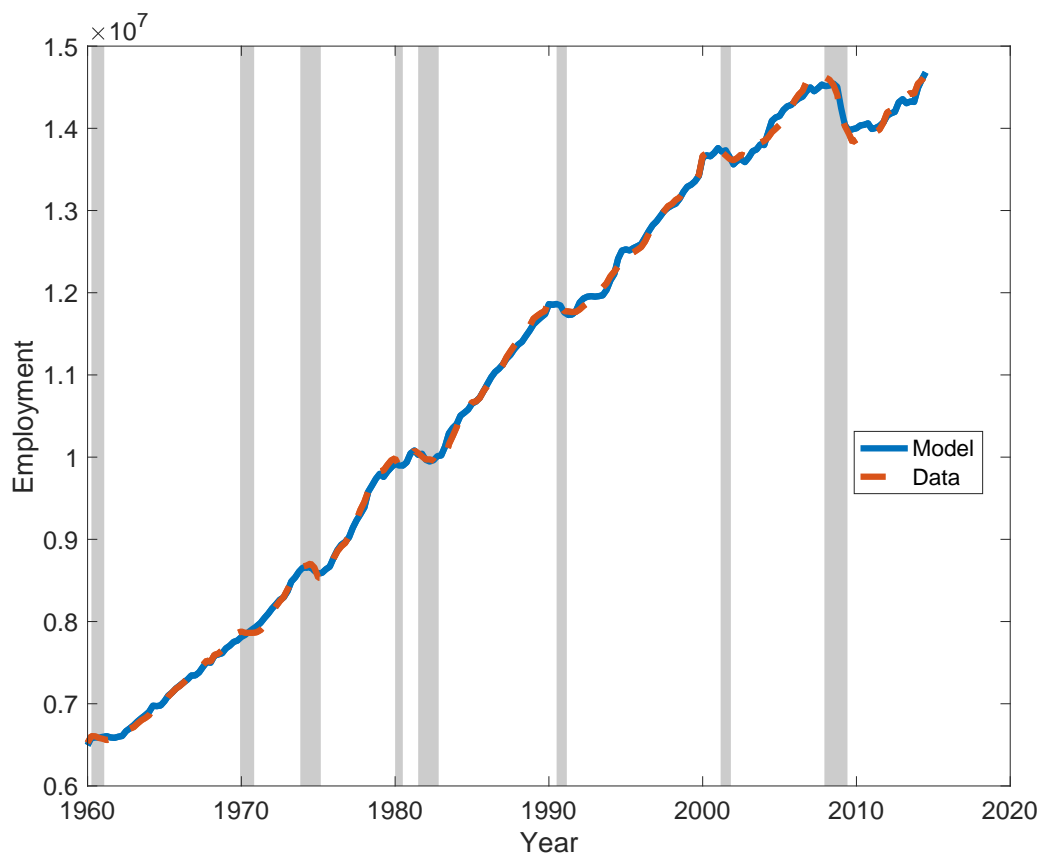


Figure 8: Simulated and actual employment from January 1960 through September 2014. NBER dated recessions are shaded.

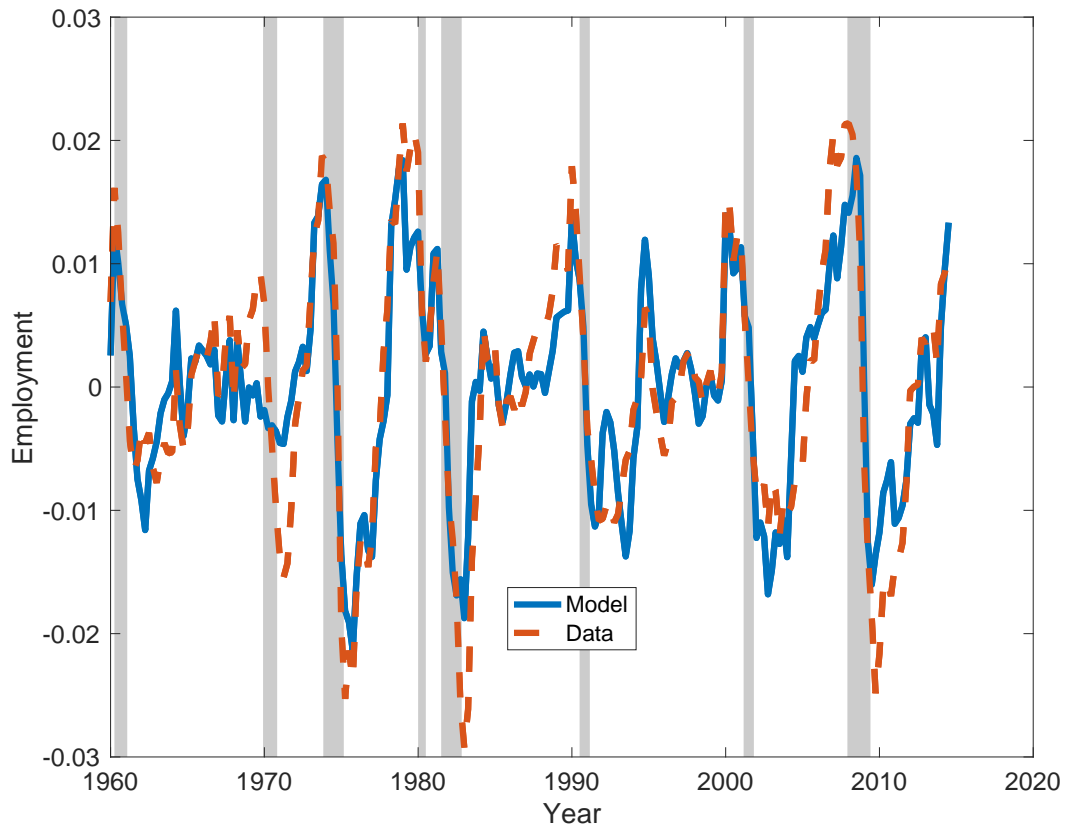


Figure 9: Log deviations from HP filtered trend for simulated and actual employment from January 1960 through September 2014. NBER dated recessions are shaded.

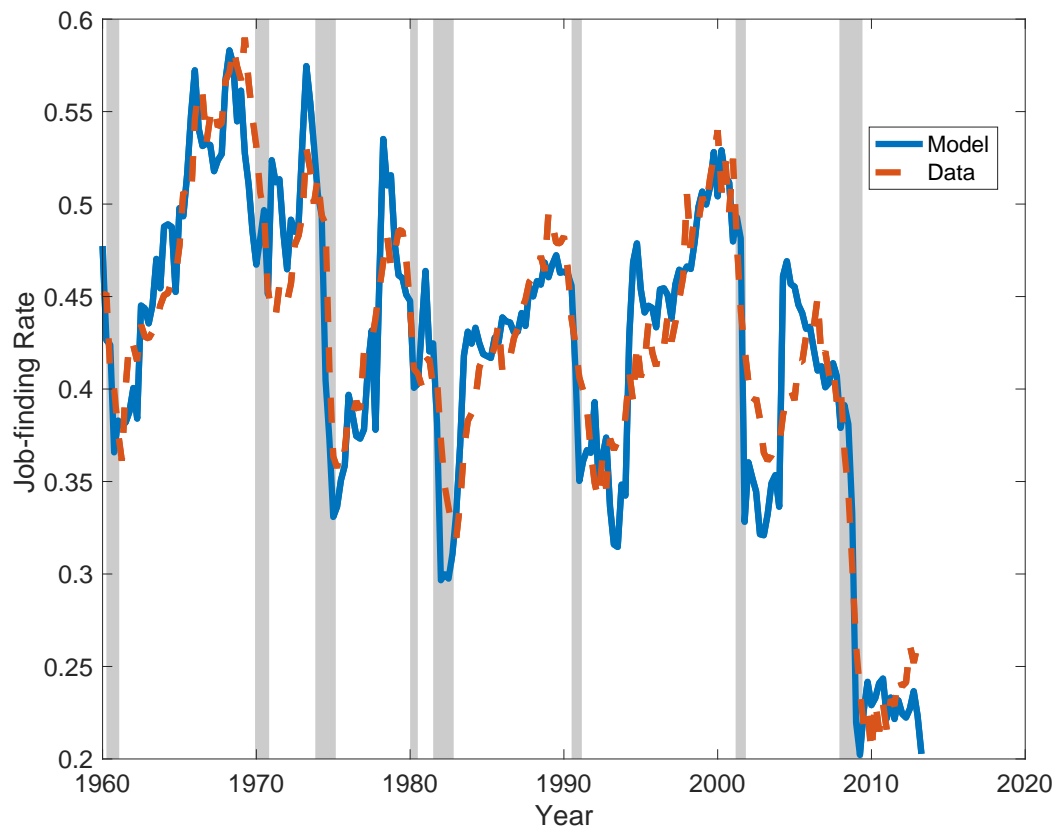


Figure 10: Simulated and actual simulated and actual job-finding rate from January 1960 through September 2014. NBER dated recessions are shaded.

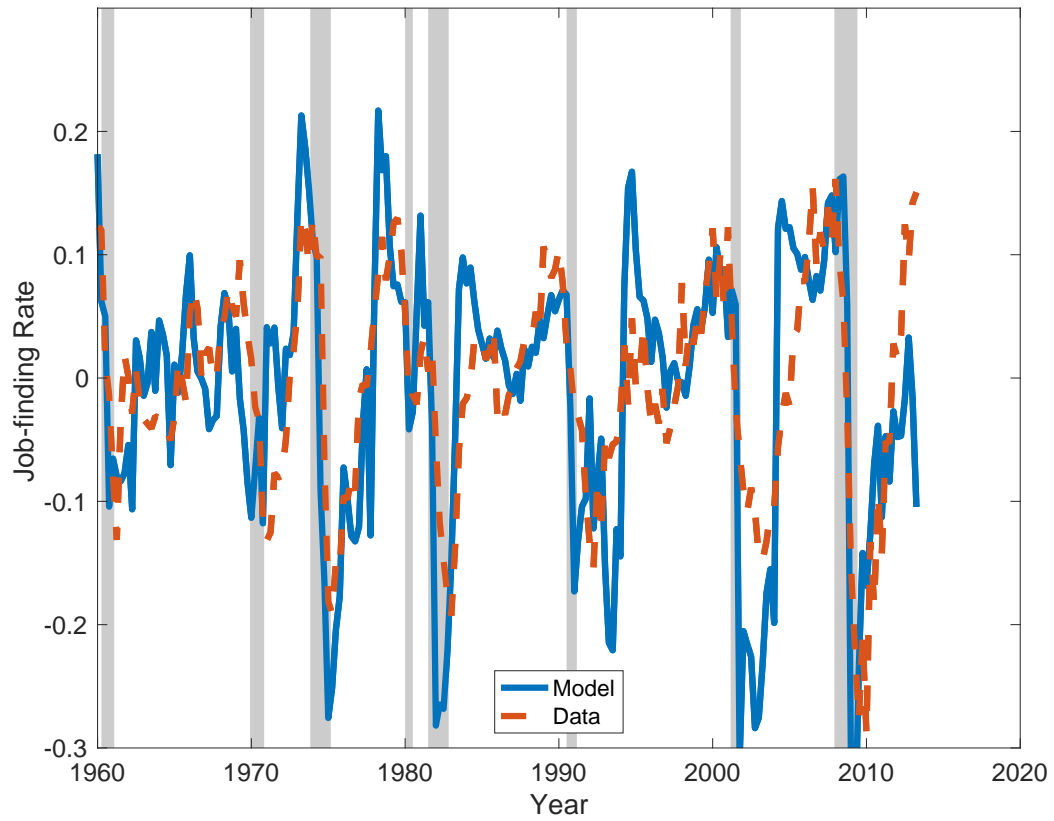


Figure 11: Log deviations from HP filtered trend for simulated and actual job-finding rate from January 1960 through September 2014. NBER dated recessions are shaded.

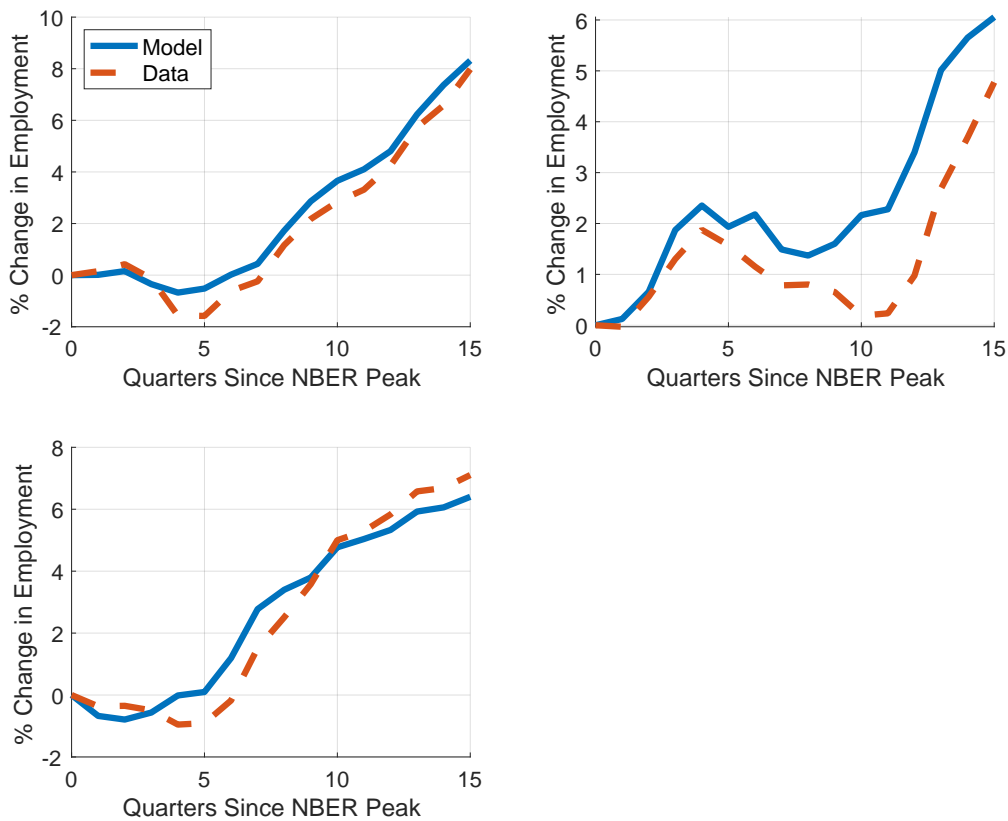


Figure 12: Simulated and actual percentage change in employment from NBER peak before the 1973-75, 1980 and 1981-82 recessions. The blue line is the model and dashed red line is the data. Data and model are not filtered. Data is from CPS, total non-farm employment.



