Uncertainty Shocks are Aggregate Demand Shocks

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We present some empirical evidence and a theoretical argument that uncertainty shocks act like a negative aggregate demand shock, which raises unemployment and lowers inflation. We measure uncertainty using survey data from the United States and the United Kingdom. We estimate the macroeconomic effects of uncertainty shocks in a vector autoregression (VAR) model and document that uncertainty shocks accounted for about one percentage point increase in the unemployment rate in the Great Recession and recovery. We present a DSGE model to show that uncertainty shocks can be contractionary in a flexible-price economy with search frictions, in contrast to the standard Real Business Cycle model. We also show that the interactions between search frictions and nominal rigidities help amplify the macroeconomic effects of uncertainty shocks.

I. Introduction

The Great Recession of 2008-2009 and the slow recovery have renewed interests in studying the macroeconomic effects of uncertainty. Some have argued that elevated uncertainty may have contributed to high unemployment in the Great Recession and the subsequent slow labor-market recovery. Indeed, measures of uncertainty surged during much of this period. Political brinkmanship around the debt ceiling debate, rollouts of new regulations, and debt crises in the euro area have contributed to a less predictable economic environment. Facing
heightened uncertainty, households have incentive to postpone or reduce purchases and firms may want to delay hiring, contributing to a high unemployment rate.

In this paper, we examine the effects of uncertainty on economic activity from both an empirical and a theoretical perspective. Using novel measures of uncertainty, we first document that a shock that raises uncertainty also raises unemployment. In particular, our evidence suggests that uncertainty has contributed significantly to the slow labor market recovery from the Great Recession. We then present a theoretical framework to highlight that labor search frictions are an important transmission mechanism; which, combined with nominal rigidities, can significantly amplify the effects of uncertainty on the unemployment rate. Both our empirical evidence and theoretical results suggest that an increase in uncertainty acts like a negative aggregate demand shock because it raises the unemployment rate and lowers inflation at the same time. This finding is important because it suggests that heightened uncertainty not only contributed to the high unemployment rate during the Great Recession and recovery, but it is also consistent with the observation that inflation has remained subdued for much of this period.

To provide empirical evidence on the macroeconomic effects of uncertainty shocks, we use direct measures of perceived uncertainty by consumers and firms from survey data in vector-autoregression (VAR) models. Specifically, we construct measures of uncertainty using data from the University of Michigan Survey of Consumers for the United States and the Confederation of British Industry (CBI) Industrial Trends Survey of firms for the United Kingdom. Both surveys tally responses that make explicit references to “uncertainty” in affecting consumers’ decisions to buy durable goods such as cars in the United States or firms’ decisions for capital expenditures in the United Kingdom. We exploit the timing of the surveys’ construction to help identify structural shocks to uncertainty. We examine their effects on three macroeconomic time series: the unemployment rate, the CPI inflation rate, and the three-month Treasury-bill rate.

A robust result that emerges from our study is that an increase in uncertainty raises unemployment and lowers inflation and short-term nominal interest rates. The negative comovement between the responses of unemployment and inflation suggests that uncertainty acts like a negative aggregate demand shock, for which monetary policy accommodates by lowering the nominal interest rate. This pattern occurs in both the United States and in the United Kingdom. It holds for different identification strategies. It also holds for a few alternative measures of uncertainty, including the VIX index studied by Bloom (2009) and the economic policy uncertainty index constructed by Baker, Bloom, and Davis (2011). The results are also robust to controlling for movements in consumer confidence, expected future income, or credit spreads, variables that can potentially mitigate the effects of uncertainty
shocks empirically (see, for instance, Gilchrist, Sim, and Zakrajsek (2010) and Baker, Bloom, and Davis (2011)).

We also find evidence that uncertainty can deepen recessions and hinder recoveries in quantitatively important ways. In our benchmark VAR model with U.S. data, uncertainty shocks accounted for an average of about one percentage point increase in the unemployment rate from early 2009 to late 2013.\footnote{The survey-based measure of uncertainty in our benchmark VAR model is broad and does not isolate a particular source of uncertainty. When we use a finer measure of uncertainty related to economic policy proposed by Baker, Bloom, and Davis (2011), we obtain similar quantitative results.} Interestingly, uncertainty shocks did not always play an important role during past recessions and recoveries. For example, uncertainty shocks contributed very little to the sharp increase in unemployment during the 1981-82 recession.

A possible reason why uncertainty shocks contributed to large increases in unemployment in the recent recession and recovery is that monetary policy has been constrained by the zero lower bound (ZLB) on the nominal interest rate during this period. This view is consistent with Basu and Bundick (2011), who find that, in a calibrated DSGE model, the adverse effects of uncertainty shocks on aggregate output are substantially amplified when the short-term nominal interest rate reaches the zero lower bound. In contrast, monetary policy in the early 1980s was not constrained by the ZLB.

To help understand the mechanisms through which uncertainty shocks can generate the observed demand-shock-like macroeconomic effects, we study a dynamic stochastic general equilibrium (DSGE) model that incorporates labor search frictions and nominal rigidities. Incorporating labor market frictions in the DSGE model enables us to examine the effects of uncertainty shocks on unemployment explicitly. Incorporating nominal rigidities allows us to study the potential importance of the aggregate demand channel. In the calibrated DSGE model, we find that uncertainty shocks can be substantially amplified through interactions between search frictions and nominal rigidities.

The model builds on the basic framework of Blanchard and Galí (2010), but with a focus on the macroeconomic effects of uncertainty shocks. The economy is populated by a large number of identical and infinitely lived households. The representative household is a family of workers, some employed and others are not. In each period, unemployed workers search for jobs and firms post vacancies at a fixed cost, with a matching technology creating new job matches between searching workers and vacancies. When a match is formed, a wage is determined from a Nash bargaining game between the new firm and the household. In each period, some employed workers are separated exogenously from their matches. Aggregate
employment in a given period is the sum of the number of workers who survive separation and the number of new matches formed.\footnote{The type of search friction that we consider here takes its root from the original contributions by Diamond (1982) and Mortensen and Pissarides (1994).}

To introduce nominal rigidities, we assume that there is a retail sector in which a large number of retailers produce differentiated retail products using a homogeneous intermediate good produced by firms as input. While the intermediate good market is perfectly competitive, the retail goods market is monopolistically competitive. The final consumption good is a Dixit-Stiglitz composite of the differentiated retail products. Each retailer sets a price for its own product subject to a price adjustment cost (Rotemberg, 1982). The retailer takes the price index and the demand schedule for its product as given. Monetary policy follows a feedback interest rate rule (i.e., a Taylor rule), under which the nominal interest rate reacts to deviations of inflation from a target and also to fluctuations in the output gap.

Since our empirical finding that uncertainty acts like a decline in aggregate demand holds for a broad set of measures of uncertainty, we consider two types of uncertainty in our model related to preferences and technologies. We find that, consistent with our empirical results, a rise in uncertainty—regardless of its source—is contractionary and lowers inflation. Under the Taylor rule, the monetary authority reacts to the declines in output and inflation by lowering the nominal interest rate.

In the DSGE model, both labor search frictions and nominal rigidities are important for amplifying the macroeconomic effects of uncertainty shocks. Absent nominal rigidities, a technology uncertainty shock—for example—generates a response of unemployment that is about one-tenth as large as that in our benchmark model. Similarly, absent significant search frictions, the effect of a technology uncertainty shock on unemployment is about one half as large as that in the benchmark model.

Nominal rigidities help amplify the effect of uncertainty shocks in a DSGE model through variations in markups (Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2011; Basu and Bundick, 2011). With sticky prices, an uncertainty shock that lowers aggregate demand also lowers the relative price of intermediate goods, which corresponds to the inverse of the markup in the retail sector. The decline in the relative price reduces the value of a new match, so that firms post fewer job vacancies and the unemployment rate rises. As more searching workers fail to find a job match, the household’s income declines further. This leads to an even greater fall in aggregate demand, which reinforces the initial decline in the relative price, creating a multiplier effect that amplifies uncertainty shocks to generate large macroeconomic fluctuations. This amplification mechanism is absent in the flexible-price model, since the relative price is constant.
Search frictions in the labor market provide an additional mechanism for uncertainty shocks to generate large increases in unemployment. This mechanism reflects the impact of uncertainty shocks on the value of a job match and the shape of the Beveridge curve, which captures the negative and convex relationship between vacancies and unemployment. When the cost of posting a vacancy is low, which would approximate an economy with small labor market frictions, equilibrium unemployment is determined along a relatively inelastic segment of the Beveridge curve. In this case, a rise in uncertainty lowers the value of a filled vacancy; but for any given decline in posted vacancies, the increase in unemployment is muted. However, when the cost of posting vacancies is high (i.e., when search frictions are more important), a given decline in posted vacancies would be associated with a much larger increase in unemployment, since equilibrium unemployment is determined along a relatively more elastic segment of the Beveridge curve.

