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Globalization Institute Working Paper 412

November 2021

Research Department

<https://doi.org/10.24149/gwp412>

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Monetary Policy Uncertainty and Economic Fluctuations at the Zero Lower Bound*

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August 2021

Abstract

We propose a TVP-VAR with stochastic volatility for the unemployment rate, core inflation and the federal funds rate augmented with survey-based interest rate expectations and uncertainty and a FAVAR with a wider set of observable variables and alternative monetary policy measures in order to explore U.S. monetary policy, accounting for the zero lower bound. We find that a rise in monetary policy uncertainty increases unemployment and lowers core inflation; the effects on unemployment in particular are robust (a gradual 0.4 percentage point increase), lasting more than two years after the initial shock. Interest rate uncertainty shocks explain a significant portion of macro fluctuations, particularly after the 2007-09 global financial crisis contributing to push the unemployment rate one percentage point higher during the early phase of the subsequent recovery. Furthermore, we find that higher interest rate uncertainty makes forward guidance shocks (but also federal funds rate shocks) less effective at moving unemployment and core inflation. We also posit a theoretical model to provide the structural backbone for our empirical results, via an “option value” channel. Theory yields sizeable real effects and a muted monetary policy transmission mechanism as firms choose to postpone investment decisions in response to heightened interest rate uncertainty.

JEL Codes: E30, E32, E43, E52.

Keywords: Monetary Policy Transmission Mechanism; Monetary Policy Uncertainty; Forward Guidance; Business Cycle Propagation; Survey-Based Forecasts.

* We thank Nathan S. Balke, Nicholas A. Bloom, Andrea Civelli, Stephen J. Cole, Marc P. Giannoni, Pavel S. Kapinos, John W. Keating, Aaron Mehrotra, Stephen Terry, Víctor Valcárcel, Willem VanZandweghe, Mark A. Wynne, and Carlos Zarazaga for helpful suggestions. We gratefully acknowledge the research assistance provided by Valerie Grossman, Jarod Coulter and Rebecca Hernández, the helpful comments and advice of Cameron Shelton, and the support of the Federal Reserve Bank of Dallas. All remaining errors are ours alone. Rachel Doehr worked on this paper partly as a visitor at the Federal Reserve Bank of Dallas, whose support is sincerely appreciated, while at Claremont McKenna College. Rachel Doehr contributed to this paper in her personal capacity. The information, views, and opinions expressed herein are solely her own and do not necessarily represent the views of Point72. Point72 is not responsible for, and did not verify for accuracy, any of the information contained herein. The views expressed in this paper are also those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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1. Introduction

The study of the macroeconomic effects of uncertainty has seen a substantial spike in interest in recent years. Given the current international and domestic political environment dominated by economic, trade, and policy uncertainty, this research could not be more relevant. While there have been periods of broad uncertainty, interest rate uncertainty—or confusion and speculation on the future path of interest rates—has received much less attention, even though the Federal Reserve has had a hand on it given that spikes in policy uncertainty can result from less clarity or vagueness in communicating the Federal Reserve’s own policies and actions.

Uncertainty regarding future interest rate movements, like general uncertainty, is of great concern to policymakers. As [Cooley et al. \(1984, p. 468\)](#) neatly reminds us, [[Lucas \(1976\)](#)] *“has expressed the view that it makes no sense to think of the government as conducting one of several possible policies while at the same time assuming that agents remain certain about the policy rule in effect.”* [Filardo and Hofmann \(2014\)](#) argue, therefore, that managing interest rate expectations (or forward guidance) has important effects on the economy that central banks must recognize. First, forward guidance policies are effective at moving the public’s expectations on the future path of the short-term interest rate. Second, forward guidance is seen as an effective tool to lower interest rate uncertainty.¹

[Doehr and Martínez-García \(2015\)](#) examine the first of these effects, asking the question of what the ultimate macroeconomic impact of shocking short-term interest rate expectations is. These authors find that short-term interest rate expectations are in and of themselves highly significant drivers of today’s unemployment and inflation. The natural research question that then follows is what are the implications of the second effect cited by [Filardo and Hofmann \(2014\)](#)—in other words, how shocks to interest rate uncertainty affect the macroeconomy. Similarly, as detailed in [Borio and Zabai \(2018\)](#)’s review of monetary policy tools, the empirical

¹ [Filardo and Hofmann \(2014\)](#) also note that forward guidance can make financial markets less sensitive to subsequent news shocks that occur after the forward guidance commitment is announced. These effects can also be important from the point of view of policymakers to the extent that an effective forward guidance policy can make the economy more resilient to financial risks, for instance.

evidence regarding the effectiveness of forward guidance is still unclear. As such, we seek to bring further clarity to the issue of how forward guidance propagates from the perspective of how it interacts with interest rate uncertainty.

In this paper, we contribute to this growing strand of literature by focusing on interest rate uncertainty, and examining its role in the broader economy, particularly as it relates to the use of forward guidance. Given that forward guidance is a key policy tool whose importance has become more apparent since the federal funds rate hit the zero lower bound (henceforth, ZLB) constraint, it is crucial to assess the effects that monetary policy uncertainty shocks have had above and beyond what can be attributed to forward guidance's role in shifting expectations about the future interest rate path.

The main contribution of our work comes from our extensive empirical analysis exploring the evidence on the macro effects of monetary policy uncertainty in the U.S., while accounting for the nonlinearities arising from the ZLB. Multiple sources of survey data and ways of measuring interest rate uncertainty and a stylized theoretical model that provides a structural framework for analyzing the role of interest rate uncertainty bring additional clarity to the empirical analysis.

First, at a high level, our workhorse theoretical model predicts a real options effect, or "wait and see" effect akin to that found in the investment under uncertainty literature, in which higher interest rate risk depresses economic activity today, as firms prefer to postpone major investment decisions until they have more certainty regarding the future path of interest rates. The theoretical model also provides a tractable structural framework that illustrates the hypothesis of non-linearities in the economy regarding the transmission of monetary policy uncertainty and the response to other policy shocks. Simply put, we show that higher levels of interest rate uncertainty and poor economic conditions can cause firms to be less sensitive on the aggregate to policy actions taken by the central bank.

Second, we use multiple measures of interest rate uncertainty, built from a variety of survey data, in conjunction with a time-varying-parameter vector autoregression (TVP-VAR) with stochastic volatility to analyze the impact of such uncertainty shocks. By allowing the

parameters to vary over time in the sample, the analysis allows us to directly compare any shifts in dynamics due to the presence of the ZLB since 2008. We also focus in on the ZLB in particular, using a factor-augmented VAR (FAVAR) to further dissect the impact of interest rate uncertainty shocks using a broader selection of variables such as financial market indicators, trade flows, etc. Finally, we empirically test the hypothesis that the economy is less sensitive to policy actions taken in the form of exogenous anticipated (news) and unanticipated (surprises) monetary policy shocks when interest rate uncertainty is high.

Summarizing our findings, we find corroborating evidence that supports the significant impact that interest rate uncertainty has on the direct and indirect effects of managing interest rate expectations, particularly when at or near the ZLB. An exogenous rise in monetary policy uncertainty depresses economic activity and inflation today, both at and away from the ZLB, with effects lasting well over two years after the initial shock in the case of economic activity (core inflation rebounds somewhat quicker). Similarly, we also deploy a FAVAR model that allows us to show how financial markets and household wealth get hit as equity and home values decrease concurrently with the pause put on investment decisions made by firms waiting for the interest rate path to become more certain. At the same time, we find significant non-linearities in the results, as measures of economic activity and inflation become less responsive to shocks to either the federal funds rate (surprises) or interest rate expectations (forward guidance news), showing that higher uncertainty further ties the hands of policymakers.

Ultimately, the results of this paper provide some validation for the idea of monetary policy “decisiveness” in lieu of monetary policy “correctness,” suggested by [Bloom \(2009\)](#). The simple act of wavering around monetary policy plans—in particular, a lack of clear communication to the public regarding what those plans may be—can be detrimental to the economy in and of itself. The fascination about interest rate policy and FOMC meeting outcomes by the public, egged on by the media in an ever more connected world, can end up resulting in similar spikes in interest rate uncertainty further constraining the efficacy of monetary policy, even without any action or statements made by the central bank. A robust

communication strategy on the part of the Federal Reserve can prevent those spikes in policy uncertainty while better supporting the economy even when policy itself does not or cannot change.

The rest of the paper is organized as follows: [Section 2](#) presents the theoretical model deriving the main hypothesis about interest rate uncertainty arising from the option value of waiting channel, [Section 3](#) introduces the data and methodologies used to investigate our research question, [Section 4](#) presents all our main empirical findings, and [Section 5](#) concludes. The [Appendix](#) provides a detailed list of all variables and sources used in our empirical analysis.

2. A Theory of Monetary Policy Risk and Irreversible Investment

[Bloom \(2009\)](#), [Bloom \(2014\)](#), [Born and Pfeifer \(2014\)](#), [Leduc and Liu \(2016\)](#), [Basu and Bundick \(2017\)](#), and [Arellano *et al.* \(2019\)](#), among many others, have investigated the macroeconomic effects—and more recent papers like [Balke *et al.* \(2021\)](#) have also explored the nonlinearities—arising from both aggregate uncertainty and micro-uncertainty. These theoretical and empirical contributions are largely motivated by the notion that uncertainty impacts real economic activity because firms can choose to postpone their investment when uncertainty heightens—in the literature this has become known as the option value of waiting channel. While this rationale hinges on the relationship between uncertainty and the returns to capital investment ([Dixit and Pindyck \(1994\)](#)), less well-understood is how monetary policy uncertainty in particular influences the investment decisions of firms and, by extension, economic activity.

To explore the implications of the option value of waiting for monetary policy uncertainty, we focus on the investment decisions of firms modeling their optimization problem in continuous-time with an investment irreversibility constraint (see, e.g., [Hartman \(1972\)](#), [Bernanke \(1983\)](#), [Abel \(1983\)](#), [McDonald and Siegel \(1986\)](#), [Bertola and Caballero \(1994\)](#), [Abel and Eberly \(1994\)](#), [Dixit and Pindyck \(1994\)](#), [Abel and Eberly \(1997\)](#), and [Calcagnini and Saltari \(2000\)](#)). Unlike much of the earlier work on investment irreversibility and uncertainty, we posit monopolistically competitive firms introducing a degree of market power. We consider a technological constraint whereby marginal returns to capital are diminishing and the optimal

capital investment decision is incremental (of the barrier control type). A tractable analytical solution can be found taking as given a constant elasticity of variance (CEV) process for the short-term interest rate (the central bank’s policy rate) whose volatility captures in a reduced-form way—and is directly caused by—monetary policy uncertainty.

With this stylized theoretical framework, we proceed to investigate the nonlinear effects of the level and volatility of the policy rate as well as the role of aggregate economic conditions on the investment decision of firms.

2.1 The Short-Term Interest Rate Process

We adopt the one-factor CEV process introduced by [Cox and Ross \(1976\)](#), but without drift as in [Cox et al. \(1980\)](#) and [Calcagnini and Saltari \(2000\)](#), in order to model the short-term interest rate. Our CEV process specifies the short-term nominal interest rate, i , as follows:

$$di = \sigma i^{\frac{3}{2}} dW, \quad i_0 > 0, \quad (1)$$

where W is a standard Wiener process. The parameter $\sigma \geq 0$ scales up the interest rate volatility, $\sigma i^{\frac{3}{2}}$, and is assumed to be less than 1 (i.e., $\sigma < 1$).² The stochastic process given by (1) is viewed as purely exogenous by the firms’ making investment decisions and as capturing monetary policy uncertainty in a reduced-form way through interest rate volatility (risk).³

There are multiple economically-relevant approaches to measure monetary policy uncertainty in this context. To illustrate this, let us first express the stochastic process given by (1) in discrete time as $i_{t+1} - i_t = \varepsilon_{t+1}$, $E(\varepsilon_{t+1}) = 0$, and $E(\varepsilon_{t+1}^2) = \sigma^2 i_t^3$. Conditional on the information available up to time t , the expectation of i_{t+h} for any forecasting horizon $h \geq 1$ is

² A CEV model without drift can be generalized to take the form: $di = \sigma i^\tau dW$, $\sigma, \tau \geq 0$. The additional assumptions that $\sigma < 1$ and $\gamma = \frac{3}{2}$ which we impose on equation (1) are not required to define a well-behaved CEV process, but are sufficient conditions to obtain a well-behaved closed-form solution for the investment problem with and without irreversibility that we investigate in this paper. It should be noted that the parameter τ plays an important role regulating the relationship between the interest rate level and volatility. Whenever $\tau < 1$, a leverage effect can be expected whereby the volatility of the interest rate increases as the interest rate falls; in turn, whenever $\tau > 1$ as is the case in (1), an inverse leverage effect arises implying that the volatility increases as the interest rate increases. This inverse leverage effect is a feature of our specification.

³ In other words, interest rate volatility movements are sensitive to public announcements about the current and future path of the interest rate and, in particular, on the “certainty” being conveyed by policymakers about the future path of interest rates.

simply $E_t(i_{t+h}) = i_t$. Hence, the forecasting error implied by the model in equation (1) becomes $e_{t,h} \equiv i_{t+h} - E_t(i_{t+h}) = i_{t+h} - i_t = \sum_{z=1}^h (i_{t+z} - i_{t+z-1})$ or, alternatively, $e_{t,h} \equiv \sum_{z=1}^h \varepsilon_{t+z}$. Given this, the standard deviation of the forecasting error, which is a commonly-used measure of uncertainty, is tied to the volatility of the process in (1), i.e.

$std_t(e_{t,h}^j) = \sum_{z=1}^h std_t(\varepsilon_{t+z}) = \left(\sum_{z=1}^h E_t(\varepsilon_{t+z}^2) \right)^{\frac{1}{2}} = \sigma \left(\sum_{z=1}^h i_{t+z-1}^3 \right)^{\frac{1}{2}}$. This shows that this measure of uncertainty captures the degree of monetary policy risk that private agents face in this interest rate environment.

There are other ways to measure monetary policy uncertainty too. First, we can compute the cumulative correction of each interest rate prediction (or a transformation of it) from $t+1$ to $t+h$ for a given forecast horizon $h \geq 1$ after expanding the information set available at $t-1$ to include all information up to time t , i.e.