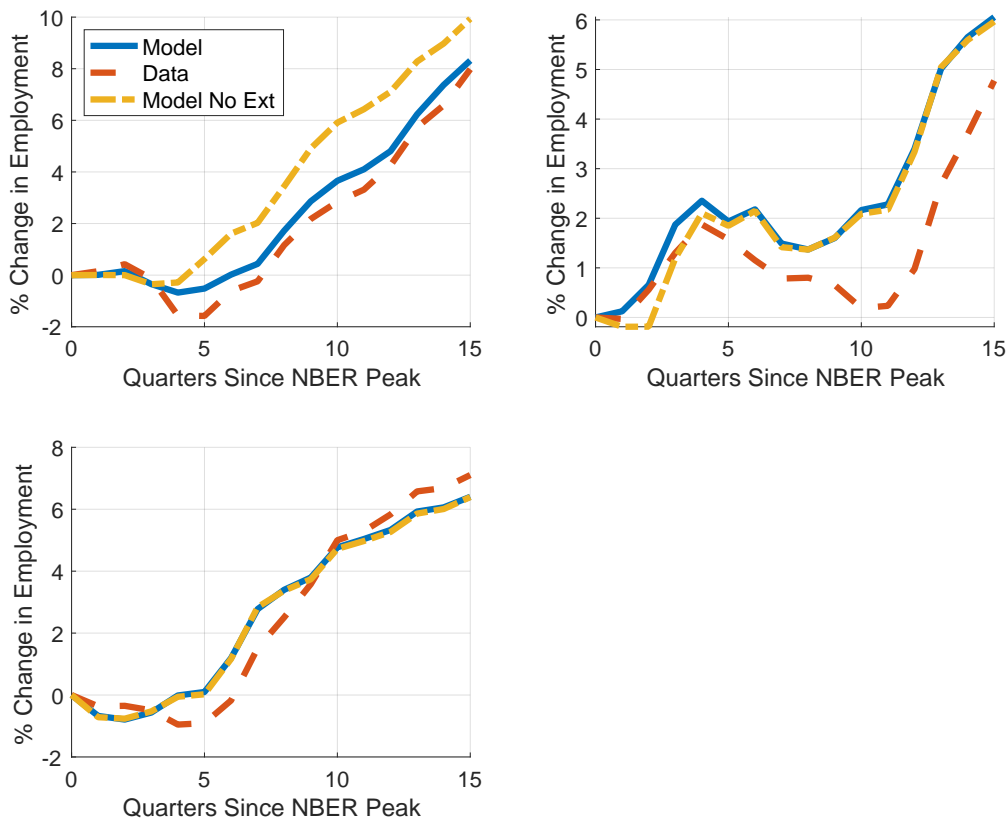


Figure 13: Simulated and actual percentage change in employment from NBER peak before the 1973-75, 1980 and 1981-82 recessions. The blue line is the model, dashed red line is the data, and the yellow dot-dashed line is the model without extensions. Data and model are not filtered. Data is from CPS, total non-farm employment.

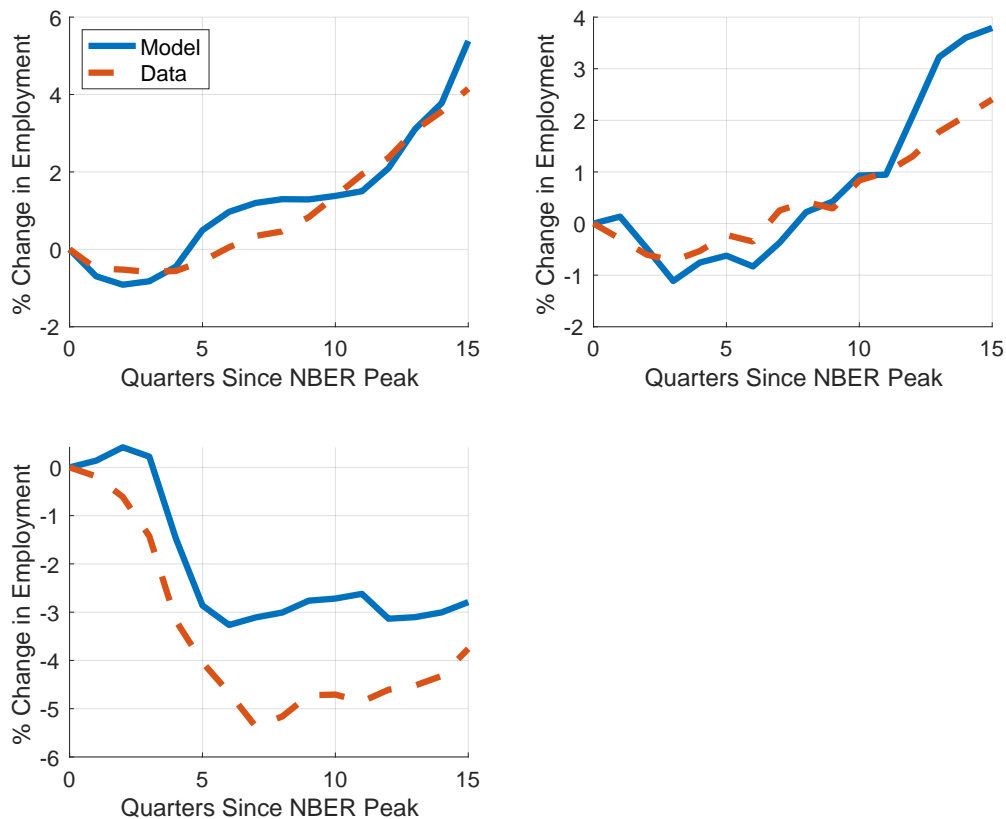


Figure 14: Simulated and actual percentage change in employment from NBER peak before the 1990-91, 2001 and 2007-09 recessions. The blue line is the model and dashed red line is the data. Data and model are not filtered. Data is from CPS, total non-farm employment.

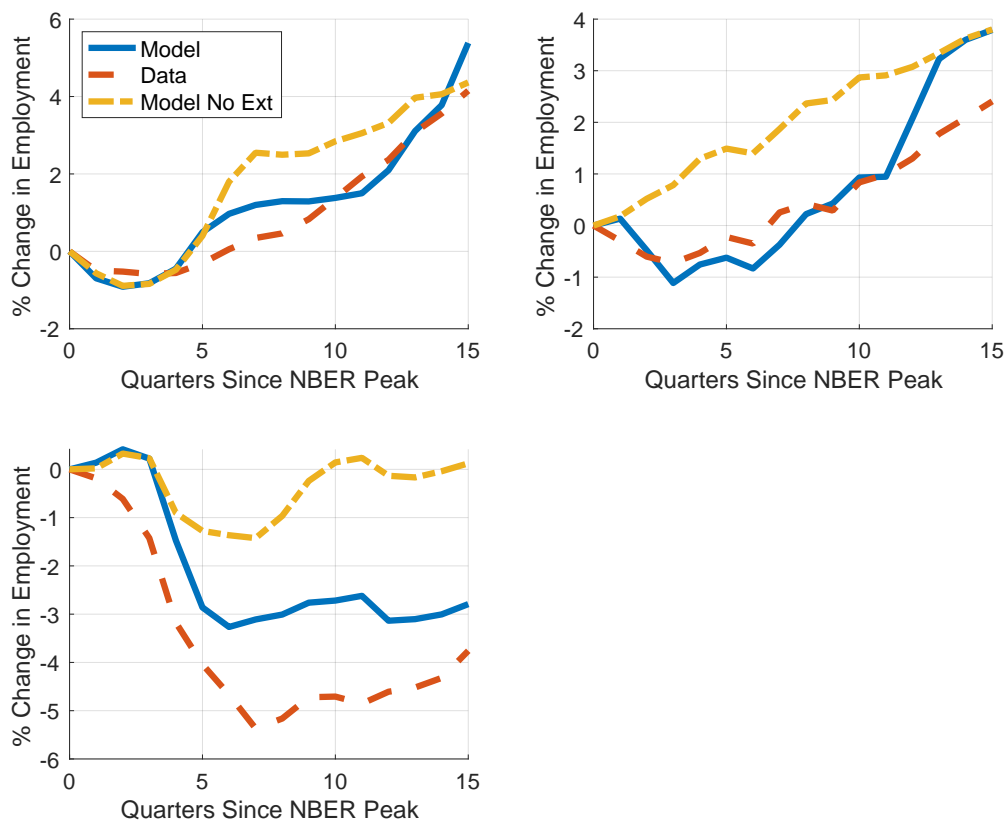


Figure 15: Simulated and actual percentage change in employment from NBER peak before the 1990-91, 2001 and 2007-09 recessions. The blue line is the model, dashed red line is the data, and the yellow dot-dashed line is the model without extensions. Data and model are not filtered.

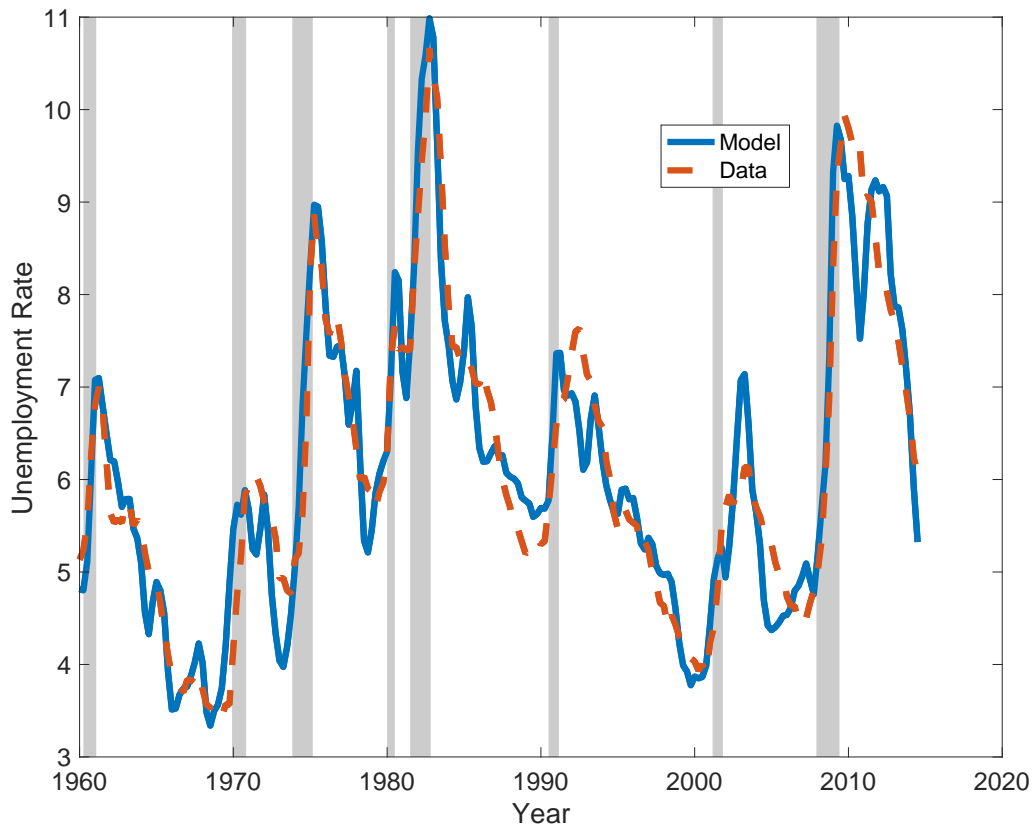


Figure 16: Simulated unemployment under rigid wages and actual unemployment from January 1960 through September 2014. NBER dated recessions are shaded.

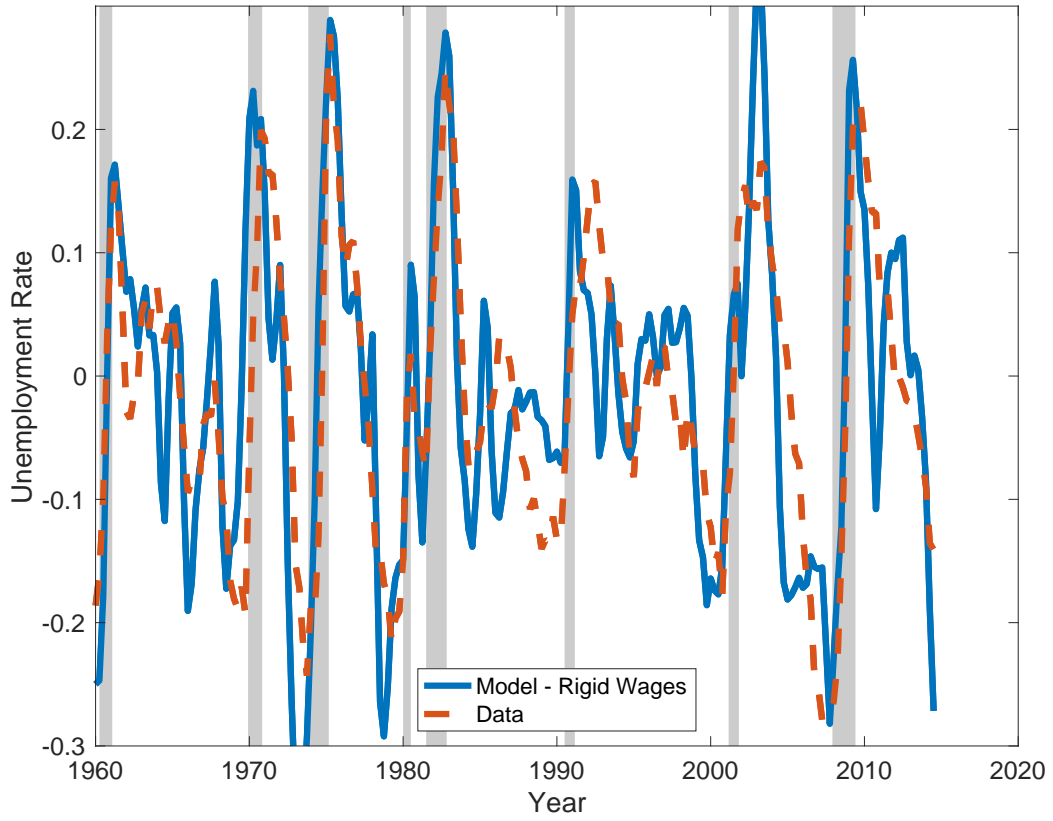


Figure 17: Log deviations from HP filtered trend for simulated unemployment under rigid wages and actual unemployment from January 1960 through September 2014. NBER dated recessions are shaded.