Labor search frictions have important implications for the macroeconomic effects of uncertainty shocks even in a flexible-price economy. Similar to the standard Real Business Cycle (RBC) model, a rise in uncertainty raises the incentive for precautionary savings and lowers the real interest rate. Thus, as in the RBC model, uncertainty can have an expansionary effect on aggregate activity (Gilchrist and Williams, 2005; Basu and Bundick, 2011). In our model with search frictions, a job match represents a long-term employment relationship. The precautionary saving effect lowers the real interest rate and tends to raise the present value of a match. Thus, all else being equal, an uncertainty shock would be expansionary and tend to lower unemployment. However, unlike the RBC model which features a spot labor market, a job match in our model represents a long-term employment relationship that is irreversible. An increase in uncertainty can therefore reduce the present value of a match, leading to higher unemployment. Depending on the sources of uncertainty, this effect, which we call the option-value effect, may dominate the precautionary saving effect, resulting in an increase in the unemployment rate and a decline in aggregate output, even when prices are flexible. When prices are sticky, an increase in uncertainty always leads to a decline in aggregate demand, which reinforces the option-value channel and generates an increase in unemployment and declines in inflation and the nominal interest rate, as we observe in the data.

Our work adds to the recent literature that studies the macroeconomic effects of uncertainty shocks in a DSGE framework. For example, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) study a DSGE model with heterogeneous firms and non-convex adjustment costs in productive inputs. They find that a rise in uncertainty makes firms pause hiring and investment and thus leads to a large drop in economic activity. Christiano, Motto, and Rostagno (2014) present a DSGE model with a financial accelerator in the spirit
of Bernanke, Gertler, and Gilchrist (1999). They find that risk shocks (i.e., changes in the volatility of cross-sectional idiosyncratic uncertainty) play an important role for shaping U.S. business cycles. Barro (2006) shows that rare disasters—a form of risk shocks—help reconcile some asset pricing puzzles in business cycle models (see also Gabaix (2012) and Gourio (2012)). Gilchrist, Sim, and Zakrajsek (2010) and Arellano, Bai, and Kehoe (2011) argue that uncertainty shocks have important interactions with financial factors. Related to the general issue of uncertainty and risks, Ilut and Schneider (2011) examine the macroeconomic implications of ambiguity aversion in an estimated medium-scale DSGE model.3

Our work is closely related to Basu and Bundick (2011), who focus on the importance of nominal rigidities to generate comovement between macroeconomic variables following an uncertainty shock. Our work is also closely related to Fernández-Villaverde, Guerón-Quintana, Kuester, and Rubio-Ramírez (2011), who examine the effects of fiscal policy uncertainty and find that it can trigger sizable adverse effects on economic activity in a model with price and wage rigidities, particularly in the case of uncertainty about taxes on capital income.4 We share a similar emphasis with these studies that uncertainty shocks work through an aggregate demand channel in the presence of nominal rigidities. We further point out that the macroeconomic effects of uncertainty can be substantially amplified by search frictions in the labor market. This point, to our knowledge, is new to the literature.

Most of the studies in the literature abstract from labor search frictions and are not designed to examine the impact of uncertainty shocks on labor market dynamics such as unemployment and job vacancies. An exception is Schaal (2012), who presents a model with labor search frictions and idiosyncratic volatility shocks to study the observation in the Great Recession that high unemployment was accompanied by high labor productivity. As in the other studies discussed here, he focuses on the effects of uncertainty on real activity, not on its interactions with inflation and monetary policy. In addition, he assumes that

3The literature suggests that rising uncertainty may hinder irreversible investment and hiring decisions, because it raises the option value of waiting. For partial equilibrium analyses of the real option value theory in the context of uncertainty shocks, see, for example, Bernanke (1983) and Bloom (2009). Romer (1990) argues that increases in uncertainty following the stock market crash in 1929 worsened the Great Depression by substantially reducing demand for consumer durable goods. For empirical evidence on the effects of uncertainty on investment, see, for example, Leahy and Whited (1996) and Guiso and Parigi (1999). For a comprehensive survey of the literature on uncertainty shocks, see Bloom (2014) and Bloom and Fernandez-Villaverde (2012).

4Fernández-Villaverde, Guerón-Quintana, Kuester, and Rubio-Ramírez (2011) report that, under their parameterization, an increase in fiscal policy uncertainty can generate a stagflationary effect, with a decline in output and a rise in inflation. Similar to Basu and Bundick (2011), our parameterization implies that the aggregate demand effects of uncertainty shocks dominate, so that inflation falls with output when uncertainty increases.
uncertainty shocks are negatively correlated with aggregate productivity, so that such shocks can have important recessionary effects. In our model, we do not assume correlations between uncertainty shocks and the level of aggregate productivity; instead, uncertainty shocks are amplified through interactions between nominal rigidities and labor search frictions.

Finally, our focus on measures of perceived uncertainty complements other approaches in the literature that capture movements in uncertainty via variations in the cross-sectional dispersion of firms’ or industry’s earnings or productivity (Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), the conditional variance of the unforecastable component in statistical models (Jurado, Ludvigson, and Ng, 2013; Scotti, 2012), forecast disagreement and discomformity (Bloom, 2009; Bachmann, Elstner, and Sims, 2011), or the volatility of fiscal instruments estimated under time-varying volatility (Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2011), among others. Our approach has the benefit of being model-free and of directly capturing the perceptions of households and firms about uncertainty. However, one associated drawback of our approach is that it relies on households and firms to correctly understand the notion of uncertainty, which could be confused with other concepts, for instance sentiment about economic activity. While this is a relevant concern, as mentioned above, we show that our measure captures effects on the economy even after controlling for movements in sentiment.

We present in Section II empirical evidence that uncertainty shocks consistently act like an aggregate demand shock. We then present in Section III a DSGE model with labor search frictions and sticky prices. We discuss in Section IV the dynamic effects of uncertainty shocks on unemployment and other macroeconomic variables in the calibrated DSGE model. We provide some concluding remarks in Section V.

II. THE MACROECONOMIC EFFECTS OF UNCERTAINTY SHOCKS: EVIDENCE

In this section, we examine the macroeconomic effects of uncertainty shocks in the data. We first present two new measures of uncertainty from survey data. We then estimate a VAR model that includes a measure of uncertainty and a few macroeconomic variables. VAR models are used in the literature as a main statistical tool to estimate the responses of macroeconomic variables to uncertainty shocks. Examples include Alexopoulos and Cohen (2009), Bloom (2009), Bachmann, Elstner, and Sims (2011), and Baker, Bloom, and Davis (2011). Existing studies focus on the effects of uncertainty on real economic activity such as employment, investment, and output. We focus on the joint effects of uncertainty on unemployment and inflation.

II.1. Measures of uncertainty. We consider two new measures of uncertainty from survey data, including a measure of perceived uncertainty by consumers from the Michigan Survey of
Consumers and a measure of perceived uncertainty by firms from the CBI Industrial Trends Survey in the United Kingdom. Since these two survey-based measures of uncertainty are new in the literature, we begin with some explanations of how these measures are constructed in the survey.

Each month since 1978, the Michigan Survey has conducted interviews of about 500 households throughout the United States, asking questions ranging from their perceptions of business conditions to expectations for future movements in prices. More important for our analysis, the survey tallies the fraction of respondents who report that “uncertain future” is a factor that will likely limit their expenditures on cars or other durable goods over the next 12 months.\(^5\)

Figure 1 shows the time-series plots of consumers’ perceived uncertainty (concerning vehicle purchases) along with the VIX index—a commonly used measure of uncertainty in the literature (Bloom, 2009). Similar to the VIX index, consumers’ perceived uncertainty is countercyclical. It rises in recessions and falls in expansions. A notable difference between the consumers’ perceived uncertainty and financial uncertainty measured by the VIX is that the 1997 East-Asian financial crisis and the 1998 Russian debt crisis led to large spikes in the VIX, but did not seem to have much impact on consumer perceptions of uncertainty. Another notable difference is that, in late 2012, the VIX index stayed at low levels despite the looming “fiscal cliff” that was expected to trigger large increases in taxes and substantial cuts in government spending if the Congress and the White House were unable to reach an agreement regarding deficit cuts. By contrast, consumer uncertainty from the Michigan survey remained elevated during this period.\(^6\)

We follow a similar procedure to construct firms’ perceived uncertainty from the CBI Industrial Trends Survey in the United Kingdom. Each quarter since 1978, the CBI has surveyed a sample of roughly 1,100 firms in the United Kingdom. We measure firms’ perceived uncertainty as the fraction of firms that report “uncertainty about demand” as a factor limiting their capital expenditures over the next 12 months.\(^7\)

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\(^5\)The question on vehicle purchases is, “Speaking now of the automobile market—do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van or sport utility vehicle? Why do you say so?” Reasons related to uncertainty are then compiled. The series is weighted by age, income, region, and sex to be nationally representative.

\(^6\)A possible explanation is that the VIX index focuses on short-term uncertainty because it is a weighted average of 30-day-ahead option prices.