$\sum_{z=1}^h (E_t(i_{t+z}) - E_{t-1}(i_{t+z})) = h(i_t - i_{t-1}) = h\varepsilon_t = he_{t-1,1}$. This uncertainty measure is motivated by the logic that greater uncertainty about the policy path tends to be associated with larger corrections of the expected path over time. As can be seen from our simple calculations, given the process in (1), this is tied back to the realized forecasting error at time t , i.e. to

$e_{t-1,1} \equiv i_t - E_{t-1}(i_t) = \varepsilon_t$.⁴ Second, we can also measure uncertainty in terms of the cross-sectional dispersion of forecasts (forecasting disagreement) assuming, in the spirit of [Lahiri and Sheng \(2010\)](#), that private agents form their forecasts using public and possibly private signals about the interest rate path of varying precision. In that scenario, the forecast of individual j ,

$E_t^j(i_{t+h})$, contains an idiosyncratic error term $u_{t,h}^j$ such that $E_t^j(i_{t+h}) = E_t(i_{t+h}) + u_{t,h}^j = i_t + u_{t,h}^j$

and its corresponding forecasting error $e_{t,h}^j \equiv i_{t+h} - E_t^j(i_{t+h}) = i_{t+h} - i_t - u_{t,h}^j = e_{t,h} - u_{t,h}^j$ becomes

$e_{t,h}^j = \kappa_j e_{t,h}$ when $u_{t,h}^j$ is proportional to the forecasting error $e_{t,h}$ such that $u_{t,h}^j \equiv (1 - \kappa_j) e_{t,h}$.

κ_j captures the degree of forecasting accuracy of j 's signals that varies across forecasters and is constant over time. Hence, calculating forecast disagreements with the cross-sectional

⁴ In our empirical analysis, we calculate this measure in absolute values adding those up across all forecasters surveyed in the data. Such transformation is more practical because the data can have sizeable corrections of opposing signs at different horizons that cancel out partially when added together.

dispersion or with the interquartile range of all forecasters ties these measures of uncertainty to the dispersion of the forecast error $e_{t,h}$ and, ultimately, to the volatility of the interest rate process in equation (1).

2.2 The Final Good Sector

Aggregate final output in the economy is homogenous and of the Dixit-Stiglitz type. There is a final good producer that operates under perfect competition and uses a constant elasticity of substitution (CES) production function with intermediate goods as the only inputs:

$$Y = \left[\sum_{j=1}^n \xi_j^{\frac{1}{\theta}} y_j^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \quad (2)$$

where Y is the final good output, y_j is the good purchased from each intermediate firm indexed $j = 1, \dots, n$, n is the number of intermediate good firms, $\xi_j > 0$ indicates the steady state shares of each intermediate good in the final good bundle and satisfies that $\sum_{j=1}^n \xi_j = 1$, and $\theta > 1$ is the elasticity of substitution among the different intermediate goods.⁵ The final good firm maximizes nominal profits according to

$$\max_{\{y_j\}} \left\{ PY - \sum_{j=1}^n P_j y_j \text{ s.t. } Y = \left[\sum_{j=1}^n \xi_j^{\frac{1}{\theta}} y_j^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \right\}. \text{ It follows from this that the demand for the}$$

intermediate good j is downward sloping and can be expressed as:

$$y_j = \xi_j p_j^{-\theta} Y, \quad (3)$$

where $p_j = \frac{P_j}{P}$ is the price of intermediate good j in units of the final good computed as the ratio of the nominal price of the intermediate good, $P_j > 0$, over the nominal price of the final

good $P = \left[\sum_{j=1}^n \xi_j P_j^{1-\theta} \right]^{\frac{1}{1-\theta}} > 0$. From here it also holds that $\left[\sum_{j=1}^n \xi_j p_j^{1-\theta} \right]^{\frac{1}{1-\theta}} = 1$.

⁵ Whenever $\theta \rightarrow +\infty$, the CES bundle in (2) converges to a linear aggregate bundle where all goods are perfect substitutes of each other. In that case, the gross markup on the price of intermediate goods that arises under monopolistic competition, $\frac{\theta}{\theta-1} > 1$, converges to one and we achieve the same allocation as would be expected under perfect competition.

2.3 The Intermediate Goods Sector and the Investment Problem

Each intermediate firm j sells its differentiated good under monopolistic competition producing its output, y_j , subject to a Cobb-Douglas production $y_j \equiv A_j F(K_j, L_j) = A_j L_j^\beta K_j^\alpha$. Labor is denoted L_j , K_j is the stock of capital, and A_j is the exogenous firm-specific productivity, while the production elasticities with respect to labor and capital are $\beta > 0$ and $\alpha > 0$, respectively. We invert the production function to obtain the labor demand of the intermediate firm j conditional on the capital stock K_j and the firm's output y_j as

$$L_j(K_j) = \left(\frac{y_j}{A_j K_j^\alpha} \right)^{\frac{1}{\beta}}.$$

Given this, the intermediate firm j sets to maximize its short-run nominal operating profits Π_j —the revenue minus the cost of the variable factor of production (labor)—subject to the downward sloping demand curve in equation (3) as follows:⁶

$$\Pi_j(K_j) \equiv \max_{y_j} P \left[p_j y_j - w_j L_j(K_j) \right] \equiv \max_{p_j} P \left[\xi_j p_j^{1-\theta} Y - w_j \left(\frac{\xi_j p_j^{-\theta} Y}{A_j K_j^\alpha} \right)^{\frac{1}{\beta}} \right], \quad (4)$$

s.t. $y_j = \xi_j p_j^{-\theta} Y$

where $w_j \equiv \frac{W_j}{P}$ is the real wage in units of the final good and W_j is the nominal wage. Under the assumption that labor is homogenous and can costlessly move across firms, it follows that all intermediate firms pay the same real wage for their workers and, therefore, $w_j = w, \forall j$.

The first-order condition from the intermediate firm j 's optimization problem in (4) is:

$$p_j(K_j) = \left(\frac{\theta}{\theta-1} \frac{w}{\beta A_j^{\frac{1}{\beta}} (\xi_j Y)^{1-\frac{1}{\beta}}} \right)^{\frac{\beta}{\beta+\theta(1-\beta)}} K_j^{\frac{-\alpha}{\beta+\theta(1-\beta)}}, \quad (5)$$

⁶ The literature recognizes that there are strategic considerations that can introduce differences in the option value of waiting across firms that depend on the timing at which each firm moves relative to its competitors (see, e.g., [Moretto \(2000\)](#)). We abstract from those considerations for tractability, but also because these strategic complementarities are absent in the class of general equilibrium models that explore the option value of waiting channel which motivated our own exploration.

which shows that the optimal price is ultimately a function of the capital stock the intermediate firm owns, K_j , plus a set of exogenous variables (the firm-specific productivity A_j) and aggregate ones (real wages w and aggregate output Y).⁷ Combining the equilibrium first-order condition in (5) with the demand equation for intermediate firm j in (3), it follows that the intermediate good firm's output is equal to:

$$y_j(K_j) = \left(\frac{\theta}{\theta-1} \frac{w}{\beta A_j^{\frac{1}{\beta}} (\xi_j Y)^{\frac{1}{\theta}}} \right)^{\frac{-\theta\beta}{\beta+\theta(1-\beta)}} K_j^{\frac{\alpha\theta}{\beta+\theta(1-\beta)}}, \quad (6)$$

and the real operating profit in units of the final good, $\pi_j(K_j) = \frac{\Pi_j(K_j)}{P}$, is:

$$\pi_j(K_j) = C_j w^{-\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} K_j^\gamma, \quad (7)$$

where

$$\gamma \equiv \frac{\alpha(\theta-1)}{\beta+\theta(1-\beta)},$$

$$C_j \equiv \left(\frac{\beta+\theta(1-\beta)}{\theta} \right) \left(\frac{\beta(\theta-1)}{\theta} \right)^{\frac{\beta\gamma}{\alpha}} \left((\xi_j)^{\frac{1}{\theta-1}} A_j \right)^{\frac{\gamma}{\alpha}}.$$

Output and real operating profits can again be expressed in terms of the intermediate firm j 's own stock of capital, K_j , plus the same set of exogenous (A_j) and aggregate variables (w, Y).

We assume diminishing marginal returns to capital in the sense that the marginal real operating profit $\frac{\partial \pi_j(K_j)}{\partial K_j} > 0$ must be positive but decreasing in K_j or, put differently, the real

operating profit function must be increasing and concave in K_j , i.e. $\frac{\partial \pi_j(K_j)}{\partial K_j} > 0$ and

$\frac{\partial^2 \pi_j(K_j)}{\partial K_j^2} < 0$. Given that under standard assumptions $K_j > 0$ and $C_j > 0$ (as well as $w > 0$

⁷ An externality arises here because the decisions of each individual firm will determine the aggregates (w, Y), yet each firm sees itself as small and takes those aggregates as out of their control when making their own decisions.

and $Y > 0$), it follows that the real operating profit function in (7) is increasing and convex on capital as long as the deep structural parameters satisfy that $0 < \gamma \equiv \frac{\alpha(\theta-1)}{\beta+\theta(1-\beta)} < 1$.

Therefore, given that we have already assumed that $\beta, \alpha > 0$ and $\theta > 1$, the increasing and convex properties of the real operating function hold if we also verify that $\beta < \frac{\theta}{\theta-1}$ and

$\alpha + \beta < \frac{\theta}{\theta-1}$.⁸ Under those additional parameter constraints, the marginal real operating profit is positive and decreasing in K_j even in certain cases where the technology displays increasing-returns-to-scale (i.e., for some cases where $\alpha + \beta > 1$).

The intermediate firm j chooses whether to install dK_j^g new units of capital (gross investment). Installed capital exponentially decays following a Poisson process with $0 \leq \delta \leq 1$ indicating the constant depreciation rate. Hence, the change dK_j in the capital stock (net investment) can be expressed as:

$$\begin{aligned} dK_j^g &= X_j dt, \\ dK_j &= dK_j^g - \delta K_j dt. \end{aligned} \tag{8}$$

Gross investment X_j is subject to an irreversibility constraint so intermediate firm j 's decision must also satisfy that:

$$X_j \geq 0. \tag{9}$$

Each unit of capital added through gross investment costs $p_k > 0$ units of the final good.

Hence, the optimal investment strategy of intermediate firm j is to maximize the expected present value of the firm's nominal net cash-flows—nominal operating profits, $\Pi_j(K_j)$, minus the costs of gross investment, $p_k X_j$ —as:

⁸ $\alpha + \beta < \frac{\theta}{\theta-1}$ is the only binding constraint given that it suffices to guarantee, together with $\alpha > 0$, that $\beta < \frac{\theta}{\theta-1}$.

$$\begin{aligned}
V_j(K_j, i) &= \max_{\{X_j(s)\}} E_t \left[\int_t^\infty \exp\left(-\int_t^s i(u) du\right) P(s) \left[\pi_j(K_j(s)) - p_k X_j(s) \right] ds \right] \\
&= \max_{\{X_j(s)\}} E_t \left[\int_t^\infty \exp\left(-\int_t^s i(u) du\right) P(s) \left[C_j w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} K_j^\gamma - p_k X_j(s) \right] ds \right], \quad (10)
\end{aligned}$$

subject to the law of motion in (8) and the irreversibility constraint in (9). In (10), the fundamental value of the intermediate firm j at time t is given in nominal terms by $V_j(K_j, i)$ while $E_t(\cdot)$ denotes the expectations operator conditional on all information available up to t .

Accordingly, the fundamental value of the intermediate firm j satisfies the following Bellman equation:

$$\begin{aligned}
iV_j &= \max_{X_j \geq 0} \left[P \left(C_j w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} K_j^\gamma - p_k X_j \right) + \frac{E[dV_j]}{dt} \right] \\
&\text{s.t. } dK_j = (X_j - \delta K_j) dt
\end{aligned} \quad (11)$$

The right-hand side of (11) has two components: one being the instantaneous nominal net cash flow, $P \left(C_j w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} K_j^\gamma - p_k X_j \right)$; the other one being the expected capital gain, $\frac{E[dV_j]}{dt}$.

The left-hand side of (11) equals the financial return from the resources tied to intermediate firm j , iV_j , which accrue from placing the fundamental value of the firm V_j on an asset that earns the prevailing interest rate i . This leads to the standard arbitrage implication that the expected return from investing in firm j must equate the market return given by i .

Given the stochastic process assumed for the interest rate in (1), applying Ito's Lemma to derive $E_t[dV_j]$ we obtain that:

$$E_t[dV_j] = \left(\frac{\partial V_j}{\partial K_j} dK_j + \frac{1}{2} \frac{\partial^2 V_j}{\partial i^2} \sigma^2 i^3 \right) dt = \left(\frac{\partial V_j}{\partial K_j} (X_j - \delta K_j) + \frac{1}{2} \frac{\partial^2 V_j}{\partial i^2} \sigma^2 i^3 \right) dt. \quad (12)$$

If we substitute equation (12) into the Bellman equation in (11), we obtain:

$$iV_j = \max_{X_j \geq 0} \left[P w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^\gamma + \frac{1}{2} \frac{\partial^2 V_j}{\partial i^2} \sigma^2 i^3 + \left(\frac{\partial V_j}{\partial K_j} - P p_k \right) X_j - \frac{\partial V_j}{\partial K_j} \delta K_j \right]. \quad (13)$$

Maximizing the right-hand side of equation (13) along the investment region (where $X_j > 0$),

we obtain the following first-order condition: $\frac{\partial V_j}{\partial K_j} = Pp_k$. In other words, the marginal increase

in the value of intermediate firm j from another unit of capital must equate the cost of that additional capital. Replacing out this first-order condition, equation (13) becomes:

$$iV_j = Pw^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^\gamma - Pp_k \delta K_j + \frac{1}{2} \frac{\partial^2 V_j}{\partial i^2} \sigma^2 i^3, \quad (14)$$

which constitutes a second-order ordinary differential equation (albeit a tractable one).

A particular solution to the Bellman equation (14) is

$$V_j(K_j, i) = P \frac{w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^\gamma - p_k \delta K_j}{i(1-\sigma^2)}. \text{ This corresponds to the fundamental value of the}$$

intermediate firm j under reversible investment.⁹ Incorporating the investment irreversibility constraint in (9), the complete solution to (14) equals the sum of that same particular solution plus the solution of the homogenous part of the ordinary differential equation. In other words, the complete solution is given by:

$$V_j(K_j, i) = P \frac{w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^\gamma - p_k \delta K_j}{i(1-\sigma^2)} + B_{1j}(K_j) i^{\phi_1}, \quad (15)$$

where $B_{1j}(K_j)$ is a scaling factor that varies with the capital stock K_j and $\phi_1 = \frac{1}{2} - \sqrt{\frac{1}{4} + \frac{2}{\sigma^2}}$ is the negative root of the characteristic equation (i.e., the economically-relevant root of the quadratic equation $\phi^2 - \phi - \frac{2}{\sigma^2} = 0$). The second term of the solution in (15), the solution to the homogenous part, captures the option value of waiting as it describes the value the firm attaches to expanding its capital stock in the future under irreversible gross investment. The negative root ϕ_1 implies that this option value term decreases when interest rates increase.