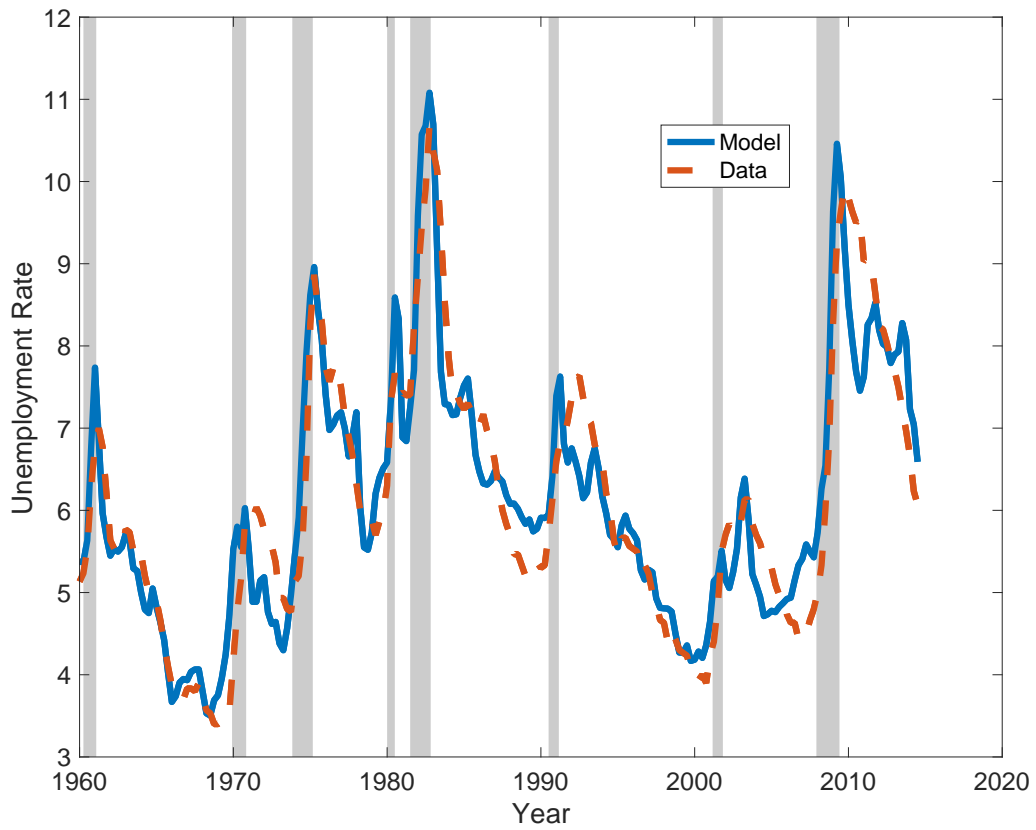


Figure 18: Simulated unemployment under endogenous separations and actual unemployment from January 1960 through September 2014. NBER dated recessions are shaded.

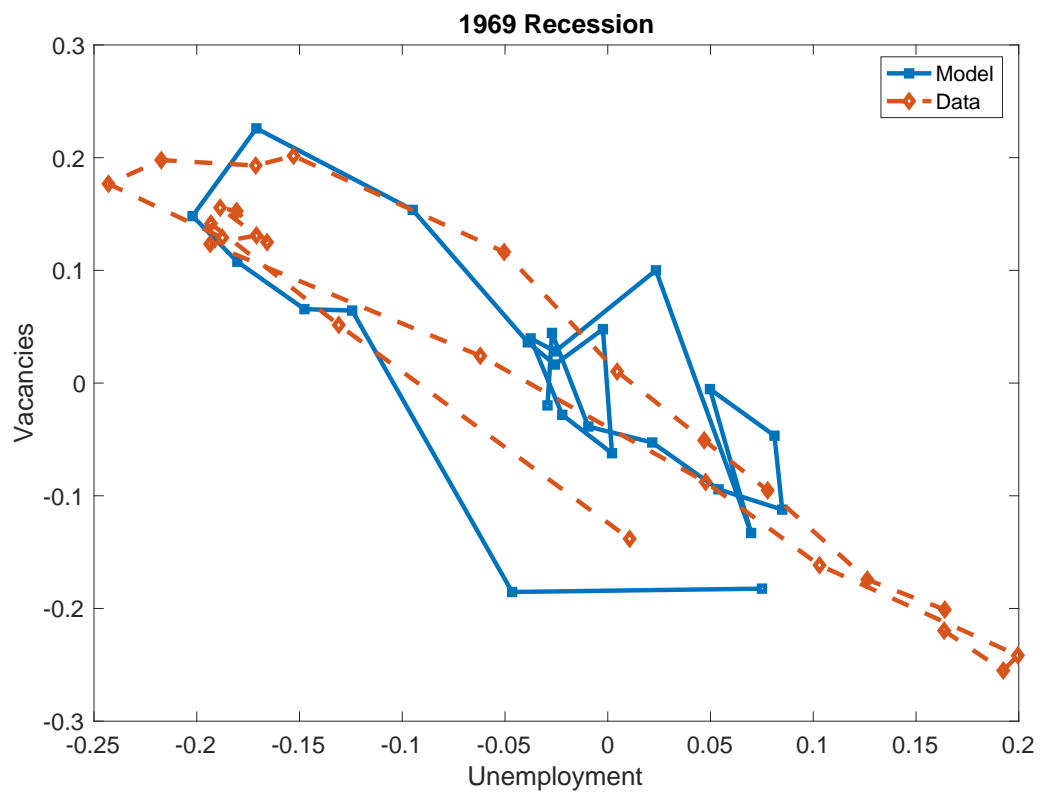


Figure 19: Beveridge curve (deviations from trend).

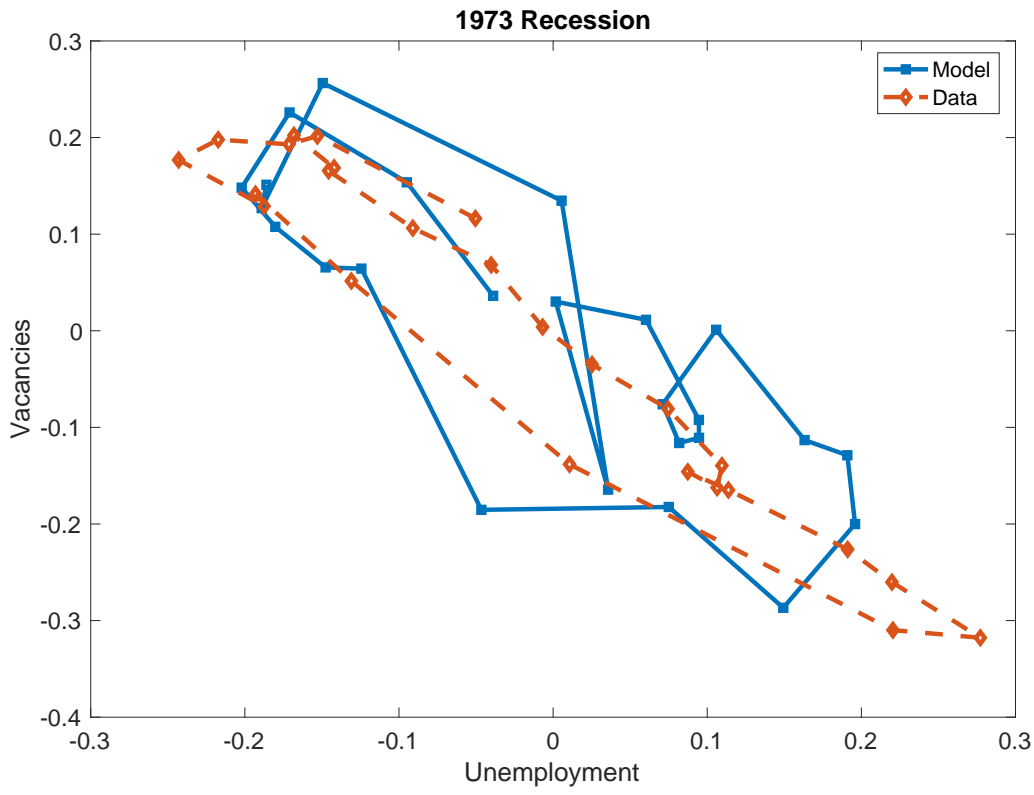


Figure 20: Beveridge curve (deviations from trend).



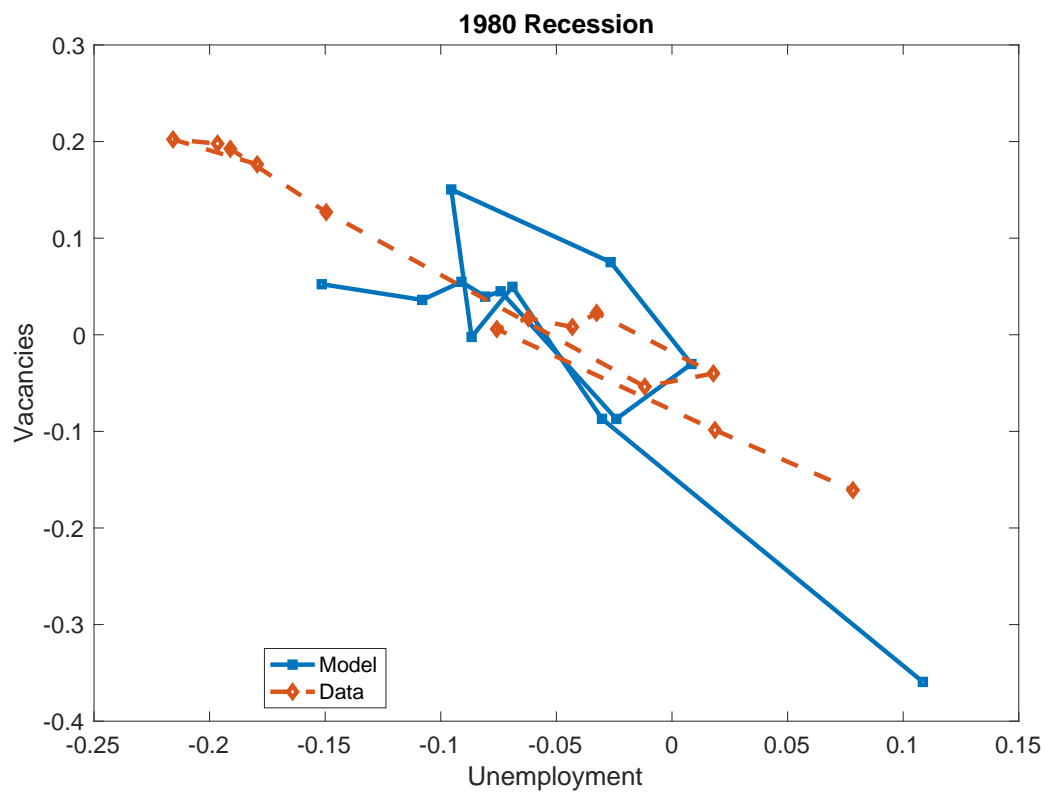


Figure 21: Beveridge curve (deviations from trend).

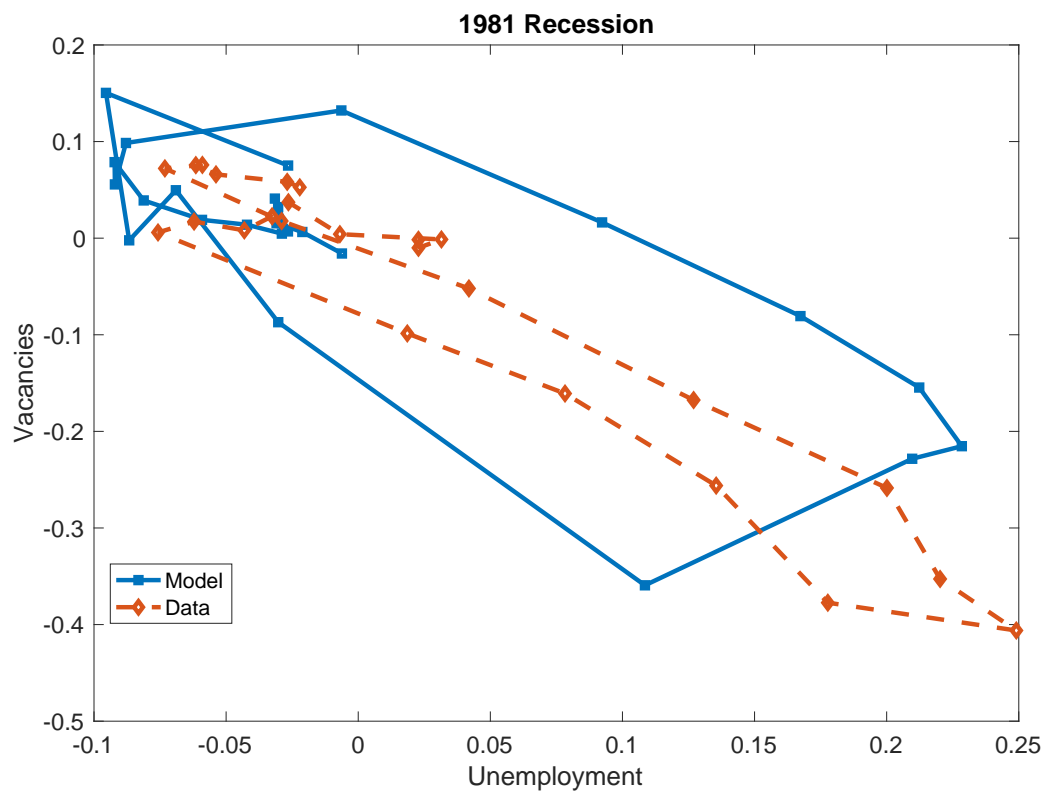


Figure 22: Beveridge curve (deviations from trend).