\(^7\)The question asked by the CBI is, “What factors are likely to limit (wholly or partly) your capital expenditure authorisations over the next twelve months?” Participants can choose “uncertainty about demand” as one of six options. Firms can provide other reasons or choose multiple reasons.
As Figure 2 shows, firms’ perceived uncertainty is also countercyclical, but it appears relatively more stable than what is reported by the Michigan survey of consumers. This difference may reflect the fact that U.K. firms are asked about a specific form of uncertainty (i.e., about the demand for their products), whereas no such specificity is attached to the measure of uncertainty in the Michigan survey.

II.2. Empirical results. We now examine the macroeconomic effects of uncertainty shocks by estimating a Bayesian vector autoregression (BVAR) model. Sims and Zha (1998) argue that sampling errors can lead to difficulties in estimating error bands for impulse responses in a VAR model with a short time-series sample of data. They propose using Bayesian priors (instead of flat priors) to help improve the estimation of error bands. We follow their approach in our analysis.

In our benchmark VAR model, we consider four variables, including a measure of uncertainty, the unemployment rate, the inflation rate measured as year-over-year changes in the consumer price index (CPI), and the three-month Treasury bills rate. The sample ranges from January 1978 to October 2013.

In our benchmark VAR model, we exploit the timing of survey interviews relative to the timing of macroeconomic data releases for identification. To examine the robustness of our results, we also consider alternative identification schemes in Section II.5.2. In the Michigan survey, phone interviews are conducted throughout the month, with most interviews concentrated in the middle of each month, and preliminary results released shortly thereafter. The final results are typically released by the end of the month. When answering questions, survey participants have information about the previous month’s unemployment, inflation, and interest rates, but they do not have (complete) information about the current-month macroeconomic conditions because the macroeconomic data have not yet been made public. Hence, our identification strategy uses the fact that when answering questions at time \( t \) about their expectations of the future, the information set on which survey participants condition their answers will not include, by construction, the time \( t \) realizations of the unemployment rate and the other variables in our VAR. Thus, we follow the approach in Leduc, Sill, and Stark (2007), Auerbach and Gorodnichenko (2012), and Leduc and Sill (forthcoming) by placing the uncertainty measure as the first variable in the VAR. This Cholesky ordering implies that uncertainty does not respond to macroeconomic shocks in the impact period, while

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8 Similarly, the questionnaires for the CBI survey must be returned by the middle of the first month of each quarter. The design of the survey implies that participants have information about the values of the variables in the VAR for the previous quarter when they fill in answers to the survey questions, but they do not know the macroeconomic data in the current quarter.
information, inflation, and the nominal interest rate are allowed to change on impact of an uncertainty shock.\(^9\)

We first look at the transmission of uncertainty shocks in the United States using the measure of consumer uncertainty from the Michigan Survey. Figure 3 presents the impulse responses in the VAR model, in which consumer uncertainty is ordered first. For each variable, the solid line denotes the median estimate of the impulse response and the dashed lines represent the range of the 90-percent confidence band around the point estimates. The figure shows that an unexpected increase in uncertainty leads to a persistent increase in the unemployment rate, which reaches a peak in about 18 months from the impact period and remains significantly positive for about three years. Heightened uncertainty also leads to a significant and persistent decline in inflation, with the peak effect also occurring roughly 18 months after the shock.

The aggregate demand effect of uncertainty is not unique to the U.S. economy. It is also present in the U.K. data. Using the measure of firms’ perceived uncertainty from the CBI Survey, we examine the effects of uncertainty shocks in a VAR model using UK data on unemployment, inflation, and the three-month nominal interest rate. Since the survey data are quarterly, we convert the unemployment rate, the inflation rate, and the three-month nominal interest rate from monthly to quarterly frequency by taking the end-of-quarter observations (e.g., unemployment for the first quarter of 1980 is the unemployment rate in March 1980 and for the second quarter, it is that in June, and so on). The sample ranges from 1979:Q4 to 2011:Q2. Figure 4 shows that an unanticipated increase in the level of uncertainty leads to persistent increases in unemployment and persistent declines in both the inflation rate and the nominal interest rate in the U.K. sample, just as those observed in the U.S. data.

II.3. Quantitative importance of uncertainty shocks. Although the estimated impulse responses of unemployment to an uncertainty shock are statistically significant, they reflect the average effects of an increase in uncertainty on unemployment in the entire sample; they do not indicate the relative importance of uncertainty shocks for unemployment in different recessions. Our sample of U.S. data covers four different recessions, with particularly large increases in unemployment in two of them: one in the early 1980s and the other during the Great Recession and recovery periods since 2008. We focus on these two recessions and

\(^9\)Bachmann and Moscarini (2011) argue that bad first-moment shocks can raise cross-sectional dispersions and time-series volatility of macroeconomic variables. In this sense, changes in measured uncertainty could reflect endogenous responses of macroeconomic variables to first-moment shocks. Our empirical approach allows measured uncertainty to react to macroeconomic shocks, but it also presumes that measured uncertainty contains some exogenous component.
ask the question: How much of the observed increases in unemployment in each of these recessions are accounted for by increases in the levels of uncertainty?

To provide an answer to this question, we calculate historical decompositions from our estimated VAR model. This calculation is a counterfactual experiment. By construction, if we have all four shocks turned on in our benchmark four-variable VAR model, the estimated VAR model would exactly match the observed time series of the unemployment rate. In our counterfactual experiment, we turn off all shocks but the uncertainty shock in the VAR model and calculate the implied unemployment path in each of the two recession periods.

Figure 5 shows the changes in the unemployment rate during the Great Recession and recovery period (the top panel) and those in the 1981-82 recession (the bottom panel). The thin blue lines indicate the actual increases in the unemployment rate (relative to the benchmark with no shocks) in each of the two recessions; the red bars indicate the simulated unemployment rate when all four shocks are turned on (and, by construction, they match the actual data exactly); and the blue bars indicate the simulated changes in the unemployment rate conditional on the estimated uncertainty shocks alone.

The figure reveals that uncertainty shocks have contributed about one-third of the actual increases in the unemployment rate in the Great Recession and recovery. In particular, since the beginning of 2009, heightened uncertainty accounted for an average of about 1 percentage point increase in the unemployment rate. In contrast, uncertainty shocks contributed nothing to the surge in unemployment during the 1981-82 recession period.

II.4. The role of monetary policy in mitigating uncertainty shocks. A possible reason for the larger role of uncertainty shocks in the Great Recession and its recovery compared with earlier recessions is that monetary policy has been constrained by the zero lower bound (ZLB) on the nominal interest rate. This interpretation is consistent with Basu and Bundick (2011), who find that, in a calibrated DSGE model, the adverse effects of uncertainty shocks on aggregate output are substantially amplified when the policy rate reaches the zero lower bound.

In reality, however, the Fed used unconventional monetary tools after the short-term nominal interest rate reached the zero lower bound. In particular, the Fed has conducted three rounds of large-scale asset purchases and provided systematic forward guidance about the future path of monetary policy. To the extent that our historical decomposition does not take into account the effects of unconventional monetary policy, our estimated contributions of uncertainty shocks to unemployment could be overstated.

To address this concern and to provide a more accurate estimate of the quantitative effects of uncertainty shocks on unemployment, we now examine a VAR model that is identical to the baseline four-variable VAR model, except that the short-term nominal interest rate series is
replaced by a long-term interest rate series. In particular, we use the two-year Treasury bond yields as an indicator of monetary policy instead of the three-month Treasury bills rate.¹⁰ Unlike the three-month Treasury bills rate, the two-year Treasury yields did not reach the zero lower bound. More importantly, the use of this longer-term interest rate helps capture the effects of unconventional monetary policy, which is designed to lower yields on long-term securities.

In our estimated VAR with the longer-term Treasury yields, the impulse responses show patterns very similar to those from the baseline VAR model with the short-term nominal interest rate.¹¹ In particular, as in our baseline model, a shock that raises uncertainty also raises the unemployment rate and lowers both the inflation rate and the two-year Treasury yields. These effects are persistent and statistically significant at the 90-percent level. However, historical decompositions calculated based on the estimated VAR model with the long-term interest rate show that uncertainty shocks contributed about 0.9 percentage point to the increase in the unemployment rate since early 2009, which is slightly smaller than the 1 percentage point average contribution obtained in our baseline VAR model with the short-term interest rate.

II.5. Robustness. The finding that uncertainty shocks act like aggregate demand shocks is fairly robust. As we have just demonstrated, it holds for data in both the United States and the United Kingdom, with two different measures of uncertainty (one reflects consumers’ perceptions of uncertainty in the United States and the other captures firms’ perceptions in the United Kingdom) that display relatively different time-series properties. We now show that the results are also robust to alternative measures of uncertainty, alternative identification assumptions, and inclusions of additional macroeconomic variables in the VAR model.

II.5.1. Alternative measures of uncertainty. There are a few other measures of uncertainty used in the literature. We focus on two particular measures, including the VIX index that captures the stock price volatility, which, as shown by Bloom (2009), leads to substantial declines in industrial output and employment in the short run; and the economic policy

¹⁰Swanson and Williams (2014) argue that the Federal Reserve’s forward guidance policy typically attempts to influence the two-year Treasury bond yields. Gertler and Karadi (2013) also argue for the use of a long-term interest rate as an indicator of monetary policy in a VAR.