⁹ In a purely deterministic counterfactual where $\sigma^2 = 0$, the particular solution is equivalent to the present discounted value of the net cash-flow of the intermediate firm.

Using the first-order condition $\frac{\partial V_j}{\partial K_j} = Pp_k$ for $X_j > 0$, we obtain that:

$$P \frac{\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta}{i(1-\sigma^2)} + \frac{\partial B_{1j}}{\partial K_j} i^{\phi_1} = Pp_k, \quad (16)$$

which is the corresponding value-matching condition. As shown in Chapter 11 by [Dixit and](#)

[Pindyck \(1994\)](#), a smooth-pasting condition which requires that $\frac{\partial^2 V_j}{\partial i \partial K_j} = 0$ must also be

satisfied by the fundamental value function. Hence, it must hold that:

$$-P \frac{\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta}{i^2(1-\sigma^2)} + \frac{\partial B_{1j}}{\partial K_j} \phi_1 i^{\phi_1-1} = 0. \quad (17)$$

Using the value-matching and smooth-pasting conditions in (16) and (17), we can eliminate

$\frac{\partial B_{1j}}{\partial K_j}$ to obtain that:

$$i = \left(\frac{\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta}{p_k(1-\sigma^2)} \right) \left(1 + \frac{1}{\phi_1} \right), \quad (18)$$

from where it also follows that

$$\frac{\partial B_{1j}}{\partial K_j} = \frac{P \gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta}{\phi_1 i^{1+\phi_1} (1-\sigma^2)} = \frac{Pp_k}{(1+\phi_1)} \left(\left(\frac{\gamma C_j K_j^{\gamma-1} - p_k \delta}{p_k(1-\sigma^2)} \right) \left(1 + \frac{1}{\phi_1} \right) \right)^{-\phi_1} \text{ or, alternatively,}$$

that $\frac{\partial B_{1j}}{\partial K_j} = \frac{Pp_k}{(1+\phi_1)} i^{-\phi_1}$.¹⁰ Note that $\phi_1 < 0$ and, moreover, that $|\phi_1| > 1$ as long as $\sigma^2 < 1$, so it

¹⁰ Using the solution for $\frac{\partial B_{1j}}{\partial K_j}$ we can find B_{1j} itself by integration as:

$$B_{1j} = \int_{K_j}^{\infty} \frac{\partial B_{1j}}{\partial K_j} dk_j = \frac{Pp_k}{(1+\phi_1)} \left(1 + \frac{1}{\phi_1} \right)^{-\phi_1} (p_k(1-\sigma^2))^{\phi_1} \int_{K_j}^{\infty} \left(\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j k_j^{\gamma-1} - p_k \delta \right)^{-\phi_1} dk_j. \text{ For this to converge, additional}$$

conditions on the deep structural parameters are needed. For instance, if $\delta = 0$, then convergence is guaranteed if $\phi_1 > \frac{1}{1-\gamma}$.

follows that $0 < \left(1 + \frac{1}{\phi_1}\right) < 1$ and accordingly the right-hand side of (18) must stay nonnegative if

$\gamma w \frac{\beta\gamma}{\alpha} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} \geq p_k \delta$. Indeed, for simplicity, we will assume that the initial stock of capital

K_{0j} must also satisfy that $\gamma C_{0j} w_0 \frac{\beta\gamma}{\alpha} Y_0^{\frac{\gamma}{\alpha(\theta-1)}} K_{0j}^{\gamma-1} > p_k \delta$.

Using the value-matching and smooth-pasting conditions in (16) and (17), we can write

$\frac{\partial V_j}{\partial K_j}$ as $\frac{\partial V_j}{\partial K_j} = P \frac{\gamma w \frac{\beta\gamma}{\alpha} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta \left(1 + \frac{1}{\phi_1}\right)}{i(1-\sigma^2)}$. Since we assume the operating profit

function displays diminishing returns to capital, we can infer from it that $\frac{\partial V_j}{\partial K_j} > 0$ is decreasing

in capital K_j (or, in other words, that $\frac{\partial^2 V_j}{\partial K_j^2} < 0$). The implication from all of this being that,

while the first-order condition for the investment region where $X_j > 0$ is given by $\frac{\partial V_j}{\partial K_j} = P p_k$,

the inaction region where $X_j = 0$ must satisfy the following inequality $\frac{\partial V_j}{\partial K_j} \leq P p_k$.

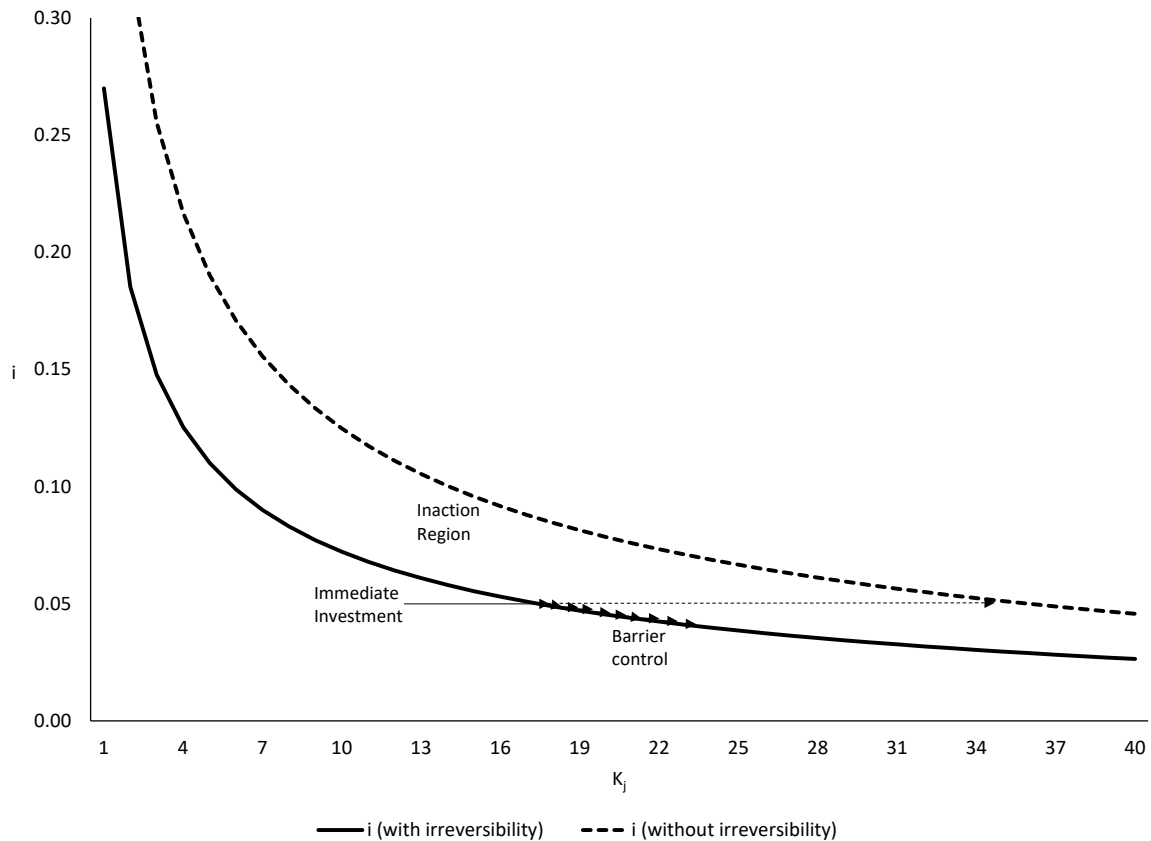
2.4 Main Takeaways

Equation (18) describes a locus of points in the (K_j, i) -space as illustrated in [Figure 1](#) below—the solid line shows the locus under irreversible investment while the dashed line maps the corresponding locus with reversible investment. Above or to the right of the plotted locus (K_j, i) , no investment is made. If interest rates fall or the capital stock decays through depreciation to meet the curve and cross it, the optimal investment policy is to invest just enough to stop that crossing from happening. This is shown in [Figure 1](#) as a series of small steps indicating a phase of gradual investment—an investment policy of the barrier control type that

This additional parameter restriction is necessary, albeit not always sufficient, for most economically-relevant cases where the depreciation rate is close to zero but positive ($\delta > 0$).

prevents the state variable (the firm's capital stock K_j) of the controlled system from crossing over the barrier (equation (18)). If after a phase of barrier control the system moves inside the inaction region, investment stops until interest rates fall or capital depreciates enough to hit the barrier again. We do not find the system below or to the left of the barrier except perhaps for a given (K_{0j}, i_0) at the initial period. In that case, the stock of capital is immediately increased by a horizontal discrete jump large enough to land the system on the barrier. Such discrete jumps in the capital stock only occur at the initial period.

Figure 1. Investment Policy with Diminishing Returns for Intermediate Firm j



Note: The dashed lines represent the locus of capital and interest rate points whenever the firm does not face an irreversibility constraint while the benchmark solid line represents the relationship when the firm faces such a constraint on investment.

Comparing the solid and dashed lines on [Figure 1](#) shows that the irreversibility constraint means that the intermediate firm j would require a lower interest rate to support a

given capital stock K_j than when gross investment is reversible.¹¹ This shows that the inaction region is larger under irreversible investment because the irreversibility constraint makes it valuable for firms to keep the option to wait unused rather than give it up to undertake new capital investments at the present moment.

The characterization of the barrier control described in (18) can be used to analyze the effect of differences in the second moment of the interest rate stochastic process given by (1) and to investigate the role the aggregate state of the economy plays:

Prediction 1. Given that by construction $\frac{\partial^2 \pi_j(K_j)}{\partial K_j^2} < 0$, we know that $\frac{\partial \pi_j(K_j)}{\partial K_j} > 0$

must be decreasing in K_j . Hence, everything else equal, capital must be higher when interest rates are lower along the barrier control described in (18), i.e.

$$\frac{\partial}{\partial K_j}(i) = (\gamma - 1)\gamma \left(\frac{w \frac{\beta\gamma}{\alpha} Y^{\alpha(\theta-1)} C_j K_j^{\gamma-2}}{p_k (1-\sigma^2)} \right) \left(1 + \frac{1}{\phi_1} \right) < 0. \quad (19)$$

Prediction 2. We find that greater interest rate risk as implied by a higher value of σ^2 has two concurring effects: first, the return on capital adjusted for depreciation increases, since

$$\frac{\partial}{\partial \sigma^2} \left(\frac{\gamma w \frac{\beta\gamma}{\alpha} Y^{\alpha(\theta-1)} C_j K_j^{\gamma-1} - p_k \delta}{p_k (1-\sigma^2)} \right) = \frac{\gamma w \frac{\beta\gamma}{\alpha} Y^{\alpha(\theta-1)} C_j K_j^{\gamma-1} - p_k \delta}{p_k (1-\sigma^2)^2} > 0; \text{ second, the option value}$$

under irreversible investment also increases given that $\frac{\partial}{\partial \sigma^2}(\phi_1) = \left(\frac{1}{(\sigma^2)^2 \sqrt{\frac{1}{4} + \frac{2}{\sigma^2}}} \right) > 0$ which, in

turn, has the implication that $\frac{\partial}{\partial \sigma^2} \left(1 + \frac{1}{\phi_1} \right) = - \left(\frac{(1-\sigma^2)}{\phi_1^2 (\sigma^2)^2 \sqrt{\frac{1}{4} + \frac{2}{\sigma^2}}} \right) < 0$.

¹¹ The counterpart of (18) assuming reversible gross investment is simply $i = \left(\frac{\gamma C_j w \frac{\beta\gamma}{\alpha} Y^{\alpha(\theta-1)} K_j^{\gamma-1} - p_k \delta}{p_k (1-\sigma^2)} \right)$.

Accordingly, under irreversible gross investment, the total effect of an increase in σ^2 on the stock of capital that firms end up owning can be ambiguous depending on which one of those two effects dominate. Given our assumption of the stochastic process of the interest rate in equation (1), the option value effect turns out to dominate and $\frac{\partial}{\partial \sigma^2}(i) < 0$. Hence interest rate risk shifts the barrier control towards the origin, as can also be seen in [Figure 1](#) comparing the cases with $\sigma^2 > 0$ and with $\sigma^2 = 0$. To see how this works out mathematically, we use equation (18) to write:

$$\begin{aligned}
\frac{\partial}{\partial \sigma^2}(i) &= \left(\frac{\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta}{p_k (1-\sigma^2)^2 \phi_1^2} \right) \left[\phi_1 (\phi_1 + 1) - \left(\frac{(1-\sigma^2)}{(\sigma^2)^2 \sqrt{\frac{1}{4} + \frac{2}{\sigma^2}}} \right) \right] \\
&= \left(\frac{\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta}{p_k (1-\sigma^2)^2 \phi_1^2} \right) \left[\phi_1 (\phi_1 + 1) - \frac{(\phi_1^2 - \phi_1 - 2) \phi_1 (\phi_1 - 1)}{2 - 4\phi_1} \right] \\
&= - \left(\frac{\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-1} - p_k \delta}{p_k (1-\sigma^2)^2} \right) \left[\frac{(\phi_1 + 1)^2}{2 - 4\phi_1} \right] < 0.
\end{aligned} \tag{20}$$

The implication of $\frac{\partial}{\partial \sigma^2}(i) < 0$ is that an increase in interest rate risk σ^2 reduces the desired capital stock or, alternatively, lowers the interest rate that would incentivize the firm to invest. Therefore, that increased risk makes it more profitable to keep the option to wait unused and delay investment even at the expense of letting the installed capital continue to depreciate. Moreover, the effect of interest rate risk on the slope of the barrier control is:

$$\frac{\partial}{\partial \sigma^2} \left(\frac{\partial}{\partial K_j}(i) \right) = (1-\gamma) \left(\frac{\gamma w^{\frac{\beta\gamma}{\alpha}} Y^{\frac{\gamma}{\alpha(\theta-1)}} C_j K_j^{\gamma-2}}{p_k (1-\sigma^2)^2} \right) \left[\frac{(\phi_1 + 1)^2}{2 - 4\phi_1} \right] > 0. \tag{21}$$

Equation (21) shows that while lower interest rate risk—resulting from a clearer communication strategy that lowers monetary policy uncertainty—shifts the locus of points on the barrier control away from the origin, reduces the inaction region and supports larger stocks of capital, that same lowering of the interest rate risk has the simultaneous effect of making capital investment decisions respond by less to declines in the interest rate along the barrier

control. In other words, the size of the economic stimulus through investment that can be achieved from a decline in the interest rate is more substantial in periods of high interest rate risk (or high monetary policy uncertainty).