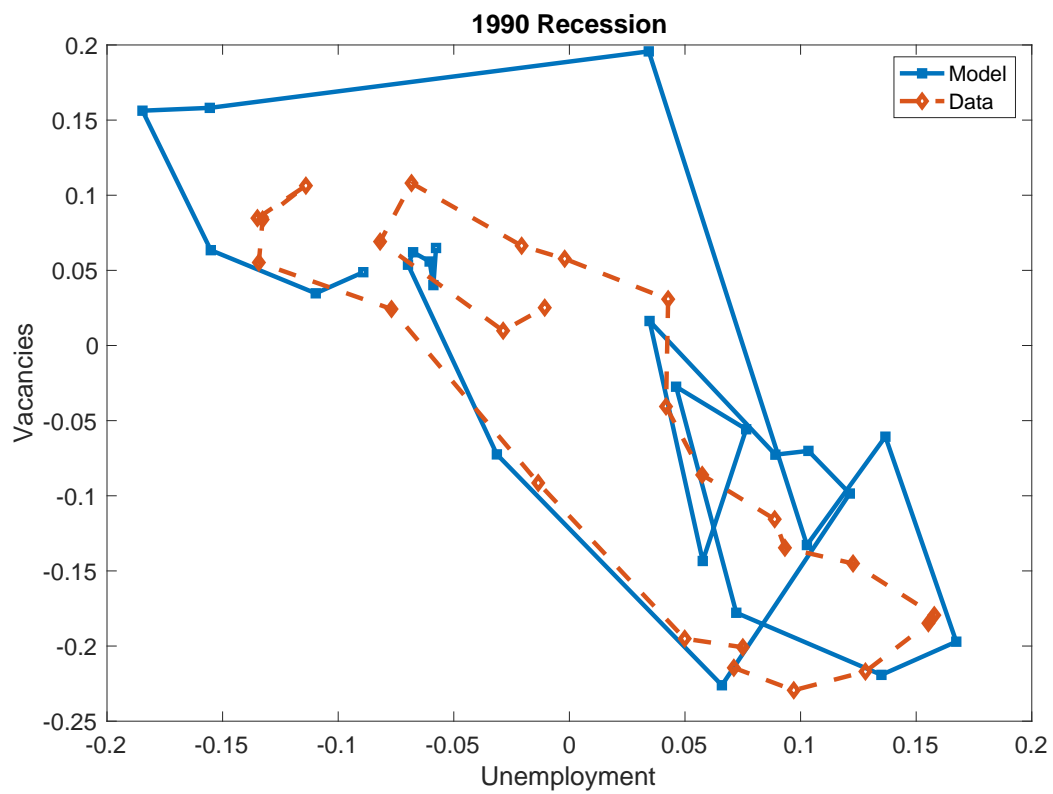


Figure 23: Beveridge curve (deviations from trend).

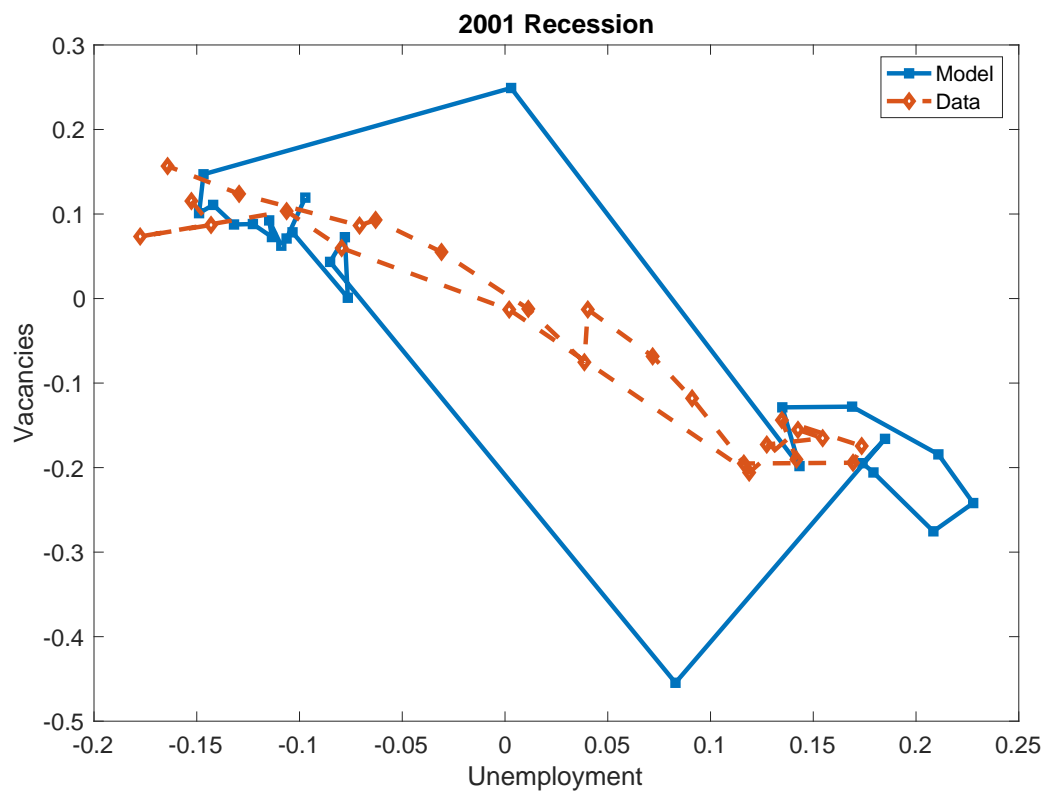


Figure 24: Beveridge curve (deviations from trend).

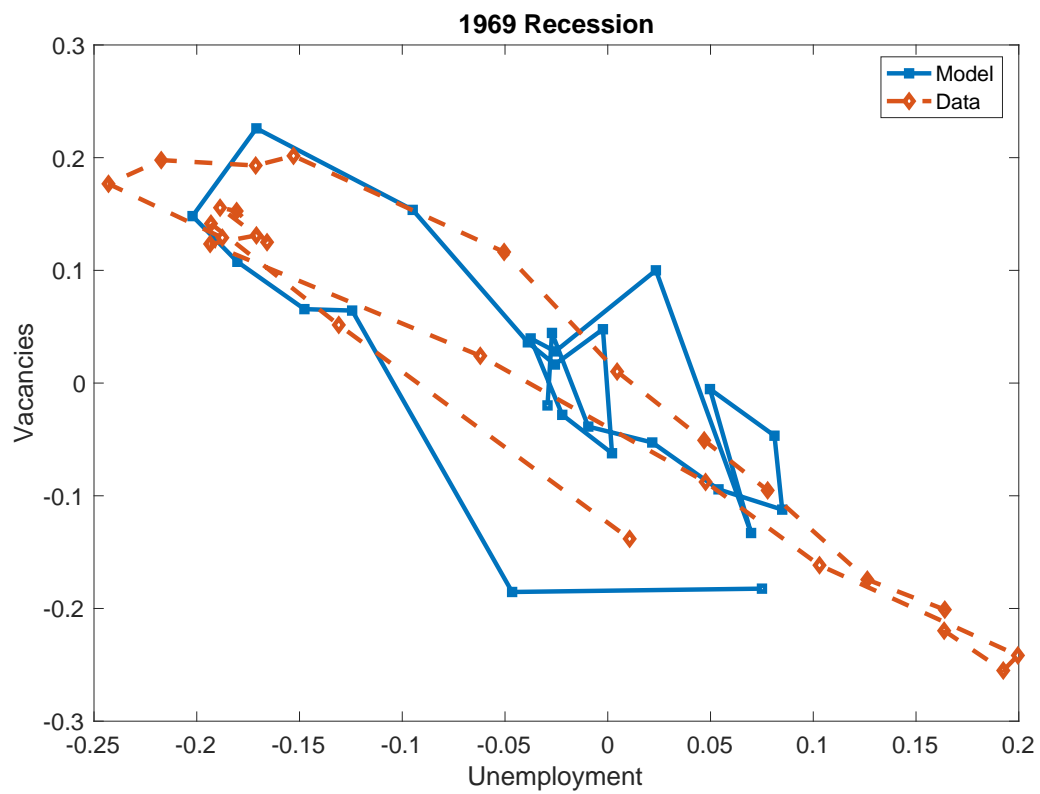


Figure 25: Beveridge curve (deviations from trend).

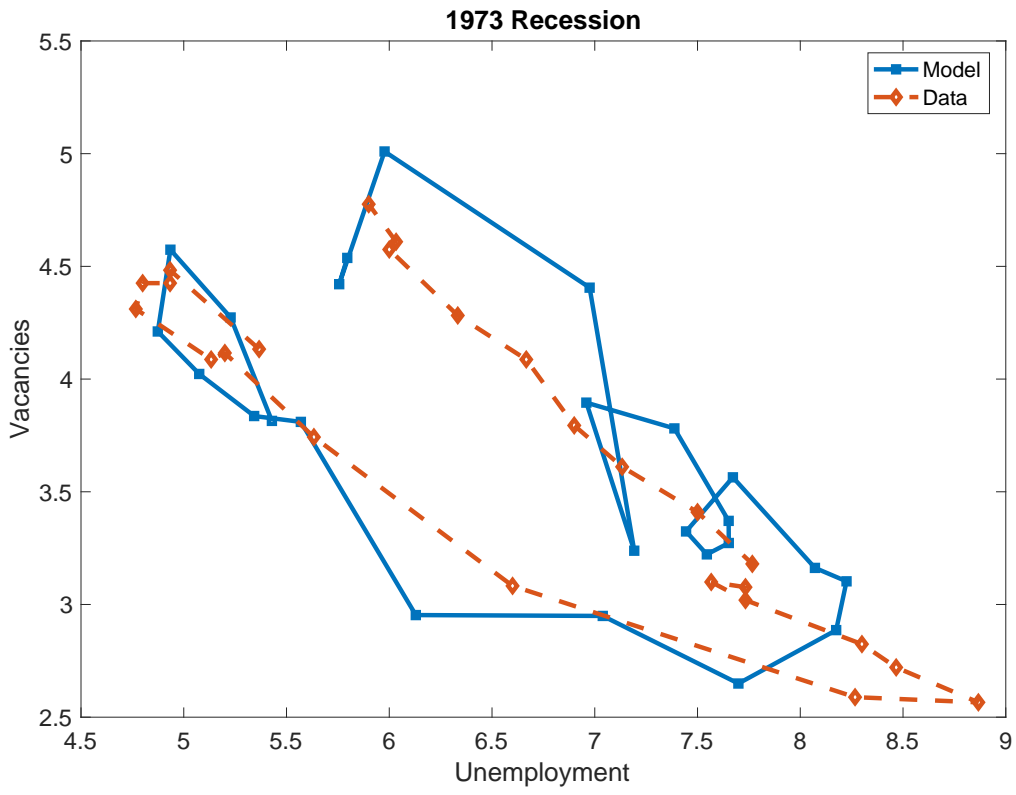


Figure 26: Beveridge curve (levels).

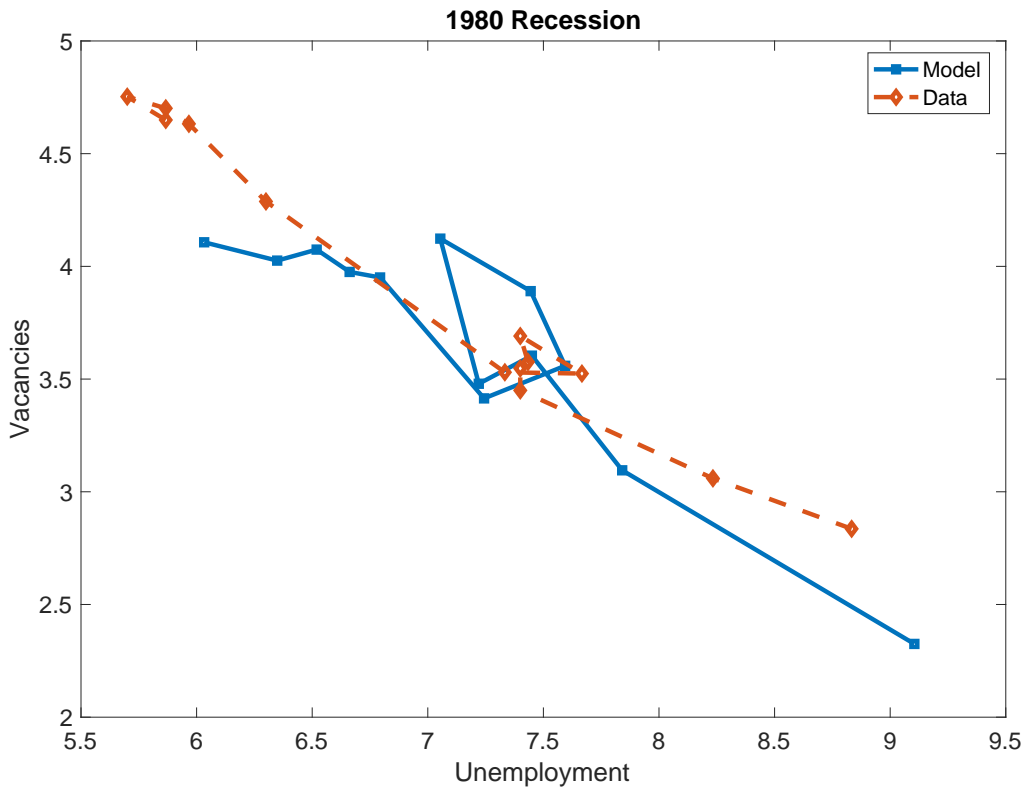


Figure 27: Beveridge curve (levels).