¹¹To conserve space, we do not display these impulse responses. These and other related materials are available in an online appendix at http://www.frbsf.org/economic-research/publications/working-papers/2012/wp12-10bk_appendix.pdf.
uncertainty index constructed by Baker, Bloom, and Davis (2011), who show that a shock to policy uncertainty foreshadows large declines in industrial output and employment.\textsuperscript{12}

Figure 6 shows that an uncertainty shock in the VAR model with the VIX index raises unemployment and lowers inflation and the nominal interest rate, just as we observe in the benchmark VAR model with the survey-based measure of uncertainty. Figure 7 shows that the effects of a policy uncertainty shock are also similar. In both cases, the responses of macroeconomic variables are persistent and statistically significant at the 90 percent level. Thus, our finding that an uncertainty shock acts like a negative aggregate demand shock is robust to these alternative measures of uncertainty.

II.5.2. Alternative identification approaches. Although the timing of the survey relative to macroeconomic data releases suggests that survey respondents do not possess complete information about the current-month macroeconomic data at the time of the interviews (which forms the basis of our Cholesky identification assumption in the benchmark VAR model), it is possible that they observe other, possibly higher-frequency variables that give them information about the time $t$ realizations of the variables in the VAR model.

To examine the sensitivity of our results to the Cholesky ordering of variables, we estimate a VAR model with uncertainty ordered last. This relatively conservative identification assumption implies that the measure of uncertainty is allowed to respond to contemporaneous macroeconomic shocks.

Figure 8 presents the impulse responses in the VAR model with consumer uncertainty based on the Michigan Survey ordered last. The responses of the three macroeconomic variables to an uncertainty shock look remarkably similar to those in the benchmark VAR with uncertainty ordered first. Under each identification strategy, a positive uncertainty shock acts like a negative aggregate demand shock that raises unemployment and lowers inflation. In response to the recessionary effects of uncertainty shocks, monetary policy reacts by easing the stance of policy and lowering the nominal interest rate.

To further examine the sensitivity of our results to the identification assumptions, we estimate a VAR model with uncertainty measured by a dummy variable that takes a value of one if there is an uncertainty event in a particular month and zero otherwise, where most of the uncertainty events are identified by Bloom (2009).\textsuperscript{13} In estimating this VAR model, we

\textsuperscript{12}The VIX index constructed by the Chicago Board of Exchange (CBOE) starts in January 1990. We extend the series back to January 1986 by using the CBOE’s VXO index for the pre-1990 periods. The policy uncertainty index is a monthly series that starts in January 1985.

\textsuperscript{13}Bloom (2009) identifies 17 uncertainty events for the periods from 1962 to 2008. To be consistent with our benchmark VAR model, we focus on the sample from January 1978 to October 2013. Our sample includes 11 uncertainty events taken from Bloom (2009) for the period between 1978 and 2008 (see his Table A.1). We extend the sample to include two new uncertainty events, one occurred in August 2011, when the debt
follow Bloom (2009) and treat the uncertainty dummy as an exogenous variable, which does not respond to changes in macroeconomic conditions. Figure 9 shows the impulse responses of the macroeconomic variables following a shock to the uncertainty dummy. The figure shows that an uncertainty shock leads to significant short-run increases in unemployment and significant declines in inflation and the nominal interest rate, although the macroeconomic responses are less persistent than those estimated from our benchmark VAR model with consumer uncertainty.

II.5.3. Larger VAR models. To further examine the robustness of our results, we estimate a few alternative VAR models that include additional macroeconomic variables. For ease of comparison, we use the consumer uncertainty series based on the University of Michigan survey in all alternative VAR models and we impose the same Cholesky identification restrictions as in our benchmark model by ordering uncertainty first.

One such larger VAR model includes, in addition to the three macroeconomic time series, a measure of labor market tightness (measured by the ratio of the job vacancy rate to the unemployment rate, or the v-u ratio). We measure job vacancies using data from the Job Openings and Labor Turnover Survey (JOLTS) combined with the Help-Wanted Index published by the Conference Board. The sample range is the same as in our benchmark VAR model (from January 1978 to October 2013). Figure 10 shows that an unexpected rise in uncertainty leads to a significant and persistent increase in the unemployment rate and a persistent decline in the v-u ratio. As in the benchmark model, the shock also lowers both the inflation rate and the nominal interest rate. These observations, as we show in the theory section, are consistent with a DSGE model with nominal rigidities and search frictions in the labor market. An uncertainty shock in this larger VAR model continues to have macroeconomic effects that are similar to a negative aggregate demand shock.

We have estimated other models that, in addition to the four variables in our baseline VAR model, also include (i) consumption of nondurables and services and business fixed investment; (ii) credit spread and stock price index; or (iii) full-time and part-time employment. We have also estimated the baseline four-variable VAR model with sample ending at the end of 2008, before the policy rates in the United States and the United Kingdom hit the zero lower bound. In each case, uncertainty shocks consistently act like an aggregate demand shock that raises unemployment and lowers inflation and the nominal interest rate.\(^{14}\)

II.6. Uncertain future or bad economic times? As shown in Figure 1, consumer uncertainty rises in recessions and falls in booms. A priori, it is possible that consumer uncertainty ceiling debate in Congress triggered a downgrade of the U.S. government debt; and the other in December 2012, when the U.S. federal government was approaching the fiscal cliff.

\(^{14}\)The results from these exercises can be found in the online appendix.
from the Michigan survey may reflect the respondents’ perceptions of bad economic times rather than an uncertain future.

To assess the extent to which consumer uncertainty might reflect their perceptions of bad economic times, we examine how much the macroeconomic effects of shocks to consumer uncertainty reflect the responses to changes in other indicators of economic conditions, such as consumer confidence. For this purpose, we follow an approach similar to Baker, Bloom, and Davis (2011) and estimate a five-variable VAR model that includes a consumer sentiment index as an additional variable to control for potential effects from movements in consumer confidence.

Figure 11 shows that the macroeconomic effects of uncertainty shocks are qualitatively similar to those estimated from the benchmark VAR. A shock to uncertainty raises the unemployment and lowers consumer sentiment, the inflation rate, and the short-term nominal interest rate. The responses of the macroeconomic variables are statistically significant at the 90 percent level. Thus, the macroeconomic effects of consumer uncertainty shocks do not seem to reflect responses of macroeconomic variables to changes in consumer confidence.

III. UNCERTAINTY SHOCKS IN A DSGE MODEL WITH SEARCH FRICTIONS

In this section, we examine the channels that transmit uncertainty shocks to the macroeconomy in a DSGE model with sticky prices and labor market search frictions. We show that uncertainty shocks in the DSGE model act like an aggregate demand shock that raises unemployment, lowers inflation, and through the Taylor rule, lowers the nominal interest rate, just as what we have seen in the data. We further show that search frictions in the labor market and sticky prices in the goods market are both important for amplifying the effects of uncertainty shocks in the model.

The economy is populated by a continuum of infinitely lived and identical households with a unit measure. The representative household consists of a continuum of worker members. The household owns a continuum of firms, each of which uses one worker to produce an intermediate good. In each period, a fraction of the workers are unemployed and they search for jobs. Firms post vacancies at a fixed cost. The number of successful matches are produced with a matching technology that transforms searching workers and vacancies into an employment relation. Real wages are determined by Nash bargaining between a searching worker and a hiring firm.

15The consumer sentiment index that we use here is a measure of consumer sentiment about current economic conditions. We have also estimate a five-variable VAR model by using the consumer sentiment index for expectations. The qualitative results are also very similar to those in the benchmark VAR model.
The household consumes a basket of differentiated retail goods, each of which is transformed from the homogeneous intermediate good using a constant-returns technology. Retailers face a perfectly competitive input market (where they purchase the intermediate good) and a monopolistically competitive product market. Each retailer sets a price for its differentiated product, with price adjustments subject to a quadratic cost in the spirit of Rotemberg (1982).

The government finances its spending and transfer payments to unemployed workers by distortionary taxes on firm profits. Monetary policy is described by the Taylor rule, under which the nominal interest rate responds to deviations of inflation from a target and of output from its potential.

III.1. The households. There is a continuum of infinitely lived and identical households with a unit measure. The representative household consumes a basket of retail goods. The utility function is given by

$$E \sum_{t=0}^{\infty} \beta^t A_t \left( \ln C_t - \chi N_t \right),$$

where $E[\cdot]$ is an expectation operator, $C_t$ denotes consumption, and $N_t$ denotes the fraction of household members who are employed. The parameter $\beta \in (0,1)$ denotes the subjective discount factor and the parameter $\chi$ measures the disutility from working.

The term $A_t$ denotes a preference shock, which follows the stochastic process

$$\ln A_t = \rho_a \ln A_{t-1} + \sigma_a \varepsilon_{a,t}. \quad (2)$$

The parameter $\rho_a \in (-1,1)$ measures the persistence of the preference shock. The term $\varepsilon_{a,t}$ is an i.i.d. standard normal process. The term $\sigma_a$ is a time-varying standard deviation of the innovation to the preference shock, which we interpret as a preference uncertainty shock. We assume that $\sigma_a$ follows the stationary process

$$\ln \sigma_a = (1 - \rho_{a_a}) \ln \sigma_a + \rho_{a_a} \ln \sigma_{a,t-1} + \sigma_{a} \varepsilon_{a,t}, \quad (3)$$

where $\rho_{a_a} \in (-1,1)$ measures the persistence of preference uncertainty, $\varepsilon_{a,t}$ denotes the innovation to the preference uncertainty shock and is a standard normal process, and $\sigma_{a}$ denotes the (constant) standard deviation of the innovation.