Prediction 3. Lower levels of economic output Y which tend to be associated with higher unemployment levels too—indicating that the aggregate economy is going through a recessionary period—shift the locus of the barrier control towards the origin enlarging the inaction region for firms:

$$\frac{\partial}{\partial Y}(i) = \frac{\gamma}{\alpha(\theta-1)} \left(\frac{\gamma w \frac{\beta\gamma}{\alpha} Y^{\alpha(\theta-1)-1} C_j K_j^{\gamma-1}}{p_k (1-\sigma^2)} \right) \left(1 + \frac{1}{\phi_1} \right) > 0. \quad (22)$$

Moreover, along the barrier control we expect that a low aggregate level of economic activity Y , *ceteris paribus*, should imply that investment responds more strongly to declines in the interest rate than when economic activity is high:

$$\frac{\partial}{\partial Y} \left(\frac{\partial}{\partial K_j}(i) \right) = (\gamma-1) \frac{\gamma}{\alpha(\theta-1)} \left(\frac{\gamma w \frac{\beta\gamma}{\alpha} Y^{\alpha(\theta-1)-1} C_j K_j^{\gamma-2}}{p_k (1-\sigma^2)} \right) \left(1 + \frac{1}{\phi_1} \right) < 0. \quad (23)$$

These types of nonlinearities in the response of capital investment to the interest rate hinted at in equations (21) and (23) will be an important consideration in our subsequent empirical analysis. Apart from that, we argue that the option-value-of-waiting effects brought forth by our theory of irreversible investment offer a plausible interpretation for our evidence which shows that, even in an environment of low (or near zero) interest rates, greater monetary policy uncertainty contributes to significantly dampen economic activity. Theory also puts the emphasis squarely on the real effects of monetary policy uncertainty consistent with our empirical findings which indicate that the impact of monetary policy uncertainty on nominal variables (core inflation) is only very modest by comparison.¹²

¹² Unlike most of the existing models that explicitly incorporate different forms of aggregate uncertainty into otherwise standard New Keynesian models, our theory does not feature nominal price stickiness yet it produces an endogenous degree of stickiness in relative prices. Intuitively, this is because the optimal pricing given by (5) implies that the intermediate firm j 's capital K_j changes slowly only through depreciation when in the inaction region, adjusting through gross investment at the barrier control. In principle, the heterogeneity across firms means that some of them will fall in the inaction region while others

3. Dataset

We use U.S. interest rate forecasts from Blue Chip Economic Indicators (BCEI) from [Aspen Publishers \(2015\)](#), a survey of leading private forecasters, to construct our uncertainty proxies, as well as to gauge monetary policy expectations. The BCEI provides the panel’s median one quarter, two quarter, three quarter, and four quarter ahead forecasts of fifteen different macroeconomic variables, in addition to the top 90th percentile and the bottom 10th percentile forecast, at monthly frequency. We use the longest consistent forecast horizon available (four quarters ahead) of the three-month Treasury bill to measure interest rate expectations and the disagreement among forecasters. We then take the reported median forecast four quarter ahead as our interest rate expectations measure and the cross-sectional dispersion of the forecasts, calculated as the difference between the top 90th percentile and the bottom 10th percentile, as our benchmark monetary policy uncertainty measure ($uncert_{t,t+4}^{10,90}$).

We rely on BCEI forecast dispersion as our preferred measure of monetary policy uncertainty for a variety of reasons. First, measures of cross-sectional disagreement derived from survey data have been suggested elsewhere in the literature as a reasonable way to portray uncertainty as we do here (see, e.g., [Bomberger \(1996\)](#), [Patton and Timmerman \(2010\)](#), [Lahiri and Sheng \(2010\)](#), or [Bachmann et al. \(2013\)](#) to mention but a few).¹³ Second, we tease out monetary policy uncertainty from the survey data on interest rate forecast disagreement to avoid confounding known default or other risks unrelated to monetary policy that are reflected in the existing financial volatility measures with monetary policy uncertainty.¹⁴ Finally, survey data comes with a consistent median interest rate forecast—unlike alternative text-analytic

move along the barrier control. However, the full exploration of the aggregate implications of the real rigidity (investment irreversibility) that underlies this observation lies beyond the scope of the paper and we leave it for future research.

¹³ Survey-based measures that use forecast errors offer another related way of describing uncertainty as illustrated by [Binge and Boshoff \(2020\)](#), among others. [Bachmann et al. \(2013\)](#) and, more recently, [Hur \(2018\)](#) argue that *ex ante* macro forecast disagreements tend to be strongly correlated with the dispersion in *ex post* forecast errors. However, relying on *ex post* forecast errors instead of forecasting disagreement for interest rate expectations, while undoubtedly captures some aspects of uncertainty, may be more prone to confounding as forecast errors also reflect a measure of “wrongness” – forecasters can be completely certain and in close agreement while proven incorrect about the future path that the interest rate takes, resulting in *ex post* large forecast error while cross-sectional dispersion of *ex ante* forecasts is low.

¹⁴ Equity market volatilities are broad measures encompassing forms of uncertainty other than what we specifically aim to capture – monetary policy uncertainty – while credit market volatility measures like the Ted spread (or various ARCH measures) confound perceived default risk along with interest rate uncertainty, again not reflecting pure monetary policy uncertainty.

measures of monetary policy uncertainty advocated by [Husted et al. \(2020\)](#), among others—which is central to our empirical analysis, as we aim to disentangle the macroeconomic effects of interest rate expectations management from reducing policy uncertainty vs. signaling the path of future rates.

The BCEI survey data provides a rich picture of the forecasters’ interest rate expectations in real time. As robustness checks, however, we also use several alternative measures of monetary policy uncertainty. We utilize data from the Survey of Professional Forecasters (SPF) from the [Federal Reserve Bank of Philadelphia \(2015\)](#), which surveys a panel of economists and offers their individual forecasts for a variety of macroeconomic variables. The dataset is at a quarterly frequency (instead of the monthly frequency of BCEI) but contains the entire panel of forecasts for the three-month Treasury bill one quarter ahead, two quarters ahead, three quarters ahead, and four quarters ahead. Having the entire panel, rather than simply the 10th percentile, median, and 90th percentile as we do with the BCEI data allows us to construct alternative measures of monetary policy uncertainty:

- $uncert_{t,t+4}^{10,90}$: we calculate the difference between the 90th and the 10th percentile on the expected three-month Treasury rate four quarters ahead as we do with the BCEI data, to test the same measure of uncertainty, only with a new data source;
- $uncert_{t,t+4}^{\sigma}$: we use the standard deviation of the cross-sectional forecasts of the three-month Treasury bill rate four quarters ahead;
- $uncert_{t,t+4}^{\Delta}$: we compute the absolute value of the sum of the quarterly revisions each forecaster makes to their expectations up to four quarters ahead, to capture their wavering around their forecasts, i.e. uncertainty is calculated adding up

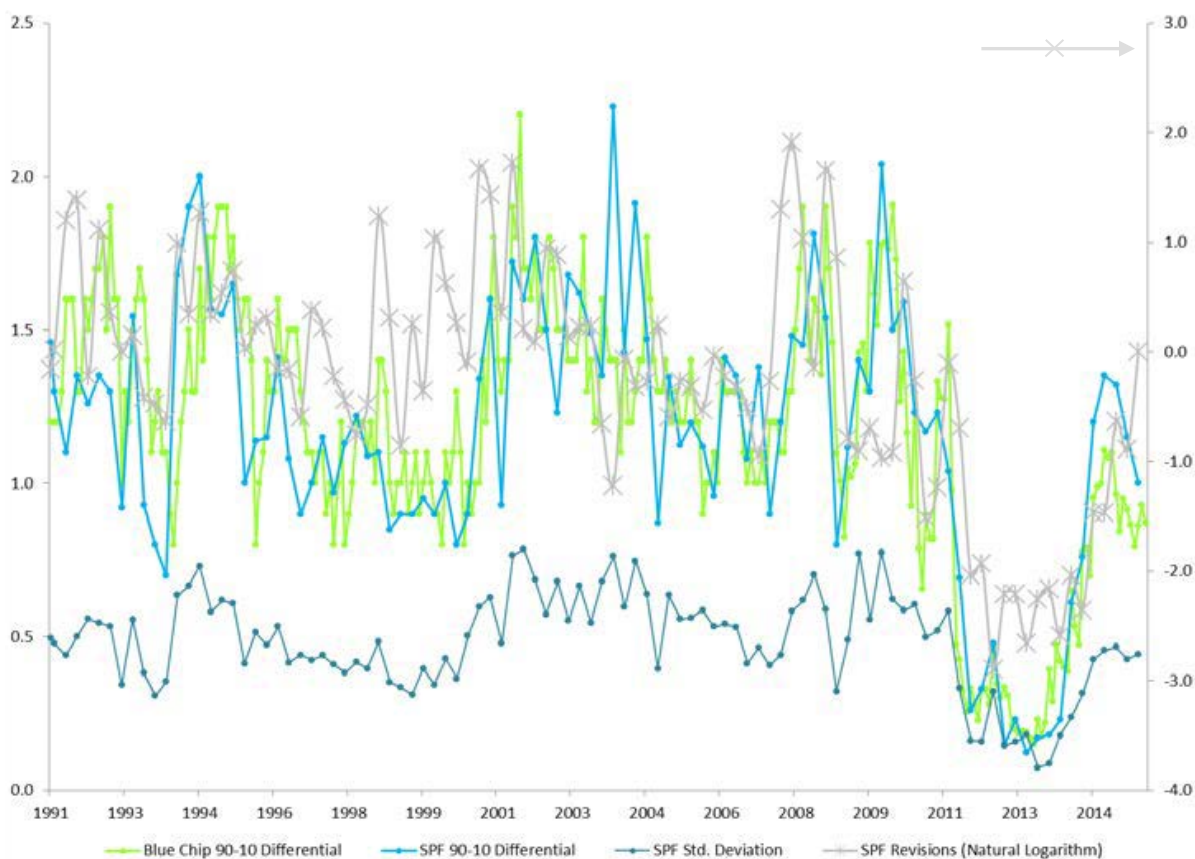
$$uncert_{t,t+4}^{\Delta} = |E_t(i_{t+4}) - E_{t-1}(i_{t+4})| + |E_t(i_{t+3}) - E_{t-1}(i_{t+3})| + |E_t(i_{t+2}) - E_{t-1}(i_{t+2})| + |E_t(i_{t+1}) - E_{t-1}(i_{t+1})|$$

across all forecasters.¹⁵

¹⁵ Each quarter, forecasters are given an opportunity to record their expectations of interest rates one, two, three, and four quarters in the future. As any particular quarterly forecast comes closer and closer to becoming the “nowcast” each quarter, private forecasters re-record their expectations for the same quarter, updated by however their opinions about the future have changed. Thus, the magnitude of how much they revise those previously held expectations reflects how much forecasters are internally wavering around their beliefs about future conditions, or the certainty of their forecast horizon.

All uncertainty measures computed with BCEI and SPF data are plotted quarterly in [Figure 2](#).

Figure 2. Monetary Policy Uncertainty Measures



Note: All data is plotted at quarterly frequency averaging the monthly BCEI 90-10 differential ($uncert_{t,t+4}^{10,90}$). The SPF uncertainty-revisions measure ($uncert_{t,t+4}^A$) is transformed in logs and plotted on the secondary axis. The period covered starts in 1991:Q3 and ends in 2015:Q2.

Apart from the U.S. monetary policy uncertainty and interest rate expectations measures, all other U.S. variables used in our empirical analysis—the core inflation rate, the civilian unemployment rate, and the federal funds rate—were obtained from the [Federal Reserve Bank of St Louis \(2015\)](#)'s FRED database.¹⁶ All data in our benchmark empirical model is at a monthly frequency from 1991:M7 through 2015:M7 to match the frequency of the survey

¹⁶ As in [Doehr and Martínez-García \(2015\)](#), we rely on the unemployment as our preferred measure of economic activity because it is less subject to data revisions—like the other variables in the benchmark model—than real GDP or real investment would be. The unemployment rate is the relevant concept of economic activity for the Federal Reserve given that its dual mandate establishes it that way. Moreover, the unemployment rate is also available at monthly frequency which has the practical benefit of allowing us to keep the monthly frequency of the benchmark model when using BCEI survey data.

data from BCEI, while all data in our alternative empirical models is at quarterly frequency from 1991:Q3 through 2015:Q2, to match the frequency of the SPF panel dataset.¹⁷

We also investigate an augmented empirical specification that exploits the survey data from BCEI together with a broad-range of 40 macro and financial variables obtained from the [Federal Reserve Bank of St Louis \(2015\)](#)'s FRED database, the financial market dataset constructed by [Shiller \(2016\)](#) (cyclically adjusted price-to-earnings and dividend yields), and the house price and exchange rate data from [Mack and Martínez-García \(2011\)](#) and [Grossman et al. \(2014\)](#).¹⁸ All this data is at quarterly frequency from 2000:Q3 through 2015:Q2. The shorter sample here is due to data availability limitations and the lower frequency due to the difficulty in obtaining consistent monthly data for some of the macro variables such as real GDP or government expenditures. Thus, all monthly data were converted into quarterly data using simple averaging.

4. Empirical Findings

4.1 Direct Effects of Monetary Policy Uncertainty

The specification of our benchmark empirical model draws from the theory laid out in [Section 2](#) but allows for a richer specification of the macro relationships partly motivated by the findings of [Doehr and Martínez-García \(2015\)](#). [Doehr and Martínez-García \(2015\)](#) augment a traditional three variable VAR (based on core inflation, unemployment, and the federal funds rate) with interest rate expectations, ultimately showing that shocks to anticipated future monetary policy can drive movements in real economic activity today. These authors showed that the current level of the federal funds rate alone, even away from the ZLB, may not fully capture the stance of the central bank which also depends on the expected path of the future interest rate. Similarly, we postulate here on theoretical grounds that not only anticipated and

¹⁷ Our sample period does not include the Federal Reserve's gradual liftoff phase that began with a quarter-point increase in December 2015, raising the federal funds rate band to a range between 0.25 and 0.5 percent. In restricting our sample in this way, we aim to focus our attention only on how monetary policy (forward guidance, in particular) managed interest rate expectations (by signaling the path of future rates and/or reducing monetary policy uncertainty) as U.S. policymakers confronted the ZLB for the first time in the post-WWII period.