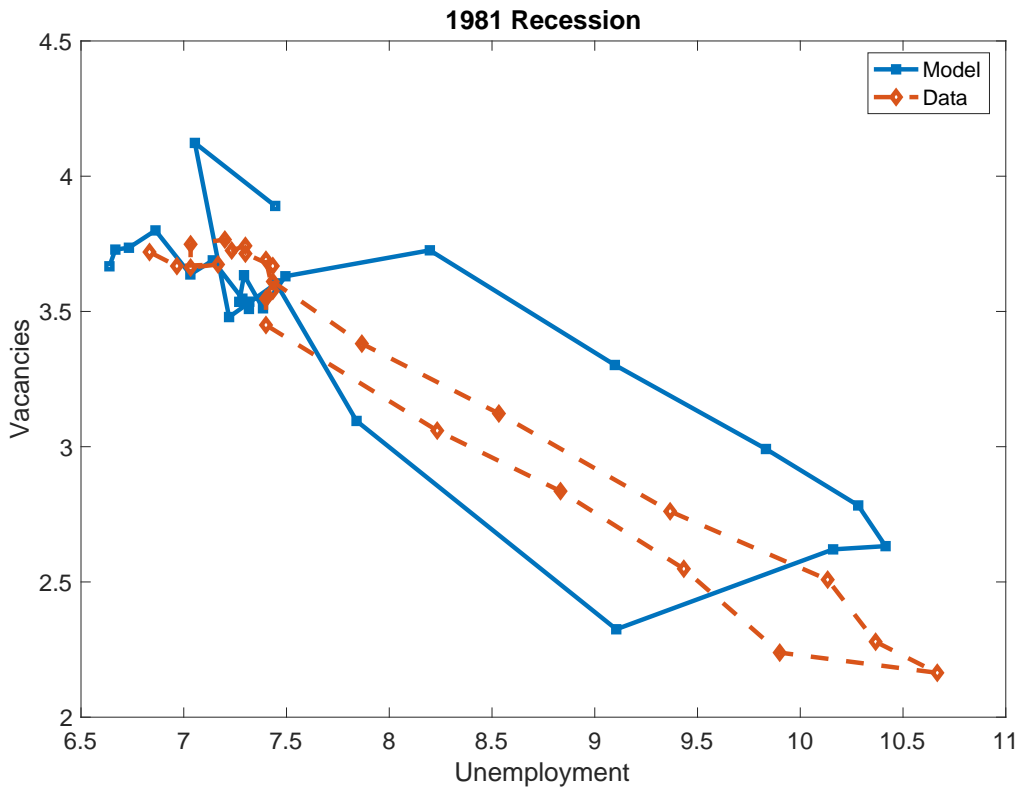


Figure 28: Beveridge curve (levels).



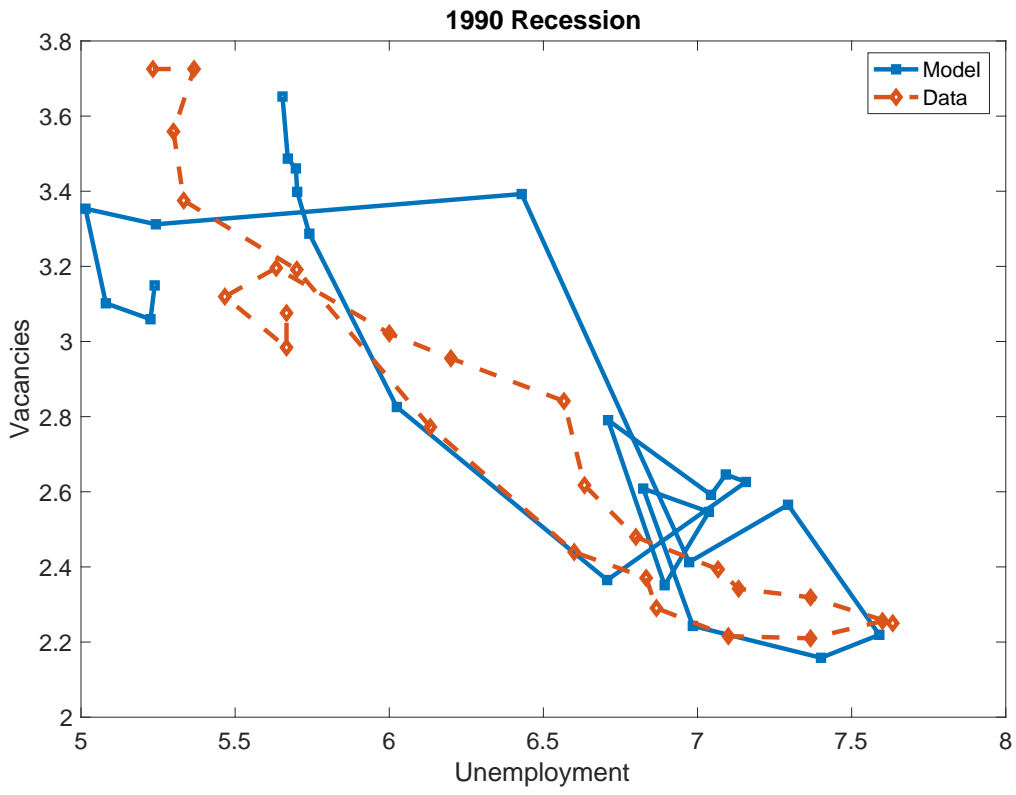


Figure 29: Beveridge curve (levels).

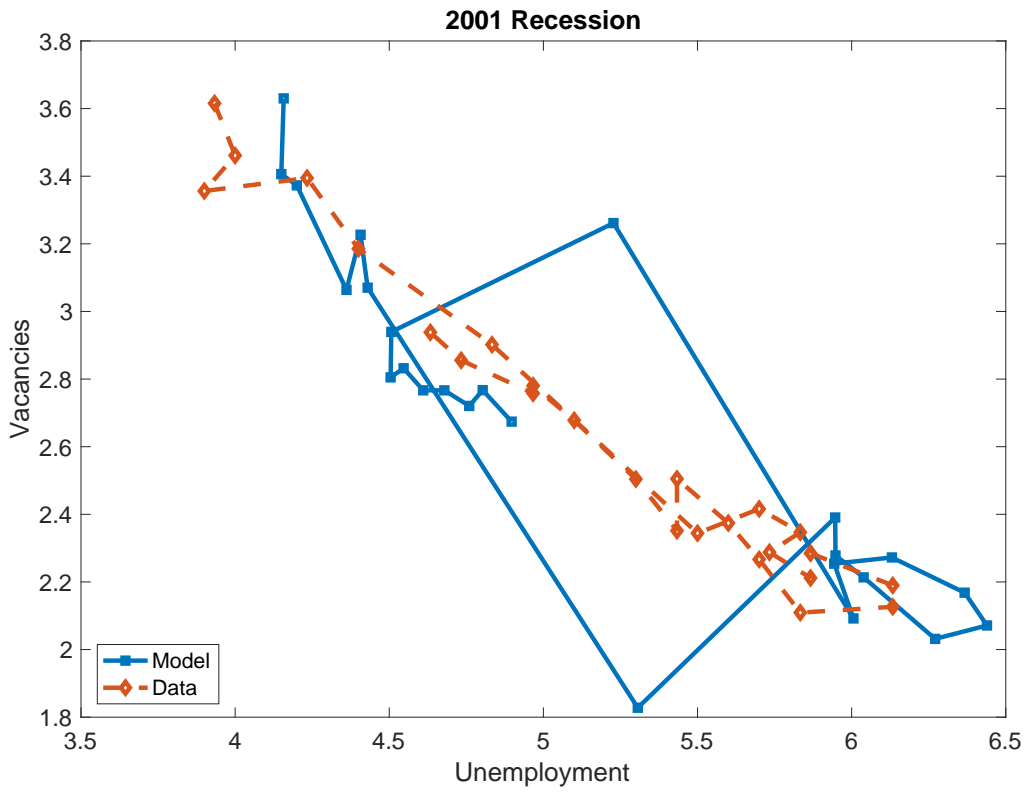


Figure 30: Beveridge curve (levels).

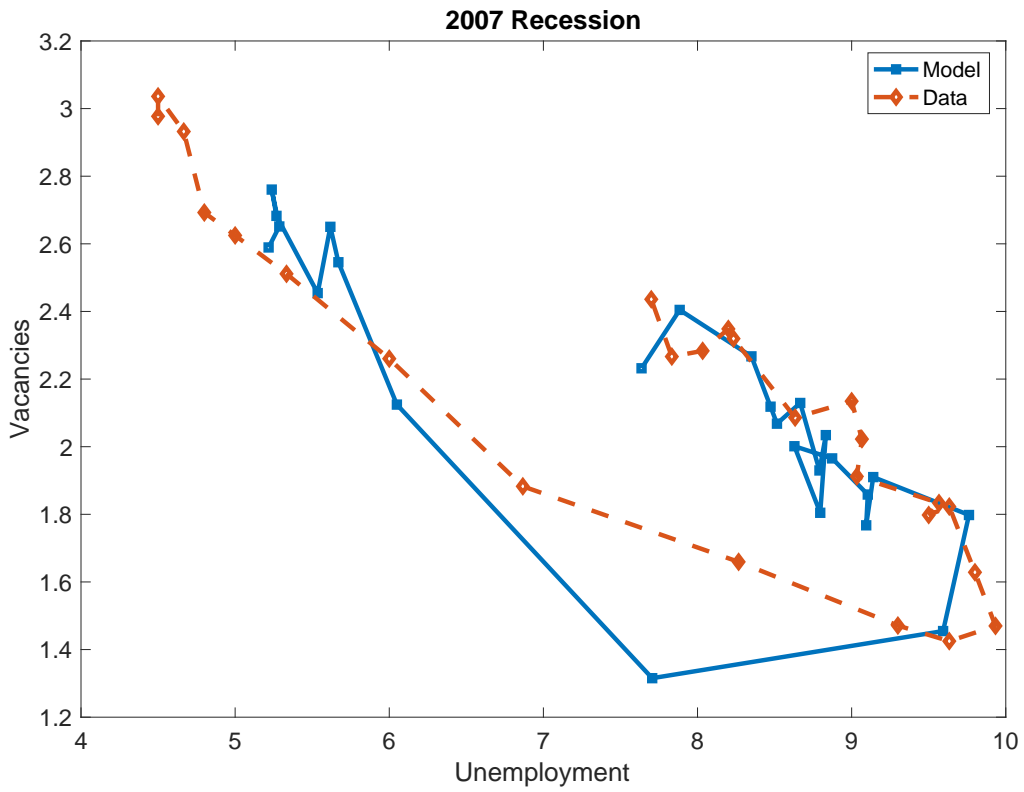


Figure 31: Beveridge curve (levels).

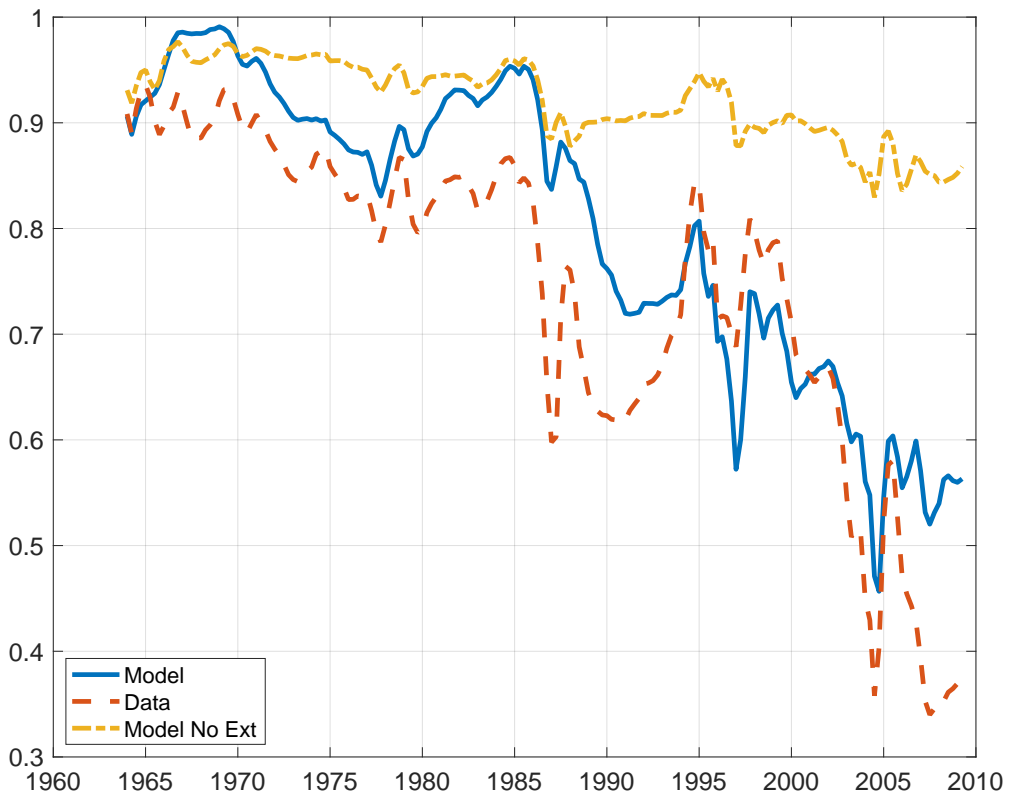


Figure 32: Rolling autocorrelation between employment and labor productivity.