The household chooses consumption $C_t$ and saving $B_t$ to maximize the utility function in (1) subject to the sequence of budget constraints

$$C_t + \frac{B_t}{P_t R_t} = \frac{B_{t-1}}{P_{t-1}} + w_t N_t + \phi (1 - N_t) + d_t, \quad \forall t \geq 0, \quad (4)$$

where $P_t$ denotes the price level, $B_t$ denotes holdings of a nominal risk-free bond, $R_t$ denotes the nominal interest rate, $w_t$ denotes the real wage rate, $\phi$ denotes an unemployment benefit, $d_t$ denotes profit income from ownerships of intermediate goods producers and of retailers.
Optimal bond-holding decisions are described by the intertemporal Euler equation

\[ 1 = E_t \beta \gamma_{a,t+1} \frac{\Lambda_{t+1}}{\Lambda_t} \frac{R_t}{\pi_t}, \tag{5} \]

where \( \Lambda_t = \frac{1}{C_t} \) denotes the marginal utility of consumption, \( \pi_t \equiv \frac{P_t}{P_{t-1}} \) denotes the inflation rate, and \( \gamma_{at} \equiv \frac{A_t}{A_{t-1}} \) denote the growth rate of the preference shock \( A_t \).

### III.2. The aggregation sector.

Denote by \( Y_t \) the final consumption good, which is a basket of differentiated retail goods. Denote by \( Y_t(j) \) a type \( j \) retail good for \( j \in [0, 1] \). We assume that

\[ Y_t = \left( \int_0^1 Y_t(j)^{\frac{\eta - 1}{\eta}} \right)^{\frac{\eta}{\eta - 1}}, \tag{6} \]

where \( \eta > 1 \) is the elasticity of substitution between differentiated products.

Expenditure minimizing implies that demand for a type \( j \) retail good is inversely related to the relative price, with the demand schedule given by

\[ Y^{d}_t(j) = \left( \frac{P_t(j)}{P_t} \right)^{\frac{1}{\eta}} Y_t, \tag{7} \]

where \( Y^{d}_t(j) \) and \( P_t(j) \) denote the demand for and the price of retail good of type \( j \), respectively. Zero-profit in the aggregate sector implies that the price index \( P_t \) is related to the individual prices \( P_t(j) \) through the relation

\[ P_t = \left( \int_0^1 P_t(j)^{\frac{1}{1 - \eta}} \right)^{1 - \eta}. \tag{8} \]

### III.3. The retail goods producers.

There is a continuum of retailers, each producing a differentiated product using a homogeneous intermediate good as input. The production function of retail good of type \( j \in [0, 1] \) is given by

\[ Y_t(j) = X_t(j), \tag{9} \]

where \( X_t(j) \) is the input of intermediate goods used by retailer \( j \) and \( Y_t(j) \) is the output. The retail goods producers are price takers in the input market and monopolistic competitors in the product markets, where they set prices for their products, taking as given the demand schedule in equation (7) and the price index in equation (8).

Price adjustments are subject to the quadratic cost

\[ \frac{\Omega_p}{2} \left( \frac{P_t(j)}{\pi P_{t-1}(j) - 1} \right)^2 Y_t, \tag{10} \]

where the parameter \( \Omega_p \geq 0 \) measures the cost of price adjustments and \( \pi \) denotes the steady-state inflation rate. Price adjustment costs are in units of aggregate output.
A retail firm that produces good \( j \) solves the profit-maximizing problem

\[
\max_{P_t(j)} \quad E_t \sum_{i=0}^\infty \frac{\beta^i \Lambda_{t+i} A_{t+i}}{\Lambda_t A_t} \left[ \left( \frac{P_{t+i}(j)}{P_{t+i}} - q_{t+i} \right) Y_{t+i}^d(j) - \frac{\Omega_p}{2} \left( \frac{P_{t+i}(j)}{\pi P_{t+i-1}(j)} - 1 \right) Y_{t+i} \right],
\]

where \( q_t \) denotes the relative price of intermediate goods. The optimal price-setting decision implies that, in a symmetric equilibrium with \( P_t(j) = P_t \) for all \( j \), we have

\[
q_t = \eta - 1 + \frac{\Omega_p}{\eta} \left[ \frac{\pi_t}{\pi} \left( \frac{\pi_t}{\pi} - 1 \right) - E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1} Y_{t+1} \pi_{t+1}}{\Lambda_t} \left( \frac{\pi_{t+1}}{\pi} - 1 \right) \right].
\]

Absent price adjustment costs (i.e., \( \Omega_p = 0 \)), the optimal pricing rule implies that real marginal cost \( q_t \) equals the inverse of the steady-state markup.

### III.4. The Labor Market

In the beginning of period \( t \), there are \( u_t \) unemployed workers searching for jobs and there are \( v_t \) vacancies posted by firms. The matching technology is described by the Cobb-Douglas function

\[
m_t = \mu u_t^\alpha v_t^{1-\alpha},
\]

where \( m_t \) denotes the number of successful matches and the parameter \( \alpha \in (0, 1) \) denotes the elasticity of job matches with respect to the number of searching workers. The parameter \( \mu \) scales the matching efficiency.

The probability that an open vacancy is matched with a searching worker (i.e., the job filling rate) is given by

\[
q_v = m_t / v_t.
\]

The probability that an unemployed and searching worker is matched with an open vacancy (i.e., the job finding rate) is given by

\[
q_u = m_t / u_t.
\]

In the beginning of period \( t \), there are \( N_{t-1} \) workers. A fraction \( \rho \) of these workers lose their jobs. Thus, the number of workers who survive the job separation is \( (1 - \rho) N_{t-1} \). At the same time, \( m_t \) new matches are formed. Following the timing assumption in Blanchard and Galí (2010), we assume that new hires start working in the period they are hired. Thus, aggregate employment in period \( t \) evolves according to

\[
N_t = (1 - \rho) N_{t-1} + m_t.
\]

With a fraction \( \rho \) of employed workers separated from their jobs, the number of unemployed workers searching for jobs in period \( t \) is given by

\[
u_t = 1 - (1 - \rho) N_{t-1}.
\]
Following Blanchard and Galí (2010), we assume full participation and define the unemployment rate as the fraction of the population who are left without a job after hiring takes place in period $t$. Thus, the unemployment rate is given by

$$U_t = u_t - m_t = 1 - N_t.$$  \hfill (18)

### III.5. The Firms (intermediate good producers)

A firm can produce only if it successfully hires a worker. The production function for a firm with one worker is given by

$$x_t = Z_t,$$

where $x_t$ denotes output. The term $Z_t$ denotes an aggregate technology shock, which follows the stationary stochastic process

$$\ln Z_t = \rho_z \ln Z_{t-1} + \sigma_z \varepsilon_{zt}.$$  \hfill (19)

The parameter $\rho_z \in (-1, 1)$ measures the persistence of the technology shock. The term $\varepsilon_{zt}$ is an i.i.d. innovation to the technology shock and is a standard normal process. The term $\sigma_z$ is a time-varying standard deviation of the innovation, which we interpret as a technology uncertainty shock. We assume that the technology uncertainty shock follows the stationary stochastic process

$$\ln \sigma_{zt} = (1 - \rho_{\sigma_z}) \ln \sigma_z + \rho_{\sigma_z} \ln \sigma_{z,t-1} + \sigma_{\sigma_z} \varepsilon_{\sigma_z,t},$$  \hfill (20)

where the parameter $\rho_{\sigma_z} \in (-1, 1)$ measures the persistence of the technology uncertainty, the term $\varepsilon_{\sigma_z,t}$ is an i.i.d. standard normal process, and the parameter $\sigma_{\sigma_z} > 0$ is the standard deviation of the innovation to technology uncertainty.

If a firm finds a match, it obtains a flow profit in the current period after paying the worker. In the next period, if the match survives (with probability $1 - \rho$), the firm continues; if the match breaks down (with probability $\rho$), the firm posts a new job vacancy at a fixed cost $\kappa$, with the value $V_{t+1}$. The value of a firm with a match (denoted by $J^F_t$) is therefore given by the Bellman equation

$$J^F_t = (1 - \tau) (q_t Z_t - w_t) + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left[ (1 - \rho) J^F_{t+1} + \rho V_{t+1} \right],$$  \hfill (21)

where $\tau$ denotes a tax rate on flow profits.\textsuperscript{16}

If the firm posts a new vacancy in period $t$, it costs $\kappa$ units of final goods. The vacancy can be filled with probability $q^v_t$, in which case the firm obtains the value of the match.