¹⁸ A detailed description of all the data we use in this paper and the sources can be found in Tables [A1](#) and [A2](#) in the [Appendix](#).

current monetary policy are important macroeconomic drivers, but that the uncertainty surrounding those expectations can also be a significant force in and of itself.

Our benchmark five-variable specification—monetary policy uncertainty, monetary policy expectations, core inflation, unemployment, and the federal funds rate—allows us to explicitly differentiate between shocks to the traditional policy tool, the federal funds rate, news shocks regarding anticipated future monetary policy, and shocks to uncertainty about future monetary policy. In this way, we are able to tease out the relative quantitative importance and dynamics of each. We argue that when addressing the issue of accurately modeling monetary policy forward guidance, only capturing the effects of a shock to anticipated monetary policy, and not the concurring effects of monetary policy uncertainty movements, would potentially underestimate the aggregate effect on the economy. Yet, we also recognize that media speculation and hype—even without any forward guidance from the central bank—could catalyze an exogenous shock to monetary policy uncertainty as well, albeit one that is out of the policymakers’ direct control. The five variable VAR specification that we use as our benchmark allows us to simultaneously analyze all of these dynamics.

Another key aspect of how we chose to examine the direct effects of monetary policy uncertainty is that of allowing the parameters in the VAR to vary over time. Given the significant shift in the dynamics of anticipated monetary policy at the ZLB found in [Doehr and Martínez-García \(2015\)](#), we adopt a time-varying parameter VAR (henceforth, TVP-VAR) specification with stochastic volatility as our framework of reference, permitting the parameters to vary each month (or quarter, depending on the specific model) to better capture any nonlinearities present in the data. Introducing stochastic volatility is particularly relevant at the ZLB to accommodate the large decline in the federal funds rate volatility (and that of other variables) during that period.

4.1.1 Empirical Methodology

TVP-VARs are widely used in the applied literature to capture the possible time-varying nature of the macroeconomy. After [Primiceri \(2005\)](#) popularized the TVP-VAR model which allows for all parameters to vary over time, many papers followed exploring a variety of aspects

of the time-varying structure of the macroeconomy with this methodology (see, e.g., [Benati and Mumtaz \(2007\)](#), [Baumeister et al. \(2008\)](#), [D'Agostino et al. \(2011\)](#), and [Bekiros \(2014\)](#), among many others). Given our goal of examining the underlying structural shifts in the U.S. economy in the presence of nonlinearities, particularly in regards to the transmission of monetary policy uncertainty and shocks to interest rate expectations at the ZLB, we also utilize the TVP-VAR modeling framework but augmented with stochastic volatility.

Allowing stochastic volatility in the TVP-VAR framework helps us capture both temporary and permanent shifts in parameters, including those that occur in the volatility of the disturbances ([Blake and Mumtaz \(2017\)](#)).¹⁹ When the true data generating process has both time-varying coefficients as well as stochastic volatility shocks, then using a model that exclusively allows coefficients to vary and assumes constant volatility may potentially bias estimates. As noted earlier, this is of particular importance when modeling the economy at the ZLB, as we do here. The ZLB truncates possible downward movements in both the federal funds rate itself, as well as in the 3-month Treasury bill expectations, driving a significant reduction in the ability of those two variables to fluctuate. Hence, a TVP-VAR with stochastic volatility captures more flexibly the role of the ZLB in the transmission of monetary policy throughout the macroeconomy than a model where the volatility of the disturbances of the interest rate, interest rate expectations, and even monetary policy uncertainty is constant.

We estimate the p th-order TVP-VAR model with stochastic volatility given by:

$$\begin{aligned} y_t &= X_t^T \beta_t + A_t^{-1} \Sigma_t \varepsilon_t, \\ X_t^T &= I_{n \times n} \otimes [1, y_{t-1}^T, \dots, y_{t-p}^T], \quad \forall t = p+1, \dots, \bar{T}, \end{aligned} \tag{24}$$

where y_t is an $n \times 1$ column-vector of n different endogenous variables, X_t is a Kronecker product of the $n \times n$ identity matrix, β_t is an $n(np+1) \times 1$ column-vector of the effects of the p lags of the endogenous variables plus a constant intercept, and \bar{T} is the sample size. The error

¹⁹ Modeling the time-varying second moments of shocks with stochastic volatility is a fairly standard practice in the literature to more easily account for possible heteroskedasticity of the disturbances, particularly when specifying an empirical model with financial shocks or, as we do ourselves, with monetary-policy-related shocks ([Nakajima et al. \(2011\)](#)). This is further confirmed by earlier works such as that of [Stock and Watson \(1996\)](#) who show that models with no time variation in coefficients do poorly in the presence of structural instability and showing that permitting significant time variation in the volatilities is key to improving the model fit.

term ε_t is a column-vector of size $n \times 1$, the matrix of standard deviations Σ_t is diagonal and time-varying:

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}, \quad (25)$$

and the matrix A_t that captures the contemporaneous relationships is lower triangular and also time-varying:

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{2,1,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n,1,t} & \cdots & \alpha_{n,n-1,t} & 1 \end{bmatrix}. \quad (26)$$

The reduced form to be estimated takes the form described in (24)-(26) above where all the time-varying coefficients follow random walks without drift and all the time-varying standard deviations follow geometric random walks without drift:

$$\begin{aligned} \beta_{j,t} &= \beta_{j,t-1} + u_t^j, \quad j = 1, \dots, n(np+1), \\ \alpha_{j,t} &= \alpha_{j,t-1} + v_t^j, \quad j = 1, \dots, \frac{(n^2-n)}{2}, \\ \ln(\sigma_{j,t}) &= \ln(\sigma_{j,t-1}) + w_t^j, \quad j = 1, \dots, n. \end{aligned} \quad (27)$$

The vector of innovations is assumed to be jointly normally distributed as follows:

$$\begin{bmatrix} \varepsilon_t \\ u_t \\ v_t \\ w_t \end{bmatrix} \sim N \left(0, \begin{bmatrix} I_{n \times n} & 0 & 0 & 0 \\ 0 & U_{n(np+1) \times n(np+1)} & 0 & 0 \\ 0 & 0 & V_{\frac{(n^2-n)}{2} \times \frac{(n^2-n)}{2}} & 0 \\ 0 & 0 & 0 & W_{n \times n} \end{bmatrix} \right), \quad (28)$$

where ε_t is the matrix of errors terms and $u_t = (\dots, u_t^j, \dots)'$, $v_t = (\dots, v_t^j, \dots)'$, and $w_t = (\dots, w_t^j, \dots)'$ consist of the innovations introduced in (27) and (28) above. The conforming matrices U , V , and W are positive definite. Moreover, V is assumed to be block diagonal implying that innovations to contemporaneous effects are uncorrelated across equations.

Consistent with the Bayesian approach, a Gibbs sampler is used to evaluate the posterior distribution of the unobservable states $\beta_{j,t}$, $\alpha_{j,t}$, and $\ln(\sigma_{j,t})$ together with the hyperparameters U , V , and W . In order to evaluate the posterior, we first need to specify the prior distributions of the parameters. The hyperparameters U , V , and W follow the independent inverse Wishart distribution while the priors for the initial states of the coefficients $\alpha_{i,t}$, $\beta_{j,t}$, and $\ln(\sigma_{j,t})$ are normally distributed. The hyperparameters and initial states are assumed to be independent. The priors are chosen to be largely consistent with those of [Primiceri \(2005\)](#), and slightly tighter than those used by [Nakajima \(2011\)](#), attributing more of the time variation to the volatility of the disturbances ($\ln(\sigma_{j,t})$) rather than the coefficients ($\beta_{j,t}$) themselves. We use a subset of the data set estimated through ordinary least squares to form estimations used in the specification of the prior distributions—specifically, the first 84 months (7 years) of the time series which entails that our estimates will cover the period from 1998:M7 (1998:Q3) onwards. The Gibbs sampler provides us with draws from the conditional posteriors over subsets of the parameter set and the data. From those, the sampler iteratively produces a numerical evaluation of the posterior.²⁰

To recover the impulse-response functions (henceforth, IRF's) after the initial model estimation, we identify five shocks (to monetary policy uncertainty, interest rate expectations, the federal funds rate, core inflation, and unemployment) by using sign restrictions on the contemporaneous reactions of the five observed endogenous variables to each shock.²¹ Sign restrictions are a manner in which we can incorporate some key theoretical implications on the estimation of the TVP-VAR framework with stochastic volatility ([Franta \(2011\)](#)). Indeed, using structural assumptions in the form of sign restrictions let us relax the oftentimes theoretically-inconsistent assumptions of the more typical recursive ordering under Cholesky, that shocks to some endogenous variables do not have any simultaneous effects on those that come before them in the recursive ordering. Moreover, sign restrictions offer us a flexible way to handle

²⁰ See [Blake and Mumtaz \(2017\)](#) for a detailed explanation of Bayesian estimation of TVP-VARs with stochastic volatility.

²¹ See [Franta \(2011\)](#) for a more technical (and detailed) explanation of the Bayesian estimation procedure using sign restrictions in TVP-VARs with stochastic volatility.

nonlinearities stemming from the floor on interest rates, that is, from the ZLB by permitting some unrestricted signs.²²

We base our sign restrictions on assumptions about the behavior of the shocks, imposing qualitative information requirements on the IRF's. We consider four different types of restrictions: positive, negative, zero, or unidentified as suggested by [Faust \(1998\)](#) and [Uhlig \(2005\)](#) and summarize our choices in [Table 1](#). Responses to shocks to monetary policy uncertainty or the effect of other shocks on monetary policy uncertainty are always left unspecified. We do explore in theory a plausible underlying mechanism for the transmission of monetary policy uncertainty (risk) in [Section 2](#), but purposefully take an agnostic view about the signs in our empirical analysis to let the data speak for itself. However, we can anticipate that the empirical evidence we uncover in our subsequent analysis turns out to be qualitatively consistent with the real effects that we predicted in theory earlier without being imposed by construction by means of identified (positive, negative, zero) sign restrictions chosen *a priori* to be consistent with the theory itself.

Other sign restrictions are taken to be consistent with the expected sign of the response given the current state of the literature—particularly, based on results found in [Doehr and Martínez-García \(2015\)](#) from their estimates of a four variable panel VAR that includes interest rate expectations in addition to inflation, unemployment, and the federal funds rate. The sign restrictions we impose on the effects from shocks to core inflation, unemployment, and the federal funds rate follow from their findings as well as from standard economic theory. The restrictions imposed on the effects from shocks to interest rate expectations account for the reversal in the response of economic activity at the ZLB documented by [Doehr and Martínez-García \(2015\)](#) by leaving that response unspecified, while restricting the response of core inflation in a manner consistent with the evidence presented by those same authors.

²² Other papers in the literature examine the transmission of monetary policy at the ZLB imposing assumptions from the very beginning of the estimation, such as treating the interest rate as a censored variable, using a Markov-switching VAR, or estimating a censored VAR where the latent variable captures the stance of monetary policy and equals the interest rate if it exceeds zero (see [Iwata and Wu \(2006\)](#), [Fujiwara \(2006\)](#), and [Nakajima \(2011\)](#)).

Table 1. Contemporaneous Sign Restrictions

	<i>Monetary Policy Uncertainty Shock</i>	<i>Monetary Policy Expectations Shock</i>	<i>Core Inflation Shock</i>	<i>Unemployment Shock</i>	<i>Federal Funds Rate Shock</i>
<i>Interest Rate Uncertainty</i>	+	Unidentified	Unidentified	Unidentified	Unidentified
<i>Interest Rate Expectations</i>	Unidentified	+	0	0	0
<i>Core Inflation</i>	Unidentified	-	+	-	-
<i>Unemployment Rate</i>	Unidentified	Unidentified	-	+	+
<i>Federal Funds Rate</i>	Unidentified	Unidentified	+	-	+

To gauge the quantitative importance of monetary policy uncertainty shocks in conjunction with a TVP-VAR, we also construct a historical decomposition of unemployment and core inflation. To do so, we adapt the procedure used by [Cesa-Bianchi \(2015\)](#) for building a sign-restricted historical decomposition to allow for time-varying coefficients, looping over time and appropriately indexing in the median draw of each time-period’s coefficients that correspond to the given residuals in the decomposition.²³

The model estimation and additional procedures were performed in Matlab using two lags of the endogenous variables ($p = 2$).²⁴ A sample of 10,000 iterations of the Gibbs sampler is used, discarding the first 2,000 for convergence.

4.1.2 Results

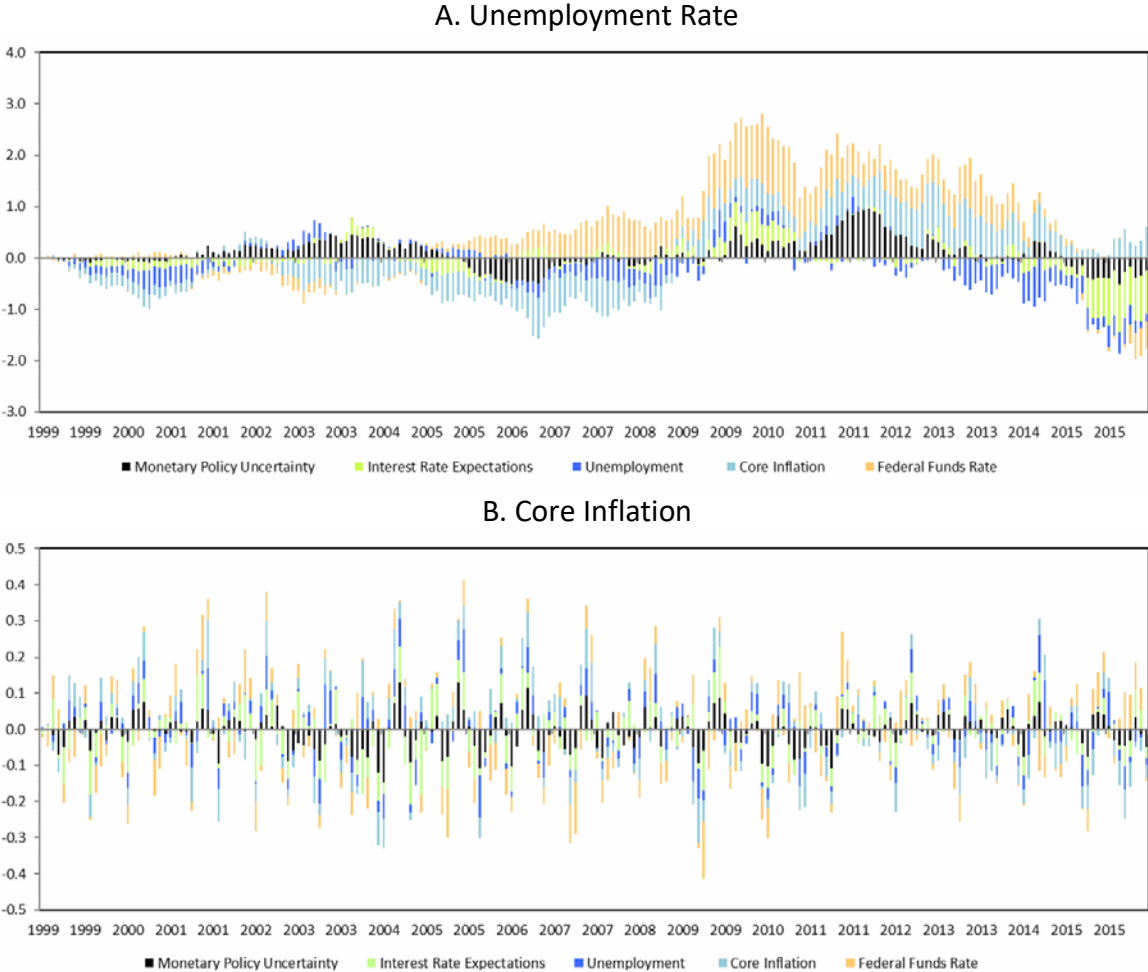
Our findings show that monetary policy uncertainty plays a significant and direct role in the broader economy. The benchmark model yields several significant insights regarding the

²³ See [Ambrogio Cesa-Bianchi \(2015\)](#) for the original historical decomposition code.