## D Tables and figures for section 3

Parameter	Description	Value
$\delta_K$	Physical capital depreciation	0.025
$\delta_L$	Job destruction	0.1
$\beta$	Discount factor	0.9968
$400 \ln(\gamma_Y)$	Steady-state output growth rate (annual)	1.7
$400 \ln(\gamma_I)$	Steady-state investment growth rate (annual)	2.9
$u$	Steady-state unemployment rate	0.055
$G/Y$	Steady-state government spending/output	0.2
$400(\pi - 1)$	Steady-state inflation (annual)	2.5
$q$	Steady-state vacancy-filling rate	0.7

Table 7: Calibrated parameters and steady-state values

Parameter	Description	Prior			Posterior	
		Distribution	Mean	St.dev.	Mode	St. dev.
$\vartheta_p$	Price stickiness parameter	beta	0.600	0.0500	0.5852	0.0293
$\bar{\tau}$	Price markup parameter	gamma	1.300	0.0500	1.5437	0.0495
$\rho_R$	Taylor rule smoothing parameter	beta	0.700	0.1500	0.7846	0.0172
$r_\pi$	Taylor rule inflation coefficient	gamma	1.700	0.1500	1.8832	0.1152
$r_y$	Taylor rule output coefficient	beta	0.030	0.0100	0.0349	0.0097
$h$	Consumption habit parameter	beta	0.500	0.1500	0.4218	0.0467
$\omega_0$	Capacity utilization adjustment cost	gamma	0.500	0.3000	1.1635	0.3134
$S''$	Investment adjustment cost	gamma	8.000	2.0000	4.5238	1.0499
$\alpha$	Capital share of income	beta	0.250	0.0500	0.1528	0.0125
$\overline{D}/\overline{w}$	Steady-state replacement rate	beta	0.200	0.1000	0.1482	0.0176
$\sigma_m$	Matching function elasticity	beta	0.500	0.1000	0.5047	0.0978
$\kappa_e$	Hiring fixed cost/output (%)	gamma	1.000	0.3000	0.3584	0.1108
$\kappa_v$	Vacancy cost/output (%)	beta	0.080	0.0500	0.0320	0.0192
$\sigma_g$	Variance of gov-t spending shock	gamma	0.100	1.0000	3.2143	0.1724
$\sigma_R$	Variance of monetary policy shock	gamma	0.350	5.0000	0.2452	0.0142
$\sigma_z$	Variance of TFP shock	gamma	0.100	2.0000	0.6165	0.0408
$\sigma_\Psi$	Inv. specific shock variance	gamma	0.100	1.0000	3.5377	0.1885
$\sigma_\zeta$	Variance of risk premium	gamma	0.100	5.0000	1.6037	0.1058
$\sigma_\tau$	Variance of price markup shock	gamma	0.100	5.0000	1.0458	0.0948
$\sigma_D$	Variance of UI shock	gamma	0.100	5.0000	6.2421	0.3278
$\sigma_{barg}$	Variance of bargaining shock	gamma	0.100	5.0000	0.0607	0.0185
$\rho_\zeta$	Persistence of risk premium	beta	0.800	0.1000	0.8048	0.0314
$\rho_D$	Persistence of UI shock	beta	0.700	0.1000	0.7617	0.0340
$\rho_{D,U}$	UI feedback on past unemployment	beta	0.200	0.1000	0.2787	0.0443

Table 8: Priors and posteriors of estimated parameters.

	Output	Unemployment	Inflation	Wages
Monetary policy	0.54	3.06	11.09	5.93
Neutral technology	58.35	37.21	8.38	2.78
Investment	31.77	20.11	11.03	2.59
Government spending	1.76	9.52	8.79	9.67
Risk premium	1.54	2.68	27.51	7.62
Price markup	3.95	15.39	4.15	15.26
Unemployment benefits	1.25	6.68	3.11	0.79
Bargaining power	0.83	5.34	25.93	55.36

Table 9: Infinite-horizon variance decomposition (%)

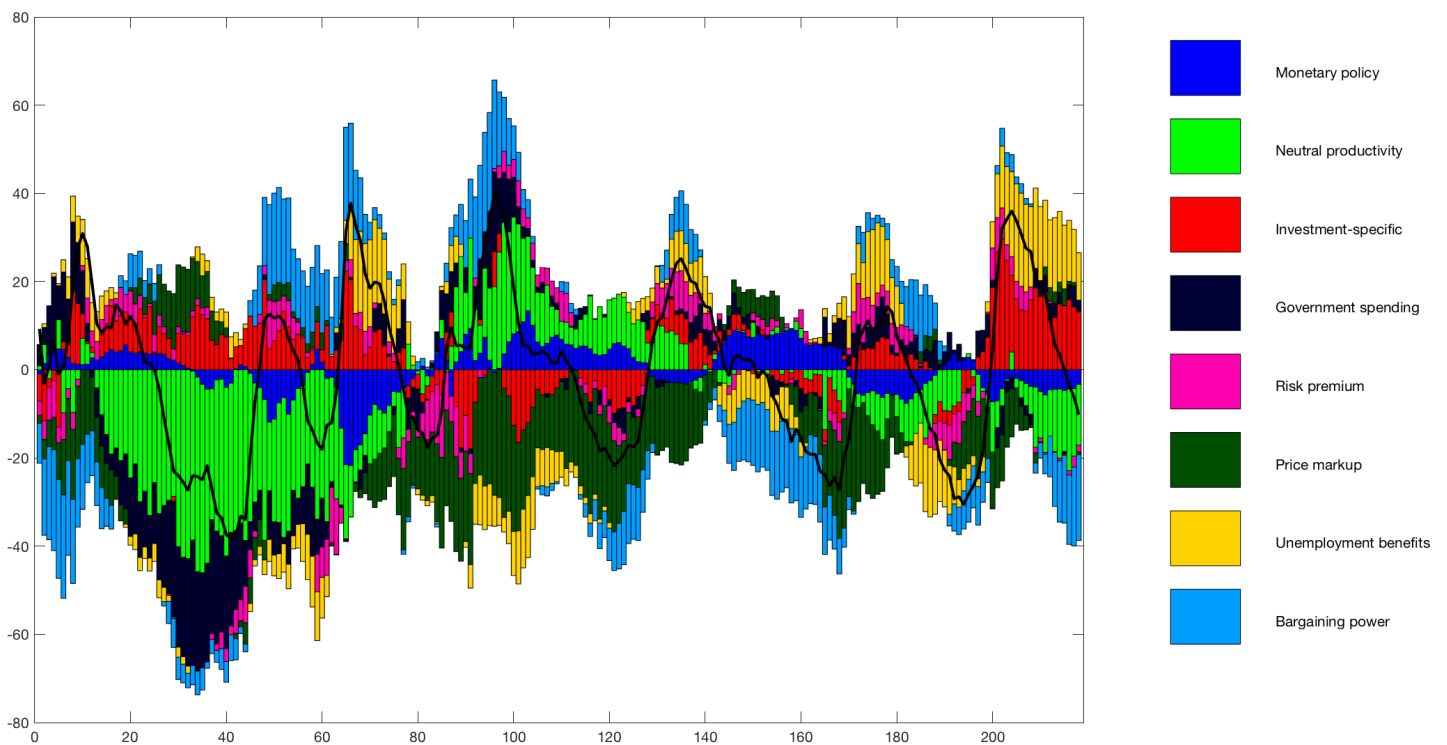


Figure 33: Historical variance decomposition of unemployment.



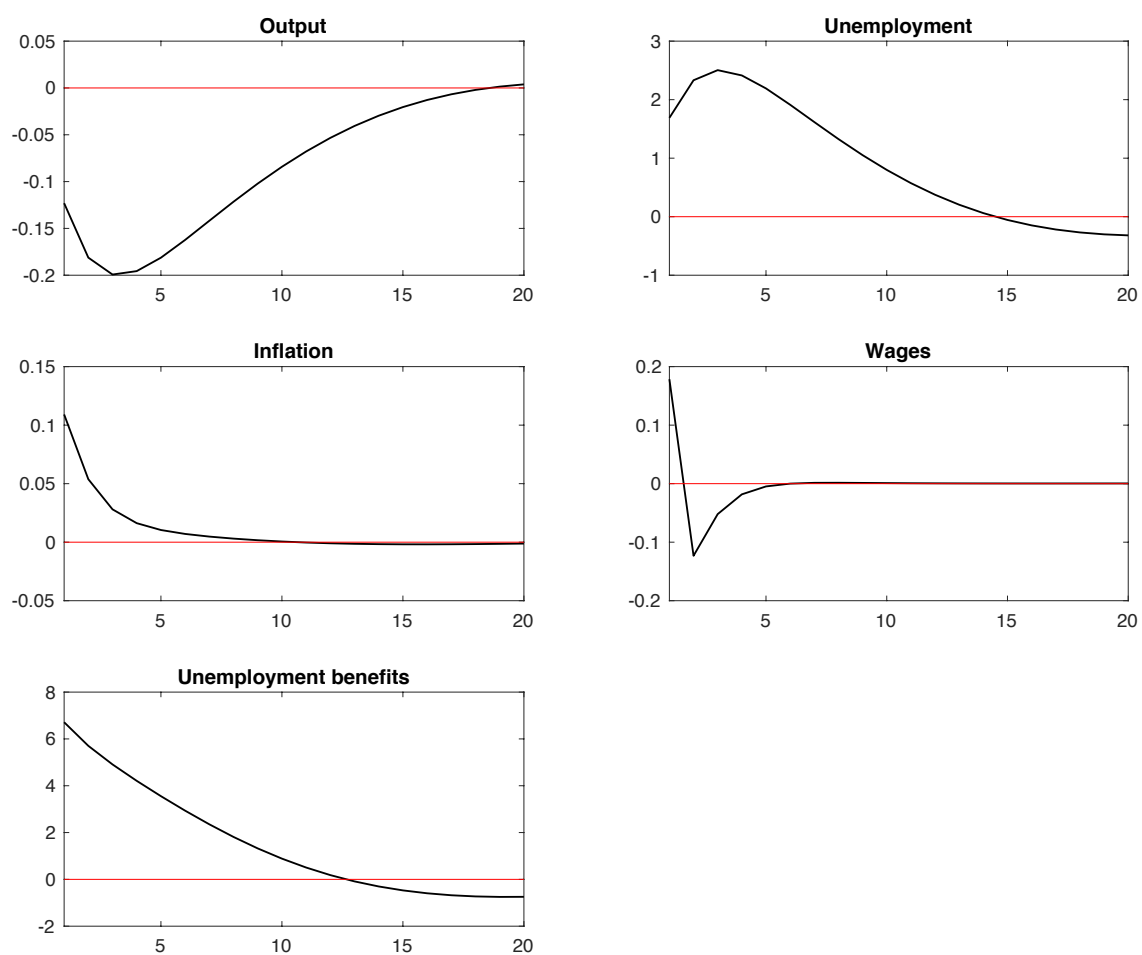


Figure 34: Impulse response to UI shock.

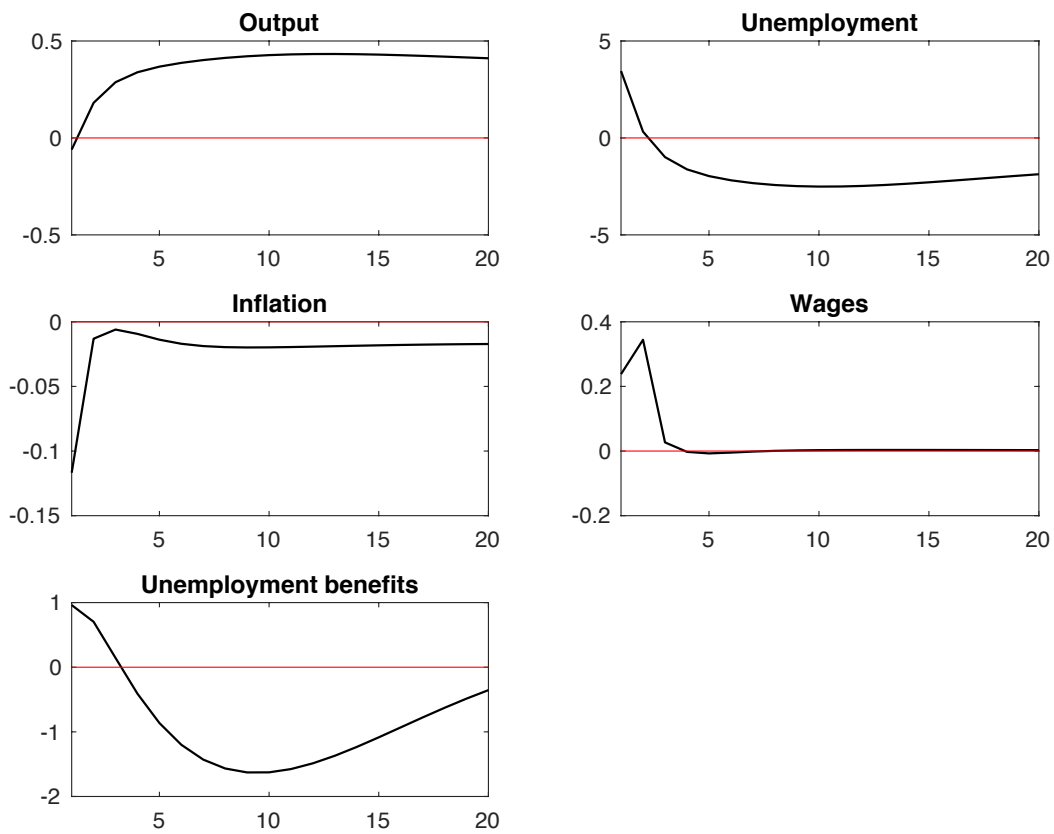


Figure 35: Impulse response to neutral productivity shock.

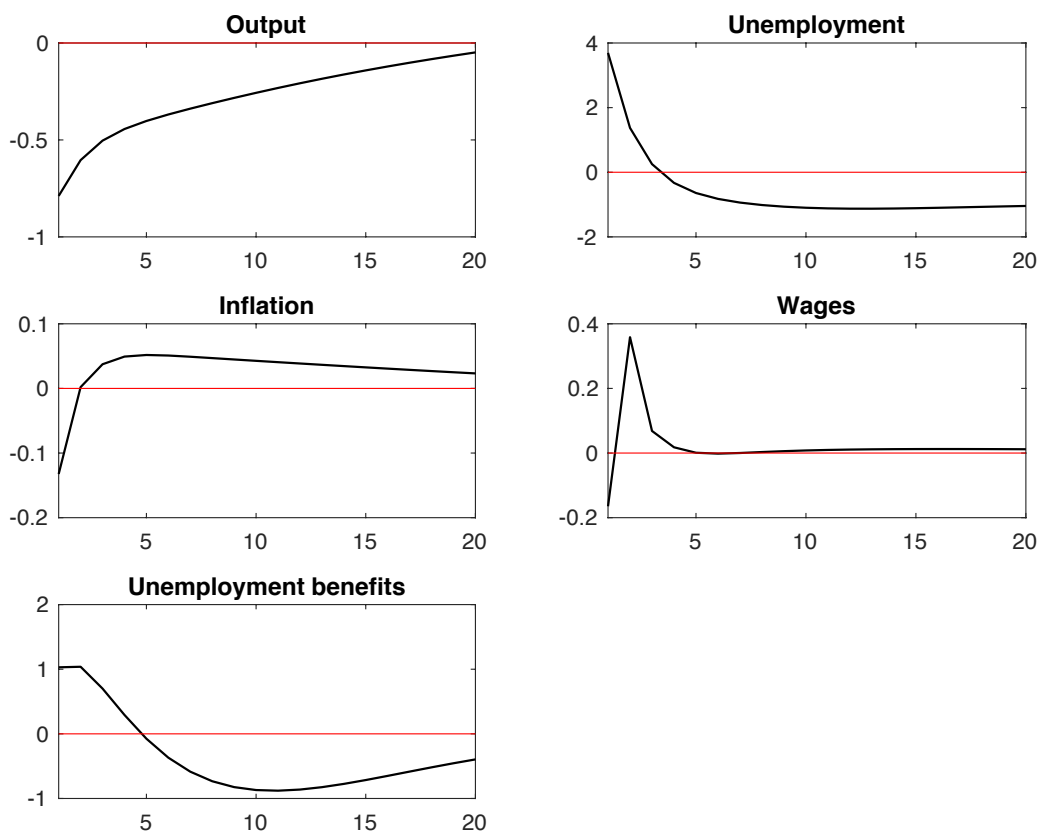


Figure 36: Impulse response to investment-specific productivity shock.