\textsuperscript{16}Incorporating profit taxes in the model helps amplify the recessionary effects of uncertainty shocks because unemployment benefits are financed by these tax revenues.
Otherwise, the vacancy remains unfilled and the firm goes into the next period with the value $V_{t+1}$. Thus, the value of an open vacancy is given by

$$V_t = -\kappa + q_t^v J_t^F + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} (1 - q_t^v) V_{t+1}.$$ 

Free entry implies that $V_t = 0$, so that

$$\frac{\kappa}{q_t^v} = J_t^F.$$ 

(22)

This relation describes the optimal job creation decisions. The benefit of creating a new job is the match value $J_t^F$. The expect cost of creating a new job is the flow cost of posting a vacancy $\kappa$ multiplied by the expected duration of an unfilled vacancy $1/q_t^v$.

### III.6. Workers’ value functions.

If a worker is employed, he obtains wage income but suffers a utility cost of working. In period $t+1$, the match is separated with probability $\rho$ and the separated worker can find a new match with probability $q_{t+1}^w$. Thus, with probability $\rho(1 - q_{t+1}^u)$, a separated worker fails to find a new job in period $t+1$ and enters the unemployment pool. Otherwise, the worker continues to be employed. The (marginal) value of an employed worker (denoted by $J_t^W$) therefore satisfies the Bellman equation

$$J_t^W = w_t - \frac{\chi}{\Lambda_t} + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left\{ [1 - \rho(1 - q_{t+1}^u)] J_{t+1}^W + \rho(1 - q_{t+1}^u) J_{t+1}^U \right\},$$ 

where $J_t^U$ denotes the value of an unemployed worker. An unemployed worker obtains the flow unemployment benefit $\phi$ and can find a new job in period $t+1$ with probability $q_{t+1}^w$. Thus, the value of an unemployed worker satisfies the Bellman equation

$$J_t^U = \phi + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left[ q_{t+1}^w J_{t+1}^W + (1 - q_{t+1}^u) J_{t+1}^U \right].$$ 

(24)

### III.7. The Nash bargaining wage.

Firms and workers bargain over wages. The Nash bargaining problem is given by

$$\max_{w_t} \ (J_t^W - J_t^U)^b (J_t^F)^{1-b},$$ 

(25)

where $b \in (0, 1)$ represents the bargaining weight for workers.

Define the total surplus as

$$S_t = J_t^F + J_t^W - J_t^U.$$ 

(26)

Then the bargaining solution is given by

$$J_t^F = (1 - b) S_t, \quad J_t^W - J_t^U = b S_t.$$ 

(27)

It then follows from equations (23) and (24) that

$$b S_t = w_t^N - \phi - \frac{\chi}{\Lambda_t} + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left[ (1 - \rho)(1 - q_{t+1}^u) b S_{t+1} \right].$$ 

(28)
Given the bargaining surplus $S_t$, which itself is proportional to the match value $J^F_t$, this last equation determines the Nash bargaining wage $w^N_t$.

If equilibrium real wage equals the Nash bargaining wage, then we can obtain an explicit expression for the Nash bargaining wage. Specifically, we use equations (22), (27), and (28) and impose $w_t = w^N_t$ to obtain

$$w^N_t(1 - b\tau_t) = (1 - b) \left[ \frac{X}{\Lambda_t} + \phi \right] + b \left( (1 - \tau_t)q_tZ_t + \beta(1 - \rho)E_t \frac{\beta\gamma a_{t+1} \Lambda_{t+1} \kappa v_{t+1}}{\Lambda_t} \right).$$

(29)

In this case, the Nash bargaining wage (adjusted for taxes) is a weighted average of the worker’s reservation value and the firm’s productive value of a job match. By forming a match, the worker incurs a utility cost of working and foregoes unemployment benefits. By employing a worker, the firm receives the marginal product from labor (net of taxes) in the current period and saves the vacancy cost from the next period.

III.8. Wage Rigidity. In general, however, equilibrium real wage may be different from the Nash bargaining solution. Hall (2005) points out that real wage rigidity is important to generate empirically reasonable volatilities of vacancies and unemployment.

There are several ways to formalize real wage rigidity (Hall, 2005; Hall and Milgrom, 2008; Gertler and Trigari, 2009; Blanchard and Galí, 2010). We follow the literature and consider real wage rigidity by assuming that

$$w_t = w^N_{t-1} (w^N_t)^{1-\gamma},$$

(30)

where $\gamma \in (0, 1)$ represents the degree of real wage rigidity.\(^{17}\)

III.9. Government policy. The government finances transfer payments for unemployment benefit through profit taxes. We assume that the government balances the budget in each period so that

$$\phi(1 - N_t) = \tau_t(q_tZ_t - w_t)N_t.$$  

(31)

The monetary authority follows the Taylor rule

$$R_t = r\pi^* \left( \frac{\pi_t}{\pi^*} \right)^{\phi_\pi} \left( \frac{Y_t}{Y} \right)^{\phi_y},$$

(32)

where the parameter $\phi_\pi$ determines the aggressiveness of monetary policy against deviations of inflation from the target $\pi^*$ and $\phi_y$ determines the extent to which monetary policy accommodates output fluctuations. The parameter $r$ denotes the steady-state real interest rate (i.e., $r = \frac{R}{\pi}$).

\(^{17}\)We have examined other wage rules as those in Blanchard and Galí (2010) and we find that our results do not depend on the particular form of the wage rule.
III.10. **Search equilibrium.** In a search equilibrium, the markets for bonds, final consumption goods, and intermediate goods all clear.

Since the aggregate supply of the nominal bond is zero, the bond market-clearing condition implies that

$$B_t = 0.$$  \hfill (33)

Goods market clearing implies the aggregate resource constraint

$$C_t + \kappa v_t + \frac{\Omega_p}{2} \left( \frac{\pi_t}{\pi} - 1 \right)^2 Y_t = Y_t,$$  \hfill (34)

where $Y_t$ denotes aggregate output of final goods.

Intermediate goods market clearing implies that

$$Y_t = Z_t N_t.$$  \hfill (35)

### IV. Economic implications of the DSGE model

To examine the macroeconomic effects of uncertainty shocks in our DSGE model, we calibrate the model parameters and simulate the model to examine impulse responses of macroeconomic variables to the two alternative sources of uncertainty shocks. We focus on the responses of unemployment, inflation, and the nominal interest rate following an uncertainty shock.

#### IV.1. Calibration.** We calibrate the structural parameters to match several steady-state observations. For those structural parameters that do not affect the model’s steady state, we calibrate their values to be consistent with other empirical studies in the literature. The structural parameters to be calibrated include $\beta$, the subjective discount factor; $\chi$, the disutility of working parameter; $\eta$, the elasticity of substitution between differentiated retail products; $\alpha$, the elasticity of matching with respect to searching workers; $\mu$, the matching efficiency parameter; $\rho$, the job separation rate; $\phi$, the flow of unemployment benefits (in final consumption units); $\kappa$, the fixed cost of posting vacancies; $b$, the Nash bargaining weight; $\Omega_p$, the price adjustment cost parameter; $\pi$, the steady-state inflation rate (which is also the inflation target); $\phi_\pi$, the Taylor-rule coefficient for inflation; and $\phi_y$, the Taylor-rule coefficient for output. In addition, we need to calibrate the parameters in the shock processes. The calibrated values of the model parameters are summarized in Table 1.

We set $\beta = 0.99$, so that the model implies a steady-state real interest rate of 4 percent per year. We set $\eta = 10$ so that the average markup is about 11 percent, in line with the estimates obtained by Basu and Fernald (1997) and others. We set $\alpha = 0.5$ following the literature (Blanchard and Galí, 2010; Gertler and Trigari, 2009). We set $\rho = 0.1$, which is broadly consistent with an average monthly job separation rate of about 3.5 percent as
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in JOLTS for the period from 2001 to 2013. Following Hall and Milgrom (2008), we set \( \phi = 0.25 \) so that the unemployment benefit is about 25 percent of normal earnings. We set \( b = 0.5 \) following the literature.

We choose the value of the vacancy cost parameter \( \kappa \) so that, in the steady state, the total cost of posting vacancies is about 2 percent of gross output. To assign a value of \( \kappa \) then requires knowledge of the steady-state number of vacancies \( v \) and the steady-state level of output \( Y \). We calibrate the value of \( v \) such that the steady-state vacancy filling rate is \( q^v = 0.7 \) and the steady-state unemployment rate \( U \) is 6 percent, as in den Haan, Ramey, and Watson (2000). Given the steady-state value of the job separation rate \( \rho = 0.1 \), we obtain \( m = \rho N = 0.094 \). Thus, we have \( v = \frac{m}{q^v} = \frac{0.094}{0.7} = 0.134 \). To obtain a value for \( Y \), we use the aggregate production function that \( Y = ZN \) and normalize the level of technology such that \( Z = 1 \). This procedure yields a calibrated value of \( \kappa = 0.14 \).

Given the steady-state values of \( m, u, \) and \( v \), we use the matching function to obtain an average matching efficiency of \( \mu = 0.65 \). To obtain a value for \( \chi \), we solve the steady-state system so that \( \chi \) is consistent with an unemployment rate of 6 percent. The process results in \( \chi = 0.523 \). We set the real wage rigidity parameter to \( \gamma = 0.8 \).