²⁴ The model uses code for a TVP-VAR with stochastic volatility and sign restrictions, made publicly available by Haroon Mumtaz at: <https://sites.google.com/site/hmumtaz77/>.

interplay between uncertainty and real economic variables. We first examine the quantitative importance of monetary policy uncertainty through the lens of a historical decomposition exercise, then turn to the IRFs themselves to further explore the dynamics and propagation of monetary policy uncertainty shocks.

Figure 3. Time-Varying Parameter Historical Decompositions: Benchmark Model



Note: TVP-VAR model with stochastic volatility. Monthly BCEI data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{10,90}$). Data from 1991:M7 through 2015:M7.

As seen in [Figure 3](#), the historical decomposition extracted from the five variable benchmark model shows that monetary policy uncertainty has proved to be a key driver of both unemployment and core inflation, accounting for movements in the unemployment rate of, on average, roughly 0.5 percentage points. In the aftermath of the 2007-09 global financial crisis (henceforth, GFC), shocks to monetary policy uncertainty pushed the unemployment rate up by

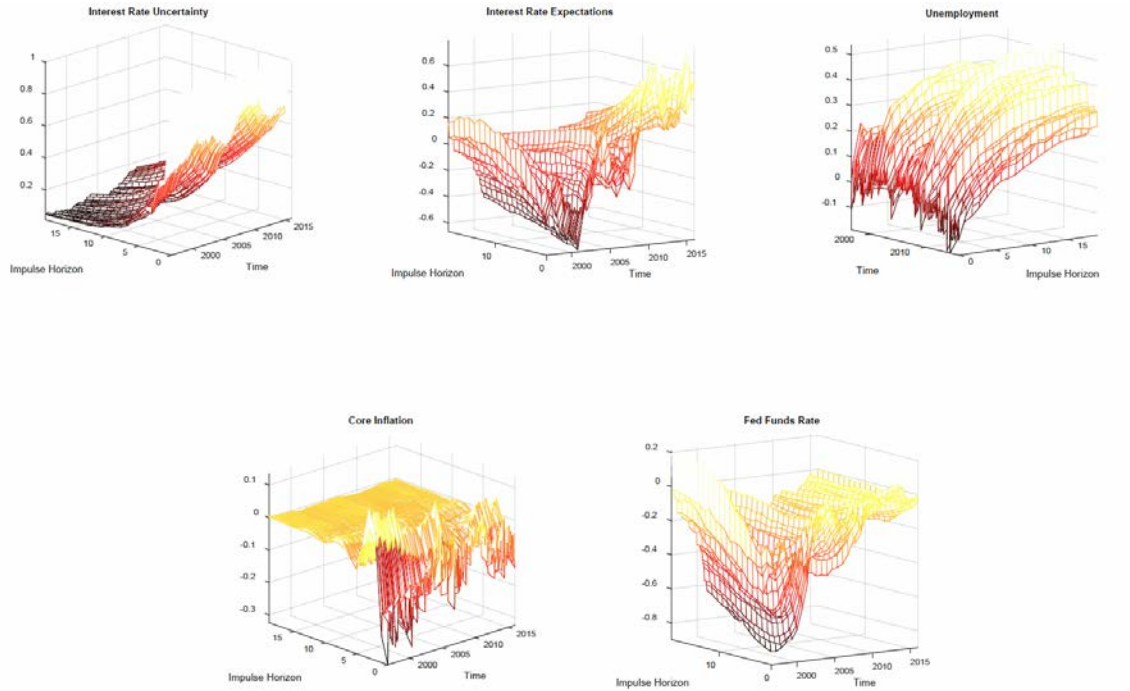
approximately 1.0 percentage point, and continued to depress employment until 2013. Overall, shocks to monetary policy uncertainty are on par with—and sometimes more significant than—shocks to both the federal funds rate and anticipated monetary policy (interest rate expectations shocks) in regard to their quantitative importance in shaping economic activity, particularly at the ZLB. Similarly, monetary policy uncertainty has explained more modest movements of as much as 0.2 percentage points in the core inflation rate, and appears as a quantitatively non-negligible driver of inflation fluctuations at the ZLB and away from it.

Given the importance of monetary policy uncertainty in driving economic activity, we next turn to the particular dynamics of uncertainty shocks. The key IRFs from the five variable, sign-restricted TVP-VAR benchmark model are presented in [Figure 4](#), showing the responses over 20 months during the time period 2001–2015 (pre- and post-GFC) to a one standard deviation shock to monetary policy uncertainty. One can clearly see that the response of output and core inflation to an increase in monetary policy uncertainty has remained relatively constant over time, even at the ZLB. An increase in monetary policy uncertainty leads to increased unemployment and depressed inflation. The response of unemployment, a gradual 0.4 percentage point increase in the unemployment rate, is sustained and lasts beyond the 20-month horizon in our plots. Core inflation, in turn, responds with a quick decrease of roughly 0.2 percentage points, lasting around six months before dissipating.

While the effects of a movement in uncertainty are largely time invariant, the effects of other shocks on uncertainty are not. [Figure 5](#) shows the responses to a positive one standard deviation shock to anticipated monetary policy (interest rate expectations). This shows, among other effects, how a shock to anticipated monetary policy—forward guidance—affects monetary policy uncertainty itself. Prior to the ZLB, monetary policy uncertainty remained nearly independent of fluctuations in interest rate expectations. During the ZLB period, however, an increase in expected interest rates leads to a significant spike in uncertainty, of a maximum value of 2.5. In turn, the effect of forward guidance was minimal on uncertainty before the ZLB. Putting this change in the context, the remarkably large reaction of monetary policy uncertainty to increases in future expected interest rates at the ZLB—the higher policy

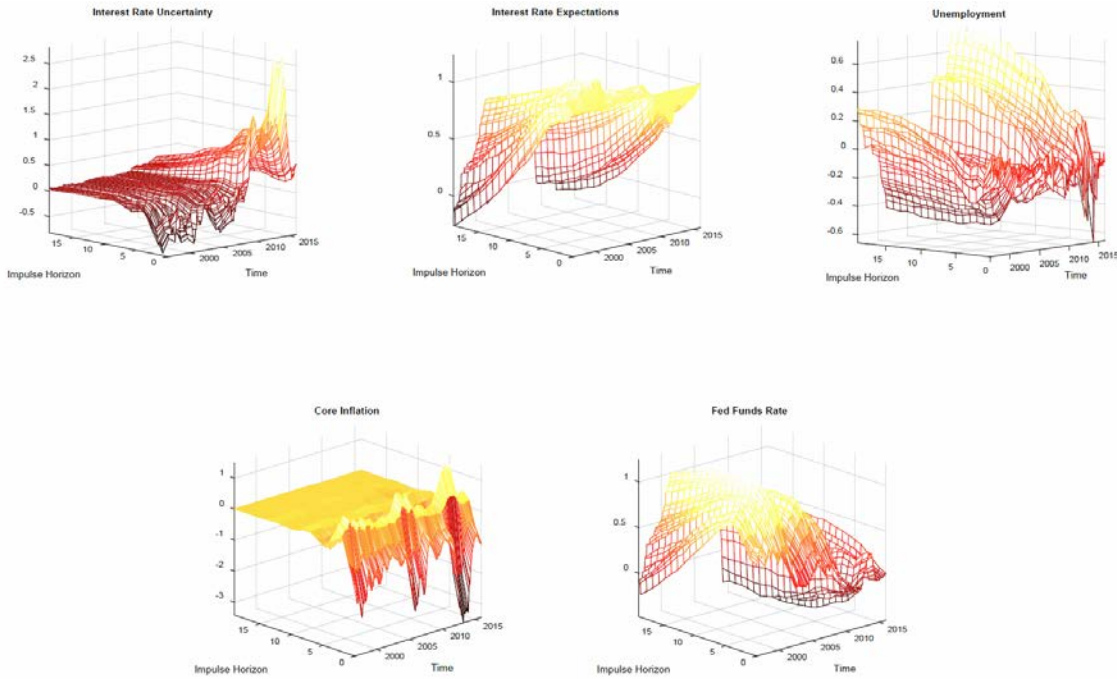
uncertainty that resulted from the evolving perception on the Federal Reserve’s interest rate lift-off strategy—highlights the delicate balancing act that policymakers were engaged in. Moreover, it also shows that the effects of an expected increase in future forward guidance are likely biased if the second-round effects from rising uncertainty are not considered as well.

Figure 4. Impulse Responses to Monetary Policy Uncertainty Shocks: Benchmark Model



Note: TVP-VAR model with stochastic volatility. Monthly BCEI data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{10,90}$). Data from 1991:M7 through 2015:M7.

Figure 5. Impulse Responses to Interest Rate Shocks: Benchmark Model



Note: TVP-VAR model with stochastic volatility. Monthly BCEI data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{10,90}$). Data from 1991:M7 through 2015:M7.

4.1.3 Robustness Checks

The benchmark model yields multiple insights regarding both the sizable effects of monetary policy uncertainty and the clear negative relationship between monetary policy uncertainty and macroeconomic activity. However, this may simply be due to the specific way we are defining monetary policy uncertainty—or the specific data source we are using in the benchmark (BCEI survey data). To test the robustness of the results in an alternative dataset as well as with alternative ways of constructing monetary policy uncertainty measures, we now turn to the [Federal Reserve Bank of Philadelphia \(2015\)](#)'s SPF survey data, first replicating the benchmark model using the $uncert_{t,t+4}^{10,90}$ proxy calculated with the new dataset, and then further exploring alternative ways of defining and calculating uncertainty.²⁵

As described previously, the SPF provides the full panel of forecasters, which allows for a more nuanced analysis. First, we replicate the benchmark model defining uncertainty as the

²⁵ The SPF dataset is quarterly while the BCEI dataset is monthly. This provides a robustness check on frequency as well.

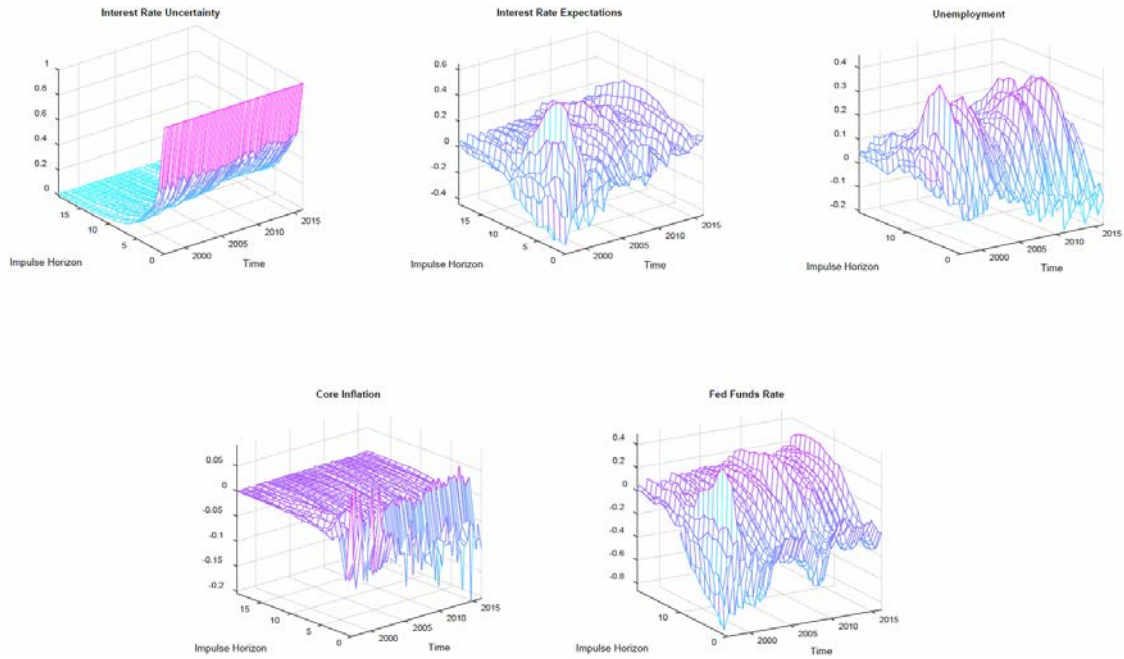
difference between the 90th percentile and the 10th percentile forecasts ($uncert_{t,t+4}^{10,90}$). [Figure 6](#) depicts the quarterly responses of the five variables to a one standard deviation shock to monetary policy uncertainty. The results of the benchmark model discussed earlier hold strong here—an uncertainty shock is met with depressed economic activity, including a sustained increase in unemployment and a short dip in core inflation. The magnitude of the responses is similar to those in the benchmark model—unemployment rises by roughly 0.3 percentage points, compared to the response of 0.4 percentage points found with the BCEI data, while core inflation falls by 0.2 percentage points, nearly equivalent to the response in the benchmark.²⁶

While the results are robust to changing the particular data source, we next consider whether defining monetary policy uncertainty differently leads to different dynamics. We can calculate uncertainty using a standard measure of cross-sectional dispersion, the standard deviation of the panel of SPF forecasters each quarter ($uncert_{t,t+4}^{\sigma}$). Results are shown in [Figure 7](#), and again confirm the findings of the benchmark. Rather than using measures of disagreement across forecasters—since the panel may display large disagreements among participants even though each of the individual forecasters may be quite confident about their own beliefs—we also compute interest rate uncertainty as the magnitude of the revisions each forecaster makes over the forecast horizon four quarters ahead ($uncert_{t,t+4}^{\Delta}$). This captures the magnitude of the forecasters wavering about the future path of the interest rate, exploiting the fact that the SPF asks forecasters to repeatedly project interest rates every quarter, rather than only asking them for their expectations for a particular quarter, and never revisiting that projection again. This uncertainty series is transformed in logs for scaling as shown in [Figure 2](#).²⁷

²⁶ Similarly, while not shown here to save space, the corresponding historical decomposition of unemployment and core inflation display dynamics consistent with those of the benchmark, confirming the quantitative importance of monetary policy uncertainty in shaping the macroeconomy. Those additional results are available upon request from the authors.