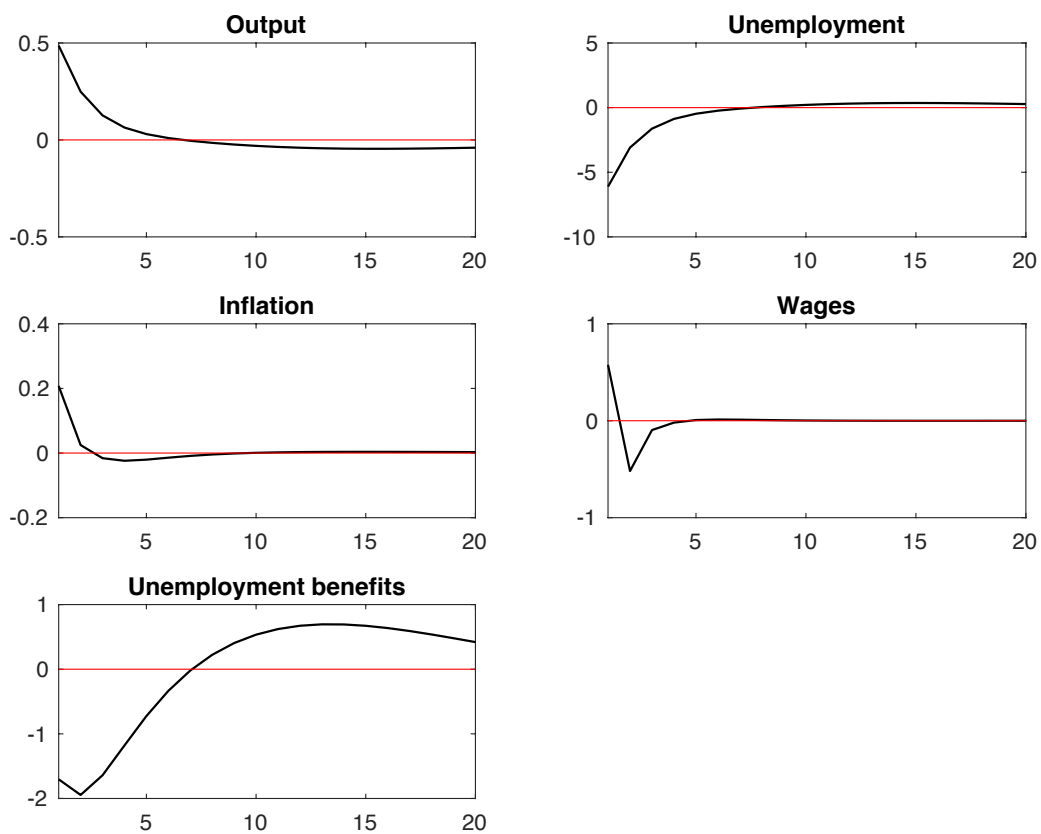


Figure 37: Impulse response to government spending shock.

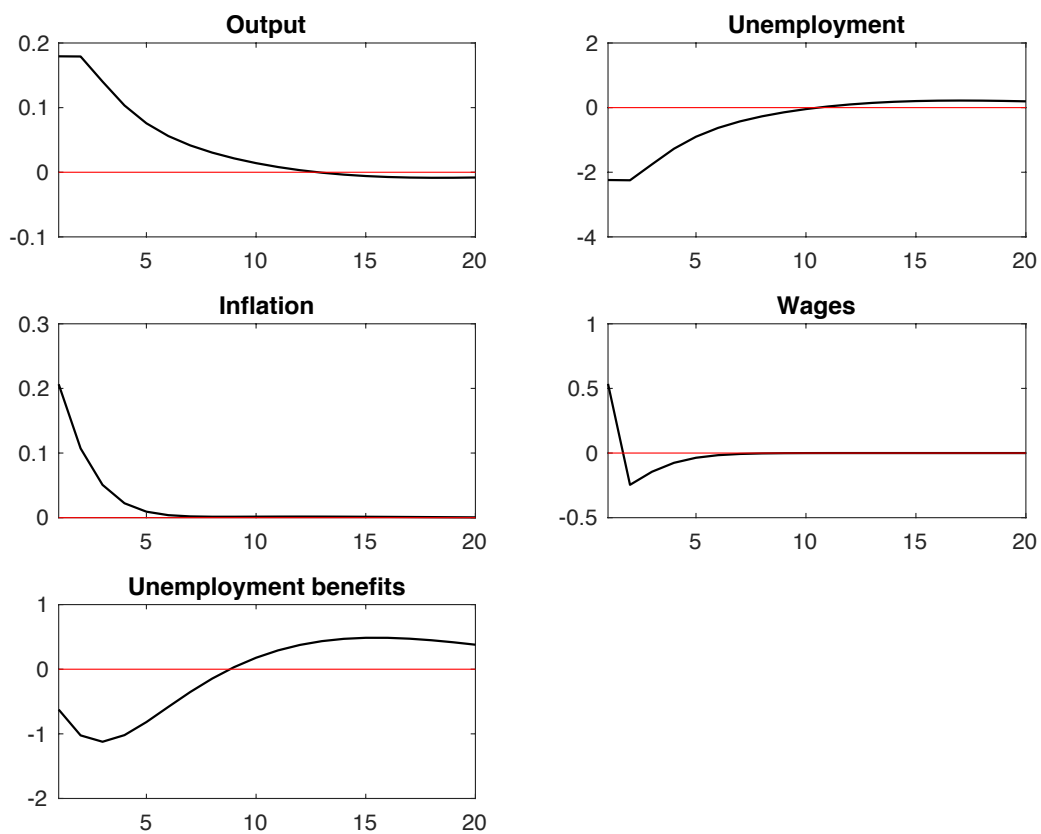


Figure 38: Impulse response to monetary policy shock.

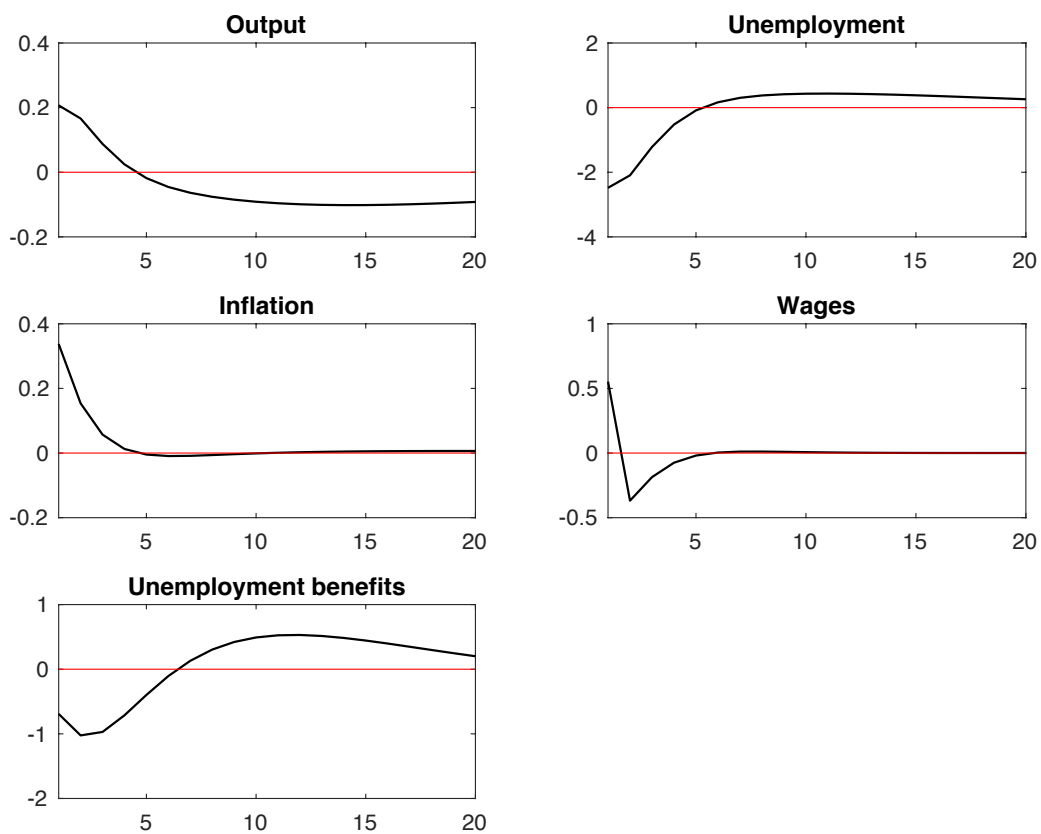


Figure 39: Impulse response to risk premium shock.



Figure 40: Impulse response to price markup shock.

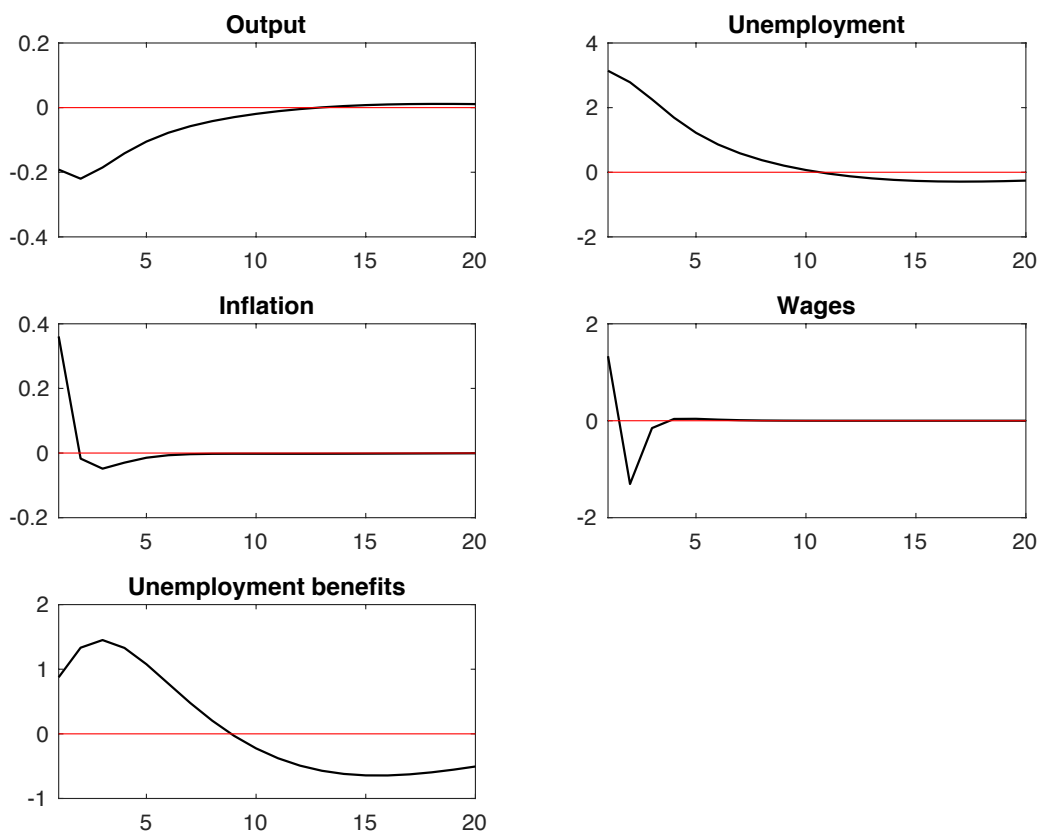


Figure 41: Impulse response to bargaining power shock.



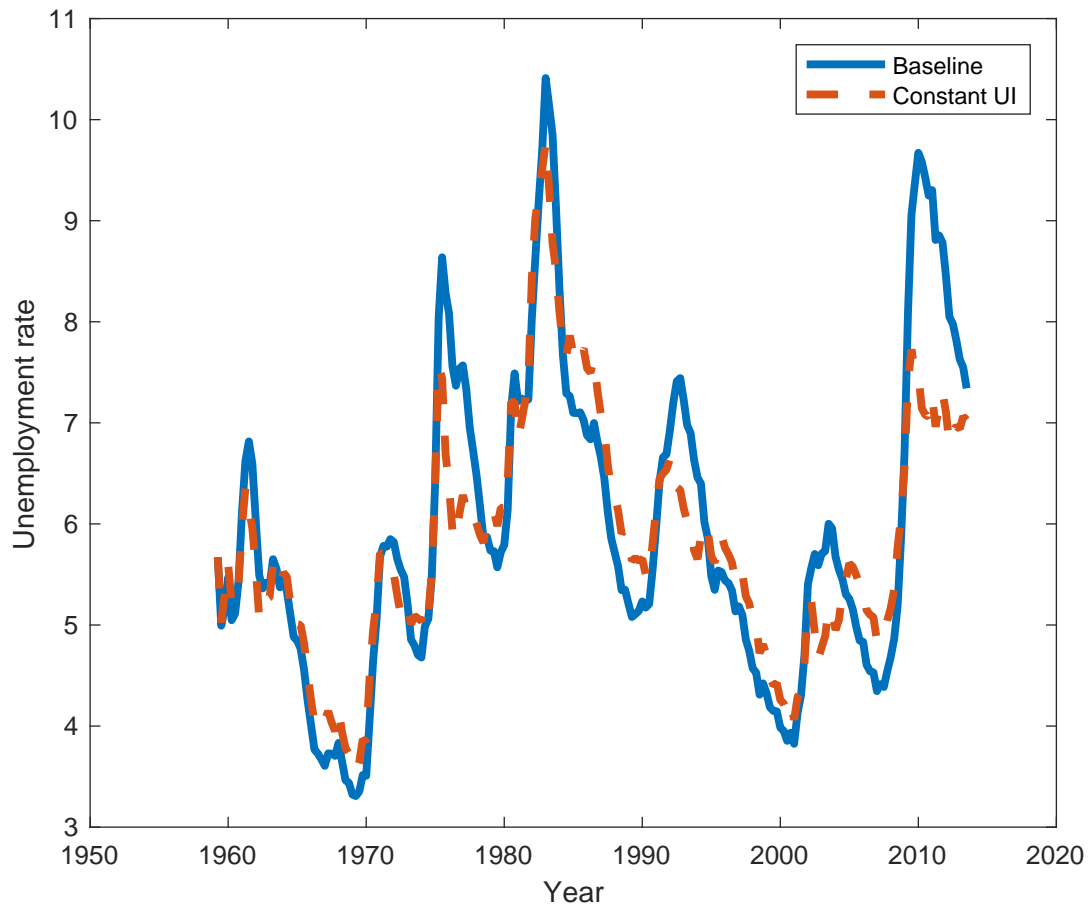


Figure 42: Simulated unemployment: actual economy vs. counterfactual economy with constant UI.