The price adjustment cost parameter \( \Omega_p \) and the Taylor-rule parameters \( \phi_\pi \) and \( \phi_y \) do not affect the model’s steady state. We calibrate these parameters to be consistent with empirical studies in the literature. We set \( \Omega_p = 112 \) so that the slope of the Phillips curve in the model corresponds to that in a Calvo staggered price-setting model a price contract of four quarters. For the Taylor rule parameters, we set \( \phi_\pi = 1.5 \) and \( \phi_y = 0.2 \). We set \( \pi = 1.005 \), so that the steady-state inflation rate is about two percent per year, corresponding to the Federal Reserve’s inflation objective.

The model does not provide information for the parameters in the exogenous shock processes. For purpose of illustration, we set the standard deviation of each of the first-moment shocks to \( \sigma_k = 0.01 \) and the persistence parameter to \( \rho_k = 0.90 \), for \( k \in \{a, z\} \).

For each of the second-moment shocks, we set the persistence parameter to \( \rho_{\sigma_k} = 0.76 \) in light of the estimated uncertainty shock processes in our benchmark four-variable VAR. Specifically, as shown in Figure 3, a one-standard deviation shock to consumer uncertainty raises the measured uncertainty on impact, which falls gradually to a level of about 34 percent of its peak in 12 months. This observation suggests that, if the uncertainty shock is approximated by an AR(1) process—as we assume in the model—then the persistence parameter should be about 0.913 at monthly frequencies (i.e., \( 0.913^{12} \approx 0.34 \)). In our quarterly model, this implies a value of the persistence parameter of about 0.76 (i.e., \( 0.913^3 = 0.76 \)). We set the standard deviation of each type of uncertainty shocks \( \sigma_{\sigma_k} \) so that the peak effect on unemployment in the model matches that in the VAR estimates. In particular, Figure 3
shows that a one-standard-deviation shock to consumer uncertainty raises unemployment by 0.16 percentage point at the peak. This effect represents a three percent increase in the unemployment rate (from 5.5 percent to 5.66 percent). Thus, we calibrate the standard deviation of the uncertainty shocks so that the model generates a peak response of the unemployment rate that is three percent higher than its steady-state level.

IV.2. Macroeconomic effects of uncertainty shocks. To examine the dynamic effects of uncertainty shocks, which are second-moment shocks in our model, we solve the model using third-order approximations to the equilibrium conditions around the steady state. We then compute the impulse responses following an uncertainty shock. We consider two different types of uncertainty shocks—preference uncertainty ($\sigma_{at}$) and technology uncertainty ($\sigma_{zt}$). We show that search frictions and nominal rigidities are both important for the transmission of uncertainty shocks.

IV.2.1. Macroeconomic effects of uncertainty in a flexible-price economy. We first examine the macroeconomic effects of uncertainty shocks in a flexible-price version of the DSGE model. We highlight the importance of labor search frictions for the transmission of uncertainty shocks. In particular, we show that, in our model with search frictions, uncertainty shocks impact the macroeconomy through two opposing effects: a precautionary-saving effect that is expansionary and an option-value effect that is contractionary. The net effect depends in part on the source of uncertainty.

Under our calibration, an increase in preference uncertainty leads to a decline in unemployment when prices are flexible, as shown in the top panel of Figure 12. This expansionary effect of uncertainty resembles that in the standard RBC model (e.g., Gilchrist and Williams (2005) and Basu and Bundick (2011)). In contrast, an increase in technology uncertainty leads to a rise in unemployment in the flexible-price economy.

To understand how the transmission of uncertainty shocks is affected by labor search frictions, Figure 12 plots the responses of the unemployment rate, the real interest rate, and the match value to the firm, $J_{t}^{F}$, following the two types of uncertainty shocks. As shown in equation (21), the value to the firm of filling a position depends on both the profit flow and the continuation value of the job match, with the latter discounted by the real interest rate. The figure shows that the real interest rate declines following each uncertainty shock, reflecting the increased precautionary saving motive by households when faced with higher uncertainty. All else equal, this effect should increase the present value of a job match.

\footnote{To compute the impulse responses, we first simulate the model for a large number of periods with no shocks hitting the economy. Once the economy converges to an ergodic state, we introduce a shock to uncertainty (with the calibrated size and persistence) and simulate the dynamic responses of the model variables using the decision rules computed from the third-order approximation solution.}
leading firms to post more vacancies, and ultimately resulting in a lower unemployment rate
as the job finding rate improves. However, in our model a job match represents a long-term
employment relationship that is irreversible and higher uncertainty can reduce the expected
value of a filled position, inducing firms to post fewer vacancies. Consequently, the job
finding rate declines and the unemployment rate rises. The irreversibility of a job match
is similar to investment irreversibility in Bernanke (1983). As such, we term this effect the
“option-value effect.”

Whether the precautionary saving motive or the option-value effect dominates depends
on the source of uncertainty. Under our calibration, Figure 12 shows that the match value
rises following an increase in preference uncertainty, but it falls following a rise in technol-
ogy uncertainty. This reflects the fact that the decline in the real interest rate is relatively
muted following a technology shock and is more than offset by the option-value channel.
Accordingly, unemployment falls following a preference uncertainty shock, but it rises fol-
lowing a technology uncertainty shock. This latter outcome contrasts with the expansionary
effects of uncertainty in the RBC model. Thus, these findings highlight the importance of
incorporating labor search frictions in the DSGE model for understanding the transmission
of uncertainty shocks.

IV.2.2. Aggregate demand effects of uncertainty in a sticky-price economy. In the presence
of nominal rigidities, however, an uncertainty shock is recessionary regardless of its source.
Figure 13 displays the effects of a shock to technology uncertainty. The figure shows that an
increase in uncertainty raises unemployment and lowers inflation and the nominal interest
rate. The rise in unemployment and the fall in inflation following an uncertainty shock
resembles what the effects of a decline in aggregate demand would be in the DSGE model.
Unlike in the flexible-price economy, preference uncertainty and technology uncertainty in
the model with nominal rigidities have very similar macroeconomic effects; they both raise
unemployment and lower inflation.19

When prices are sticky, the recessionary effects of uncertainty shocks work through an
aggregate demand channel. Heightened uncertainty lowers demand for retail goods and thus
for intermediate goods. The relative price of intermediate goods falls, reducing firms’ profit
flow and the value of a job match. A decline in the real wage could have mitigated the fall
in profit. However, with real wage rigidities (as we assume in the model), this mitigating
effect is dampened. Firms respond to the decline in the match value by posting fewer
vacancies. With fewer vacancies available, the job finding rate for searching workers declines
and the unemployment rate rises. As more workers are unemployed, household income falls,

19To conserve space, we do not display the impulse responses following a shock to preference uncertainty.
Those impulse responses are available in the online appendix.
reinforcing the initial decline in aggregate demand and further amplifying the recessionary
effects of uncertainty on macroeconomic activity.

Since uncertainty depresses aggregate demand, it also lowers inflation. Under the Taylor
rule, the central bank lowers the nominal interest rate to alleviate the adverse effects of
uncertainty. Nonetheless, equilibrium unemployment still rises and equilibrium inflation still
falls following a rise in uncertainty. Thus, the theory’s predictions are broadly in line with
our empirical evidence that uncertainty shocks act like a negative aggregate demand shock.

IV.3. The importance of search frictions and nominal rigidities. We have shown that
an uncertainty shock acts as a negative demand shock that depresses aggregate activity. This
effect is not unique to our model with search frictions and sticky prices. Similar effects have
also been found in the standard DSGE model without search frictions (Basu and Bundick,
2011; Fernández-Villaverde, Guerón-Quintana, Kuester, and Rubio-Ramírez, 2011). However,
incorporating search frictions is important because they interact with nominal rigidities
to amplify the aggregate demand effects of uncertainty shocks.

To illustrate the amplification mechanism for uncertainty shocks through labor search
frictions, we display in Figure 14 the Beveridge curve (BC) and the job creation curve
(JCC). The intersection of these two curves determines the equilibrium vacancy rate $v$ and
the number of unemployed searching workers $u$.\footnote{Under the timing of our model, $u$ is the number of unemployed workers who are searching for jobs. Total unemployment is the fraction of searching workers who remain without a job after matching occurs (i.e., $U = u - m$; see equation (18)).}

The Beveridge curve describes the inverse relation between $v$ and $u$ implied by the matching
technology. In particular, the matching function (13) implies that

$$v = \left( \frac{\hat{\rho}(1 - u)}{\mu} \right)^{\frac{1}{1-a}} \left( \frac{1}{u} \right)^{\frac{a}{1-a}},$$

where we have imposed the steady-state relation that $m = \frac{\rho}{1-\rho}(1 - u) \equiv \bar{\rho}(1 - u)$. This
Beveridge curve relation reveals that, for any given matching efficiency parameter $\mu$ and
elasticity parameter $a$, the vacancy rate $v$ is a convex function of the number of searching
workers $u$.