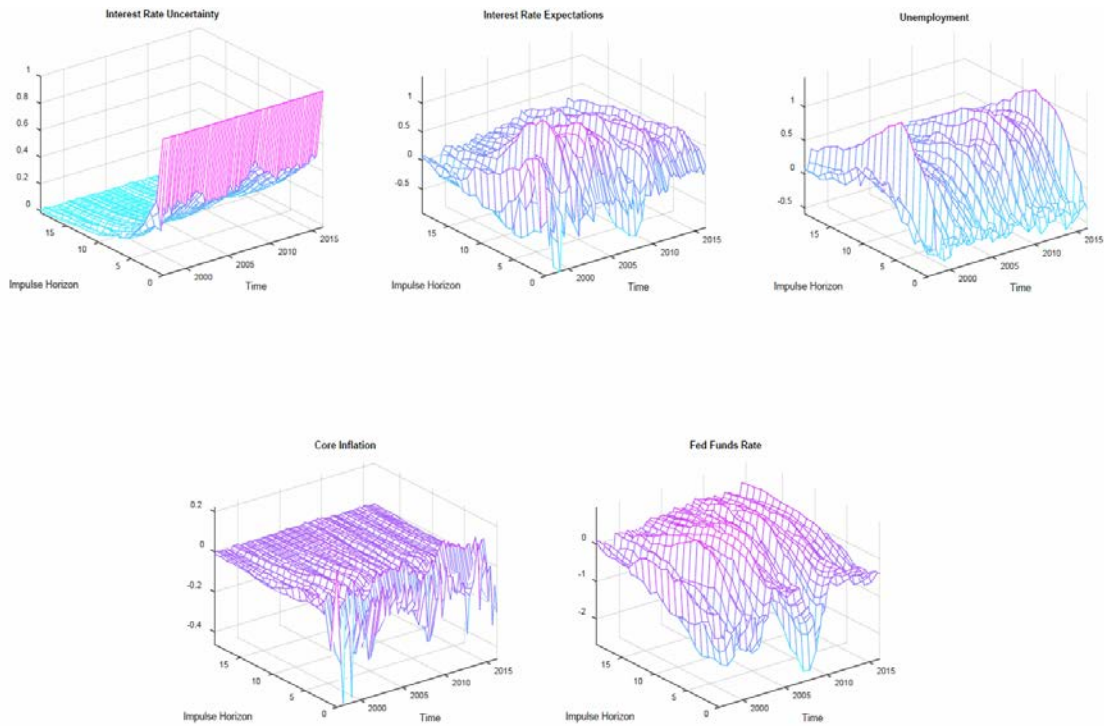
²⁷ We tend to find in the SPF that when forecasters make a significant revision to their expectations, it tends to be a very large correction across all four quarters ahead, whereas if there is no major pressing need to make a forecast revision, all forecasts are largely left unchanged. This may reveal a degree of information stickiness in the expectations formation process too.

Figure 6. Impulse Responses to Monetary Policy Uncertainty Shock: Alternative Model (I)



Note: TVP-VAR model with stochastic volatility. Quarterly SPF data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{10,90}$). Data from 1991:Q3 through 2015:Q2.

Figure 7. Impulse Responses to Monetary Policy Uncertainty Shocks: Alternative Model (II)

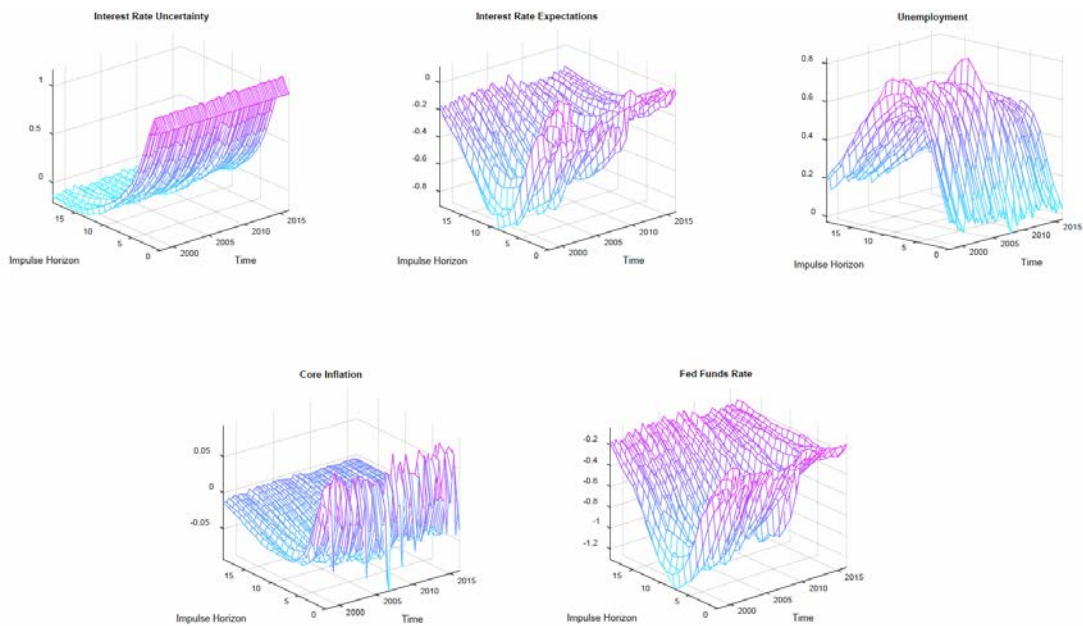


Note: TVP-VAR model with stochastic volatility. Quarterly SPF data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{\sigma}$). Data from 1991:Q3 through 2015:Q2.

[Figure 8](#) shows the results from the five variable model run using our SPF revisions data as the proxy for policy uncertainty. As seen in the IRFs, the responses of the macroeconomic aggregates to an uncertainty shock remain largely consistent with the benchmark, again confirming the robustness of the results. The response of output is even greater than in the benchmark, as the unemployment rate rises by slightly over 0.5 percentage points, again for a sustained period. Core inflation, on the other hand, responds with a quick positive spike, after which it slightly decreases for an extended period, by approximately 0.05 percentage points.

In summary, switching the data source, data frequency, and defining interest rate uncertainty in various ways do not change the dynamics found overall.

Figure 8. Impulse Responses to Monetary Policy Uncertainty Shocks: Alternative Model (III)



Note: TVP-VAR model with stochastic volatility. Quarterly SPF data with uncertainty measured as the absolute value of the sum of the quarterly revisions ($uncert_{t,t+4}^{\Delta}$). Data from 1991:Q3 through 2015:Q2.

4.2 A Closer Look at the ZLB

While our benchmark model is motivated by economic theory to augment the three variable VAR with interest rate expectations and monetary policy uncertainty, and robust to measuring interest rate uncertainty in different ways and to alternative survey data, the five variable model itself may be somewhat stylized to fully capture the U.S. macroeconomy. Of

particular concern in this regard is the use of a multiplicity of monetary policy tools in the post-GFC era, given that balance sheet policies and forward guidance announcements (news) do not appear to be perfect substitutes for hikes in the policy rate or for each other nor necessarily propagate through the same transmission channels ([Caldara et al. \(2021\)](#)). The benchmark model may be subject to misspecification due to omitted policy variables as well as from the omission of other important variables and linkages that can flesh out the transmission of monetary policy under different (and evolving) policy tools.

To test the robustness of the results presented earlier to including a wider range of economic variables, we next implement a factor-augmented VAR (FAVAR). The FAVAR approach, pioneered in [Bernanke et al. \(2005\)](#), was designed to solve precisely this issue, the difficulty that arises from including large sets of variables in traditional VARs. The following FAVAR analysis also hones in on the ZLB period, rather than the entire sample period. While the results from the TVP-VAR do display parameter instability between 2000 and 2015, the dynamics at the ZLB are largely consistent—the structural shifts appear to occur primarily between the ZLB and non ZLB regimes, rather than within the ZLB regime itself. The FAVAR is also able to determine the effect of monetary policy uncertainty shocks on other variables such as on financial market prices and volatility, exchange rates, industrial production, and more.

4.2.1 Empirical Methodology

The FAVAR model closely follows the approach of [Bernanke et al. \(2005\)](#). Y_t refers to the interest rate uncertainty measure $uncert_t^{10,90}$, the same measure used in the benchmark model, beginning in fourth quarter 2008 at the onset of the ZLB period.²⁸ The K unobserved factors relevant to this analysis are summarized by the $K \times 1$ vector, F_t . The dynamics of the factors in F_t and of monetary policy uncertainty in Y_t are given by:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t, \quad (29)$$

²⁸ The data is transformed into quarterly data using simple averaging, due to the difficulties arising from obtaining consistent monthly data on such a large vector of variables.

where $\Phi(L)$ is a conformable lag polynomial of finite order d and the error term, v_t , has a mean of zero and covariance matrix Q .²⁹ Because the factors are unobservable, this system cannot be directly estimated. Thus, we take a wide set of informational time series, the N observable variables collected in the $N \times 1$ vector X_t , and posit it is related to the unobservable factors F_t and the observed factors Y_t by the following relationship:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \quad (30)$$

where Λ^f is an $N \times K$ matrix of factor loadings, Λ^y is $N \times 1$ matrix, and the $N \times 1$ vector of error terms are mean zero and uncorrelated. In this way, the large set of variables X_t is driven by the forces of both Y_t and F_t . The full list of 40 variables in X_t included in the FAVAR model can be found in the [Appendix](#); it incorporates measures such as manufacturing, equity markets, interest rate expectations, federal funds rate, exchange rates, and alternative monetary policy tools indicators.

[Bernanke et al. \(2005\)](#) divides the blocks of variables X_t into either fast-moving time series, which can respond contemporaneously to shocks to monetary policy uncertainty, or slow-moving time series, which do not. Given that we are only identifying the shock to monetary policy uncertainty here, we allow almost all variables in X_t to respond contemporaneously to shocks to monetary policy uncertainty, Y_t , i.e., we treat the variables as fast-moving by default. Similarly, the direction of the responses is left unspecified and unrestricted, allowing the data to speak for itself, consistent with the manner in which the uncertainty shock was identified in our benchmark model. The one exception to all of this is government expenditures, our fiscal policy indicator, which we leave as a slow-moving variable, given the lengthy time it takes for legislation to pass (one would not expect it to be less than three months), let alone the time required to implement it.

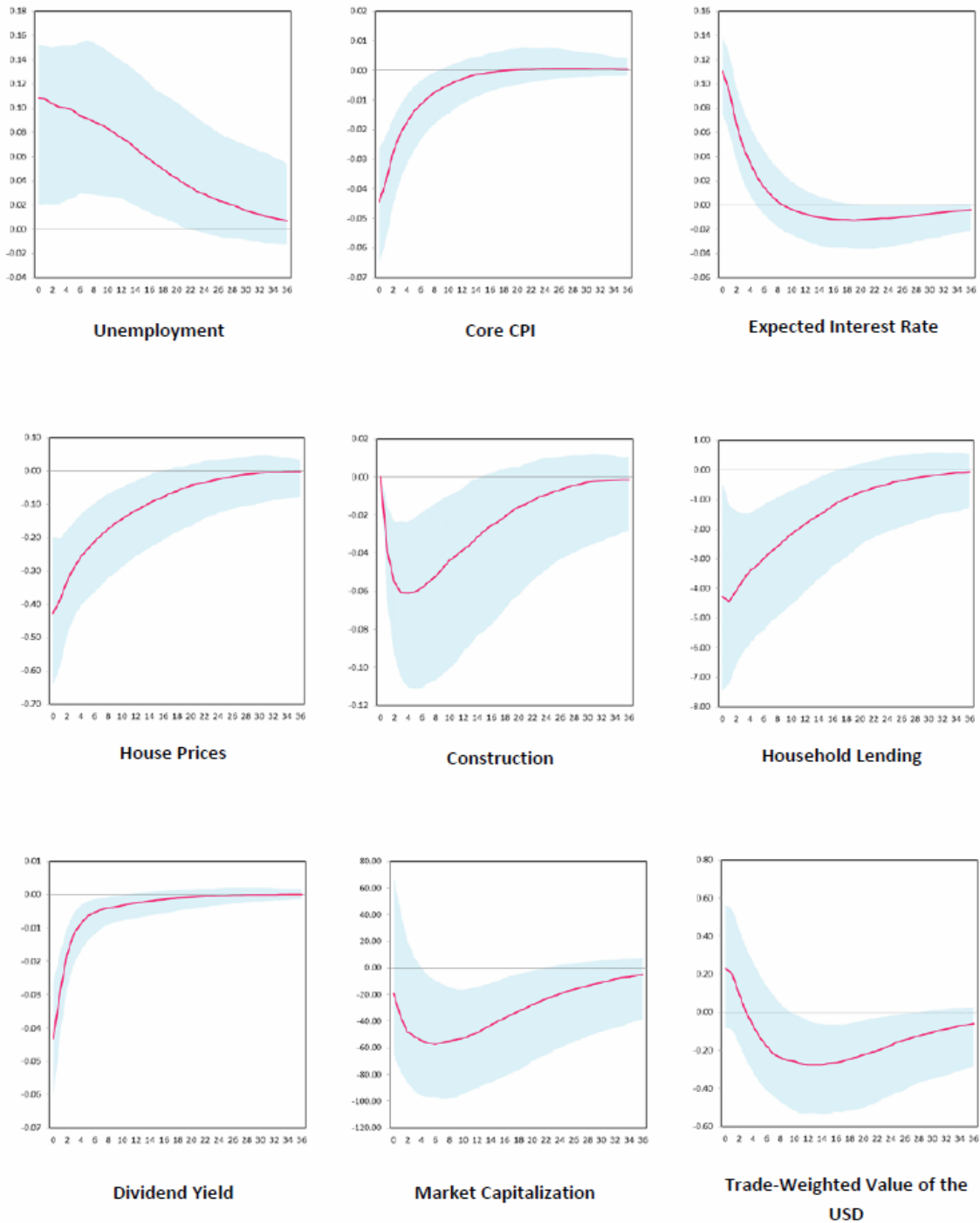
²⁹ To maintain consistency with the benchmark model, the FAVAR specification also uses two lags.