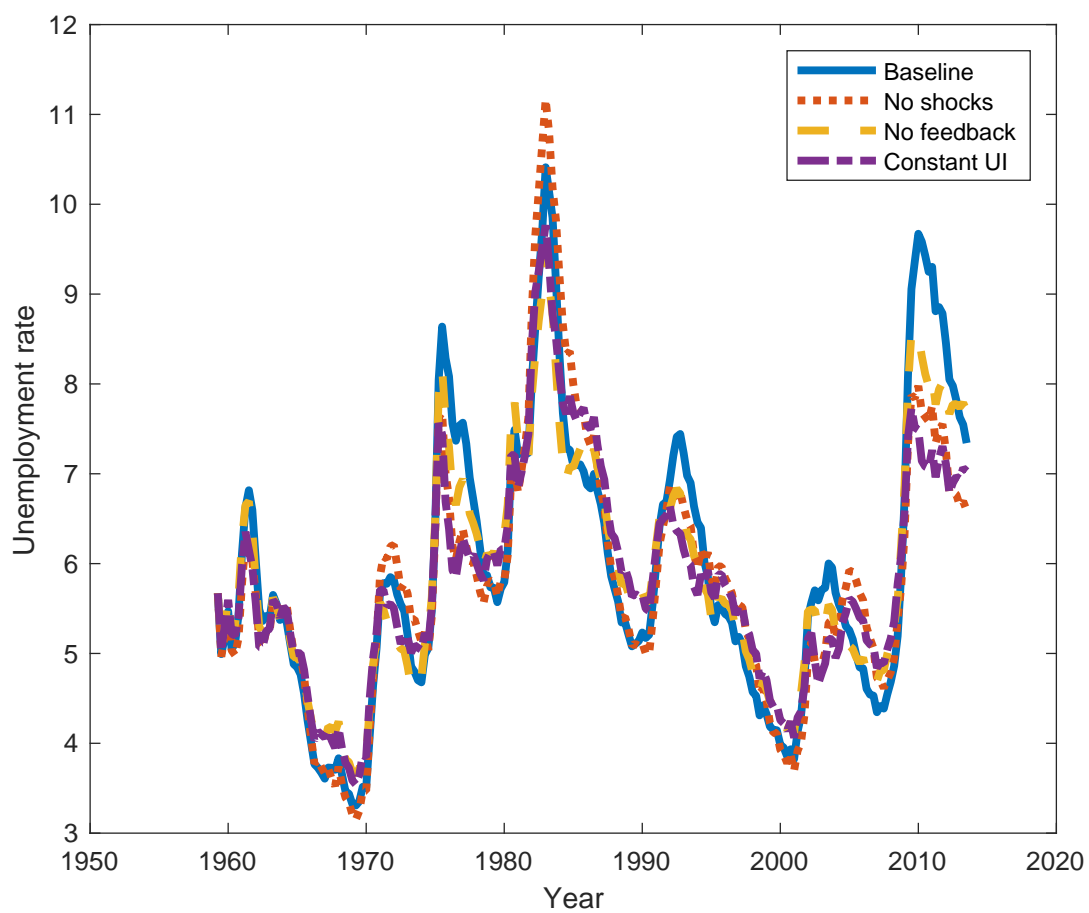


Figure 43: Effects of UI shocks and the systematic component of UI on unemployment fluctuations.

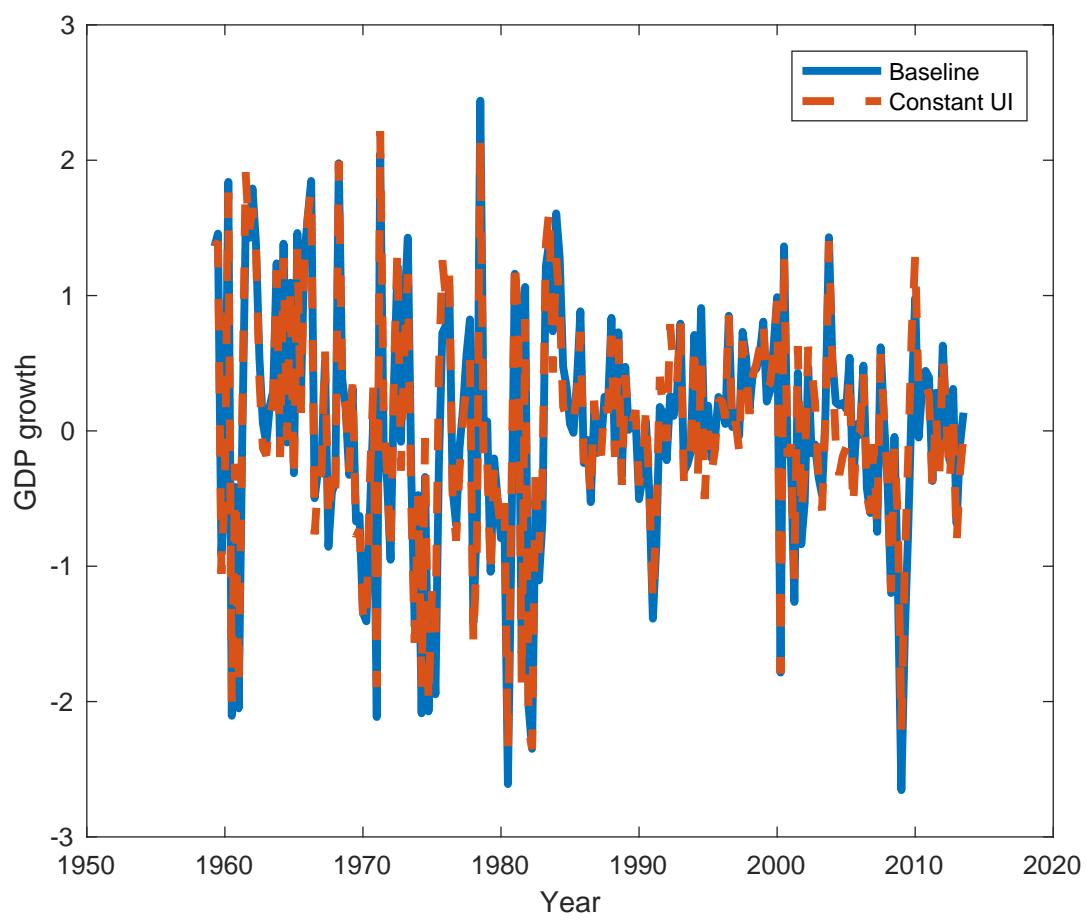


Figure 44: Simulated output: actual economy vs. counterfactual economy with constant UI.

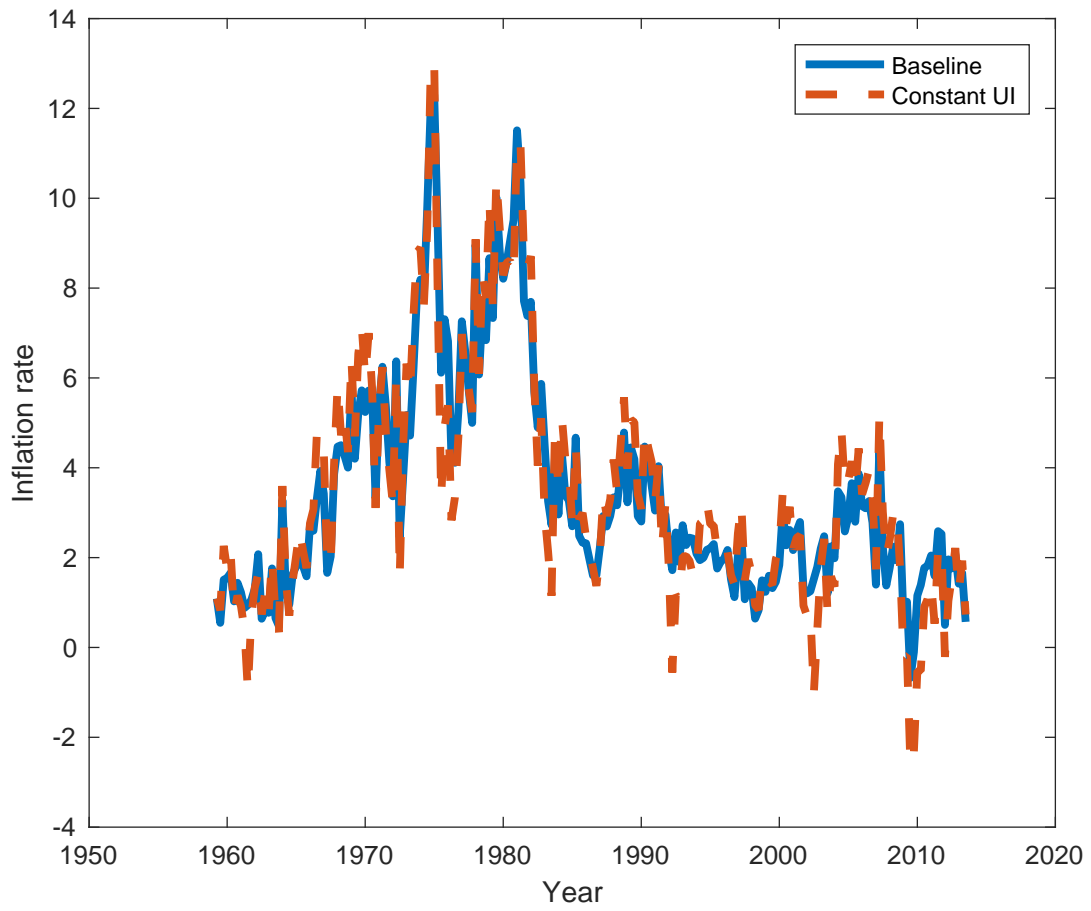


Figure 45: Simulated inflation: actual economy vs. counterfactual economy with constant UI.

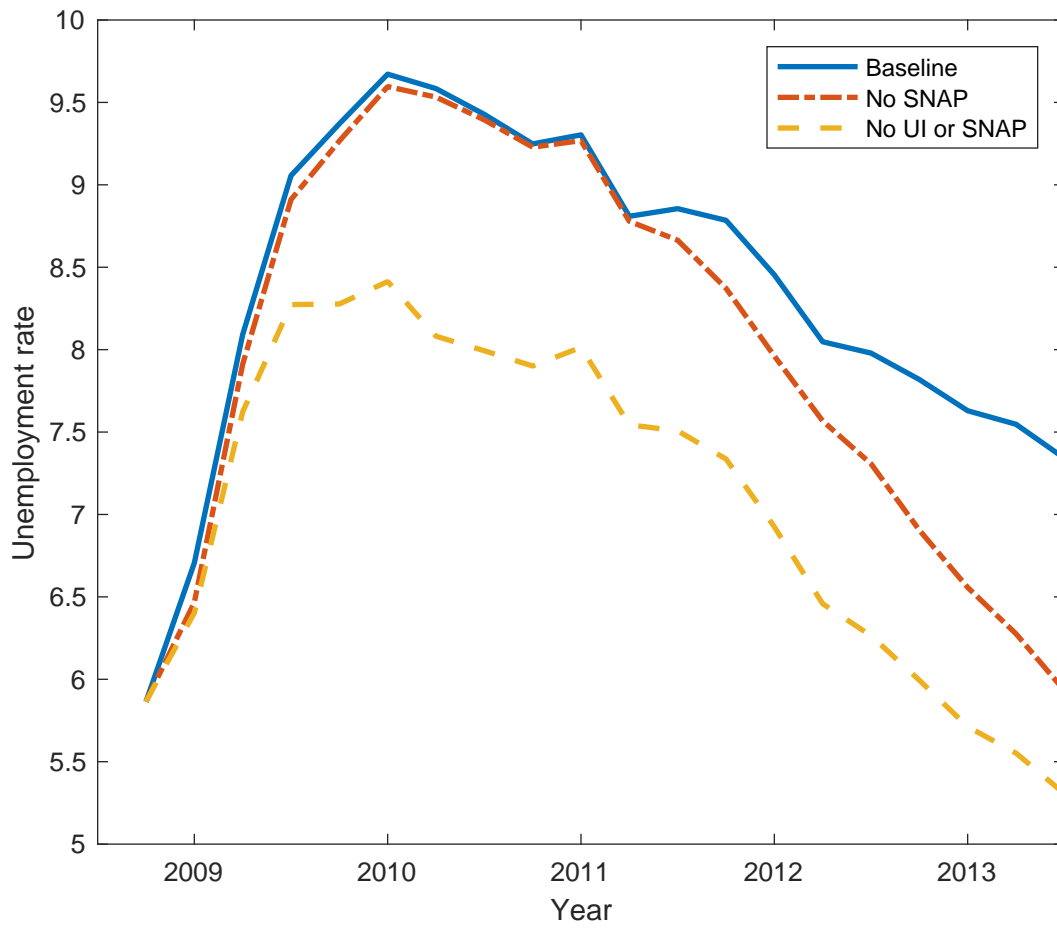


Figure 46: Effects of additional social safety nets.