The job creation curve describes the optimal vacancy posting decision in equation (22). It
represents a positive relation between $v$ and $u$ for any given match value $J^F$ and vacancy
cost $\kappa$. In particular, the JCC is described by the relation

$$v = \left( \frac{\mu J^F}{\kappa} \right)^{\frac{1}{a}} u,$$
where we have used the definition of the vacancy filling rate \( q^v = m^v \) and the matching function (13).

First, consider the labor market equilibrium in our benchmark model. Suppose the initial (steady-state) equilibrium is at point \( A \) in Figure 14. As we discussed in the previous section, an increase in uncertainty lowers the value of a job match (i.e., \( J^F \) declines) through the aggregate demand channel. Thus, the JCC rotates downward, leading to a new equilibrium at point \( B \), with a lower vacancy rate and a higher unemployment rate. This downward rotation of the JCC predicted by the theory is consistent with the empirical responses of the labor market tightness (i.e., the \( v-u \) ratio) shown in Figure 10.

Now, consider a counterfactual economy with a smaller cost of vacancy posting \( \kappa \). In such an economy, search frictions are less important than in our benchmark economy. If vacancy costs are smaller, firms will post more vacancies, implying a higher job finding rate for a searching worker.\(^{21}\) From equation (37), a lower value of \( \kappa \) implies a higher value of \( v \) for any given \( u \). Thus, the job creation curve (the solid black line denoted by \( JCC' \)) is steeper than that in the benchmark economy (the solid blue line denoted by \( JCC \)). Accordingly, the labor-market equilibrium implies a higher vacancy rate and a lower unemployment rate (point \( A' \)). When the level of uncertainty increases, the job creation curve rotates downward along the Beveridge curve, reaching the new equilibrium at point \( B' \). As in the benchmark model, the increase in uncertainty lowers the vacancy rate and raises the unemployment rate. But because the Beveridge curve represents a convex relation between \( v \) and \( u \), the increase in unemployment in this counterfactual economy with a lower vacancy cost is smaller than that in the benchmark economy.\(^{22}\)

The quantitative importance of having both search frictions and nominal rigidities is illustrated in Figure 15. The figure shows the impulse responses of unemployment following a technology uncertainty shock. The solid line indicates the impulse responses of unemployment in the calibrated benchmark DSGE model with both search frictions and nominal rigidities. The dashed line shows the impulse responses in the flexible-price model (with \( \Omega_p = 0 \) imposed). The dashed and dotted line shows the impulse responses in a model that is identical to the benchmark model except that the vacancy cost parameter \( \kappa \) is set to a smaller value (0.05 instead of the benchmark calibration of 0.14).

Consistent with our intuition illustrated through the Beveridge curve and the job creation curve, Figure 15 shows that both search frictions and sticky prices help amplify the effects of

\(^{21}\)Our model does not completely nest the standard RBC model with a spot labor market. In the extreme case with \( \kappa = 0 \), the vacancy-posting decision problem is not well defined.

\(^{22}\)Petrosky-Nadeau and Zhang (2013) also emphasize the importance of the convexity of the Beveridge curve and the associated nonlinear dynamics for the numerical approximation of the standard search model.
uncertainty shocks. Specifically, the response of unemployment to a technology uncertainty shock in the benchmark model is about twice as large as that in a model with a smaller magnitude of search frictions and about ten times as large as that in a model with flexible prices. Thus, absent either search frictions or nominal rigidities, the effects of uncertainty shocks on unemployment would be substantially muted. A very similar pattern emerges following a preference uncertainty shock (see the online appendix).

V. Conclusion

In this paper, we study the macroeconomic effects of uncertainty shocks and show that uncertainty shocks act like aggregate demand shocks both in the data and in a DSGE model with search frictions and sticky prices.

Using novel measures of uncertainty from survey data, we document robust evidence that an uncertainty shock leads to a rise in unemployment and declines in inflation and the nominal interest rate. This result is robust to alternative measures of uncertainty, alternative identification strategies, and alternative model specifications.

To help understand the transmission mechanisms of uncertainty shocks, we present a DSGE model with search frictions and nominal rigidities. We first highlight that uncertainty shocks can be contractionary in a flexible-price economy with search frictions, in contrast to the standard RBC model. We then show that that interactions between search frictions and nominal rigidities help significantly amplify the macroeconomic effects of uncertainty shocks. Absent either frictions, the recessionary effects of an uncertainty shock would be substantially muted. Consistent with the evidence, our DSGE model predicts that an uncertainty shock—regardless of its source—raises unemployment and lowers inflation and the nominal interest rate, and thus acts like a negative aggregate demand shock.

To highlight the aggregate demand effects of uncertainty shocks, we have focused on a stylized model that abstracts from some realistic and potentially important features of the actual economy. For example, the model does not have endogenous capital accumulation and is thus not designed to study the effects of uncertainty shocks on business investment. To the extent that investment adjustments are costly, investors are likely to cut back investment expenditures when they face higher levels of uncertainty. Thus, incorporating endogenous capital accumulation in our model with search frictions may have important implications for the quantitative magnitude of the responses of potential and equilibrium output. However, in light of several recent studies in the literature (Basu and Bundick, 2011; Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2011), incorporating capital accumulation in a DSGE model with nominal rigidities is unlikely to change the qualitative transmission mechanism of uncertainty shocks that we have identified in this paper.
In our model, uncertainty shocks raise equilibrium unemployment by lowering the value of job matches, thus reducing job creation. Meanwhile, we have assumed that the job separation rate is exogenous. Therefore, the responses of equilibrium vacancy and unemployment represent a movement along the downward-sloping Beveridge curve. A more realistic model should incorporate endogenous job separation along the lines of den Haan, Ramey, and Watson (2000) and Walsh (2005), which is likely to further strengthen the aggregate demand effects of uncertainty shocks that we have studied in this paper. This should be a fruitful avenue that we intend to pursue in future research.
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REFERENCES


Table 1. Parameter calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>value</th>
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<tr>
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<td>Structural parameters</td>
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<td>$\beta$</td>
<td>Household’s discount factor</td>
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<td>$\chi$</td>
<td>Scale of disutility of working</td>
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<td>Matching efficiency</td>
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<td>$\kappa$</td>
<td>Vacancy cost</td>
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<td>$b$</td>
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<td>$\Omega_p$</td>
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<td>$\sigma_k$</td>
<td>Mean value of volatility of shock</td>
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<td>$\rho_{\sigma_k}$</td>
<td>Persistence of uncertainty shock $\sigma_{kt}$</td>
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<tr>
<td>$\sigma_{\sigma_k}$</td>
<td>Standard deviation of uncertainty shock $\sigma_{kt}$</td>
<td>(adjusted)</td>
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Figure 1. Consumers’ perceived uncertainty from the Michigan Survey of Consumers in the United States (solid line) versus the VIX/VXO index from the Chicago Board of Exchange (dashed line). The grey shaded areas indicate NBER recession dates in the United States. Data frequencies are monthly. The consumer uncertainty series starts in January 1978 and the VIX/VXO series starts in January 1986. Both series end by October 2013. Three-month moving averages are plotted.
Figure 2. Firms’ perceived uncertainty from the CBI Industrial Trends Survey in the United Kingdom. The grey shaded areas indicate recession dates in the United Kingdom. Data frequency is quarterly. Sample ranges from 1980:Q1 to 2011:Q1.
Figure 3. The effects of a one-standard deviation shock to perceived uncertainty in the Michigan Survey of Consumers: uncertainty measure ordered first. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
Figure 4. The effects of a one-standard deviation shock to perceived uncertainty in the CBI Industrial Trends Survey in the United Kingdom. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
Figure 5. Historical decomposition. The figures show the contributions of uncertainty shocks to the increases in unemployment in the Great Recession and recovery (top panel) and in the 1981-82 recession (bottom panel).
Figure 6. The effects of a one-standard deviation shock to the VIX index. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
Figure 7. The effects of a one-standard deviation shock to policy uncertainty. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
The effects of a one-standard deviation shock to perceived uncertainty in the Michigan Survey of Consumers: uncertainty measure ordered last. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
Figure 9. The effects of shock to uncertainty dummies. The solid lines represent median responses of the variables. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
Figure 10. The effects of a one-standard deviation shock to perceived uncertainty in the Michigan Survey of Consumers in the VAR model augmented with the vacancy-unemployment ratio. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
Figure 11. The effects of a one-standard deviation shock to consumers’ perceived uncertainty from the Michigan Survey in the VAR model augmented with the consumer sentiment index (current conditions). The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent error bands for the estimated median impulse responses.
Figure 12. Impulse responses to uncertainty shocks in the DSGE model with flexible prices. The first row shows the responses to preference uncertainty and the second row shows those to technology uncertainty.
Figure 13. Impulse responses of macroeconomic variables to a technology uncertainty shock in the DSGE model with sticky prices.
Figure 14. The amplification mechanism through labor market search frictions.
Figure 15. Impulse responses of unemployment to a technology uncertainty shock in the benchmark DSGE model (“Benchmark”), the flexible-price model (“Flex prices”), and a model with low vacancy costs (“Low \( \kappa \)”).