4.2.2 Results

The results from the FAVAR both confirm the dynamics found while at the ZLB in our benchmark TVP-VAR model with stochastic volatility, as well as shed additional light on the broader effects of movements in policy uncertainty. [Figure 9](#) depicts select IRFs from a one standard deviation increase in monetary policy uncertainty. Even when considering a much broader set of variables like we do here, we still find that unemployment responds by rising nearly 0.12 percentage points on impact, and does not die down to original levels for five years, while core inflation falls on impact much more modestly, dissipating after no more than one year. Looking at financial markets, we find a significant dampening of overall market capitalization and dividend yield, with the former taking over six years to fully recover to pre-shock levels, and the latter bouncing back after roughly a year. Real household wealth is similarly impacted, with house prices falling on impact, a detrimental response that becomes coupled with a decrease in lending to households. Longer term projects also display such dynamics, as construction expenditures fall.

From an open economy perspective, we find that the U.S. dollar shows a statistically significant weakening a few quarters after the initial shock. As such, the exports channel may provide some relief from the other dynamics, as the weaker domestic currency incentivizes less spending on imports, and the relatively stronger foreign currencies stimulate spending on domestic goods. Nevertheless, including this exchange rate channel in the FAVAR model has an effect, but it does not appear to be enough to offset the other dynamics caused by uncertainty, as the model yields clearly depressed overall economic activity from monetary policy uncertainty shocks—albeit somewhat smaller, this decline in overall economic activity is still in line with the findings of our benchmark model.

Figure 9. FAVAR Select Impulse Response Functions to Monetary Policy Uncertainty Shocks
During the ZLB Period



Note: FAVAR model. Quarterly BCEI data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{10,90}$). Data from 2008:Q4 through 2015:Q2.

4.3 Indirect Effects of Monetary Policy Uncertainty

While there are clear detrimental direct effects that result from an increase in monetary policy uncertainty, there may be other more nuanced dynamics that relate to the effectiveness of policy actions themselves. In [Section 2](#), we build a theoretical model that proposes indirect effects of monetary policy uncertainty where interest rate risk make policy actions less effective at stimulating economic activity (through investment). We theorize that a firm either engages in some action or falls into inaction, and that firms exist along that action-inaction spectrum. Policy actions such as interest rate changes catalyze the firms to move their position from inaction to make a particular decision or vice versa—be it hiring or spending more on new capital as a response to expansive policy or tightening budgets and postponing projects as a response to contractionary policies. Our stylized model suggests that a rise in monetary policy uncertainty shifts the line demarcating the threshold for engaging in such actions (the barrier control) inward, closer to the origin. This has the implication of leaving firms that were active at the barrier inside the inaction region and, therefore, reduces aggregate investment and economic activity. In turn, although policy rates sustain lower capital levels along the new threshold resulting from higher policy uncertainty, the slope of the new threshold is also steeper for those firms eventually pushed back into action either through interest rate cuts or because of the gradual depreciation of their stock of capital. As such, policy becomes more effective on the margin when interest rate uncertainty is high. Here, we consider if the aggregate dynamics predicted by theory in response to varying interest rate uncertainty are consistent with the empirical evidence. We also explore whether a decline in economic activity (high unemployment) makes monetary policy actions, both traditional interest rate shocks as well as forward guidance (interest rate expectations shocks), more effective at stimulating the macroeconomy.

4.3.1 Empirical Methodology

To gauge such indirect effects of monetary policy uncertainty, we turn back to the benchmark TVP-VAR model and its corresponding IRFs. If indirect effects exist, we can exploit the time-varying nature of the model, and test for them by extracting the IRFs at each month in

the entire time sample, then run a multivariate analysis that considers the size of the response of unemployment and core inflation to a federal funds rate or expected interest rate shock relative to the level of policy uncertainty in that particular month. Put differently, we use several different measures of the magnitude and shape of the IRFs (cumulative effect over the forecast horizon, maximum effect during the forecast horizon, and slope of the IRF) as the dependent variable, and the level of monetary policy uncertainty as the key independent variable. Of course, we also control for other macroeconomic factors in the model that could also explain fluctuations in the shape of the IRFs, including the levels of unemployment, core inflation, interest rates, and interest rate expectations. We focus the multivariate regression analysis on two policy actions—the shock to the federal funds rate and the shock to interest rate expectations—in conjunction with the responses of unemployment and core inflation to those two shocks. In this way, we can determine how the level of monetary policy uncertainty and economic conditions in any given month influence the effectiveness of the monetary policy transmission. The regression analyses are estimated using ordinary-least squares.

4.3.2 Results

We find strong evidence that monetary policy uncertainty has an indirect effect on the macroeconomy by dampening the effects of monetary policy from the federal funds rate and expectations of the future interest rate (forward guidance) shocks. The regression results are shown in Tables [2](#) and [3](#) below. Focusing first on traditional monetary policy (the federal funds rate), we find in [Table 2](#) that higher interest rate uncertainty dampens the effects of a federal funds rate shock on both unemployment and core inflation. *Ceteris paribus*, a one-unit increase in measured monetary policy uncertainty is associated with a decline of 51.4 units in the cumulative effect over the entire IRF of the response of unemployment to a federal funds rate shock. Putting this in context, the average level of monetary policy uncertainty over the sample is 1.1 and the average cumulative response of unemployment during the most recent time period, the ZLB, is about 120. Thus, a one-unit increase in measured uncertainty, which approximately doubles the typical level of interest rate uncertainty, is associated with an equivalent 43 percent fall in the total effectiveness of a federal funds rate shock at moving

output, significant at the 95 percent level. Looking at the maximum impact, we find similar dynamics—a one-unit increase in monetary policy uncertainty is associated with a fall in the maximum response of the unemployment rate by 2.9 units, again significant at the 95 percent level. This evidence is consistent with the predictions from the theory derived in [Section 2](#) when the inward shift of the barrier control associated with a high policy uncertainty scenario causes in the aggregate more firms to postpone their decisions and fewer to act even though those fewer willing and able to do so are more sensitive to monetary accommodation. This delayed action when policy uncertainty is high becomes a major drag at the ZLB because in that case policymakers have essentially no room to cut rates in order to bring firms back to invest. As hinted by theory, we also find some evidence that economic conditions (the level of unemployment in particular) also play a role in determining the efficacy of federal funds rate shocks on economic activity.

Turning to the non-linearities in core inflation, the dynamics are similar. A one-unit increase in measured interest rate uncertainty is associated with a fall in the cumulative response of core inflation of 3.2 units. Given that the average cumulative response of core inflation during the ZLB is 7.4, this is approximately a 43 percent fall in the total effectiveness of a federal funds rate shock. Similarly, the same increase in policy uncertainty is associated with a fall of 1.2 units in the maximum response of core inflation to the federal funds rate shock, both significant at the 95 percent level.

Finally, we consider if the same non-linear effects arise in response to monetary policy actions embedded in interest rate expectations shocks as they do from federal funds rate shocks. Turning to the responses of output and inflation to a one standard deviation shock to interest rate expectations (defined as the median expected yield on the 3-month Treasury Bill), we find dynamics consistent with those found when examining the non-linearities on the propagation of federal funds rate shocks. [Table 3](#) displays the regression results from the effects of policy uncertainty on an interest rate expectations (forward guidance) shock.

Table 2. Indirect Effects of Monetary Policy Uncertainty: Empirical Analysis of the Effectiveness of Federal Funds Rate Shocks

	Shock: Federal Funds Rate									
	Response: Unemployment					Response: Core Inflation				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	Cumulative Impact	Maximum Impact	Minimum Impact	Slope Impact (through s=4)	Slope Impact (through s=8)	Cumulative Impact	Maximum Impact	Minimum Impact	Slope Impact (through s=4)	Slope Impact (through s=8)
Interest Rate	-51.38***	-2.932***	-2.230***	-2.801***	-2.729***	3.169***	-1.202***	2.764***	0.645***	0.403***
Uncertainty	(7.258)	(0.543)	(0.269)	(0.492)	(0.446)	(0.406)	(0.190)	(0.403)	(0.090)	(0.055)
Federal Funds Rate	3.837	0.318	0.050	0.308	0.283	0.439	-0.169	0.439	0.081	0.055
	(5.328)	(0.398)	(0.197)	(0.361)	(0.328)	(0.298)	(0.139)	(0.296)	(0.066)	(0.041)
Interest Rate	-17.29**	-1.194**	-0.646**	-1.115**	-1.031**	0.528	-0.254	0.450	0.133	0.078
Expectations	(6.921)	(0.518)	(0.256)	(0.469)	(0.426)	(0.387)	(0.181)	(0.384)	(0.086)	(0.053)
Unemployment	5.984***	0.858***	-0.200**	0.786***	0.656***	0.019	0.029	-0.041	-0.026	-0.012
	(2.194)	(0.164)	(0.081)	(0.149)	(0.135)	(0.123)	(0.057)	(0.122)	(0.027)	(0.017)
Core Inflation	-4.882	0.007	-0.271	-0.085	-0.165	0.159	0.048	-0.115	-0.005	0.0001
	(12.490)	(0.934)	(0.462)	(0.846)	(0.768)	(0.698)	(0.327)	(0.693)	(0.155)	(0.095)
Constant	116.600***	5.036***	7.210***	4.642***	4.808***	-10.14***	3.985***	-8.950***	-1.991***	-1.257***
	(17.970)	(1.344)	(0.665)	(1.218)	(1.106)	(1.005)	(0.470)	(0.998)	(0.223)	(0.137)
Observations	233	233	233	233	233	233	233	233	233	233
R-squared	0.669	0.678	0.618	0.688	0.687	0.685	0.650	0.656	0.696	0.698

Note: TVP-VAR model with stochastic volatility. Quarterly BCEI data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{10,90}$). Standard errors in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Indirect Effects of Monetary Policy Uncertainty: Empirical Analysis of the Effectiveness of Interest Rate Expectations Shocks

Shock: Interest Rate Expectations										
	Response: Unemployment					Response: Core Inflation				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	Cumulative Impact	Maximum Impact	Minimum Impact	Slope Impact (through s=4)	Slope Impact (through s=8)	Cumulative Impact	Maximum Impact	Minimum Impact	Slope Impact (through s=4)	Slope Impact (through s=8)
Interest Rate	-4.285***	-0.213***	-0.040**	-0.079***	-0.128***	1.422***	-0.500***	1.200***	0.294***	0.182***
Uncertainty	(0.419)	(0.020)	(0.020)	(0.016)	(0.017)	(0.122)	(0.048)	(0.114)	(0.0269)	(0.016)
Federal Funds Rate	0.110 (0.308)	0.069*** (0.015)	-0.042*** (0.015)	-0.015 (0.011)	-0.007 (0.012)	-0.116 (0.090)	0.018 (0.036)	-0.040 (0.084)	-0.021 (0.020)	-0.013 (0.012)
Interest Rate Expectations	0.107 (0.400)	-0.064*** (0.019)	0.051*** (0.019)	0.018 (0.015)	0.011 (0.016)	0.129 (0.117)	-0.006 (0.046)	-0.041 (0.109)	0.018 (0.026)	0.011 (0.016)
Unemployment	1.711*** (0.127)	0.102*** (0.006)	0.022*** (0.006)	0.020*** (0.005)	0.046*** (0.005)	-0.141*** (0.037)	-0.013 (0.015)	-0.015 (0.035)	-0.013 (0.008)	-0.010** (0.005)
Core Inflation	-0.038 (0.721)	0.018 (0.034)	0.012 (0.035)	0.020 (0.027)	0.012 (0.029)	0.249 (0.210)	-0.091 (0.083)	0.219 (0.197)	0.052 (0.046)	0.032 (0.029)
Constant	-6.716*** (1.038)	-0.252*** (0.049)	-0.347*** (0.050)	-0.179*** (0.038)	-0.265*** (0.042)	-2.117*** (0.303)	1.157*** (0.120)	-2.342*** (0.283)	-0.530*** (0.067)	-0.321*** (0.041)
Observations	233	233	233	233	233	233	233	233	233	233
R-squared	0.763	0.837	0.161	0.310	0.629	0.631	0.477	0.470	0.541	0.559

Note: TVP-VAR model with stochastic volatility. Quarterly BCEI data with uncertainty measured as 90-10 differential ($uncert_{t,t+4}^{10,90}$). Standard errors in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Focusing first on the response of unemployment, we find that a one-unit increase in measured monetary policy uncertainty is associated with a fall in the cumulative response of unemployment of 4.3 units. Put in context, the average cumulative response of unemployment to an interest rate expectations shock at the ZLB is 3.4 units. As such, if monetary policy uncertainty were to increase by even only 10 percent, this would be associated with a fall in the total effectiveness of a forward guidance shock at moving unemployment of 12.6 percent of the typical cumulative response of 3.4 units. The same effect appears in regards to the maximum response of unemployment. Turning to the effects on core inflation, the dynamics are consistent with those found in the analysis of the unemployment rate—a statistically significant fall in the effectiveness of forward guidance shocks at moving both the cumulative responses and maximum responses of core inflation.

In essence, there is strong evidence supporting indirect effects of monetary policy uncertainty as well as direct effects as suggested by the theory presented in [Section 2](#). Not only do higher levels of interest rate uncertainty pose higher risk and cause a direct cooling of economic activity, but they actively dampen the aggregate effectiveness of monetary policy at stimulating the economy by weakening the magnitude, length, and shape of the responses of unemployment and core inflation to policy shocks (federal funds rate and even expectations shocks).

5. Concluding Remarks

Putting the pieces of this puzzle together reveals a distinct picture of U.S. monetary policy. Monetary policy uncertainty has always been present in and of itself, as seen in [Figure 2](#), in any way one chooses to define it (dispersion of interest rate forecasts, the wavering of forecasters around their predictions, multiple data sources, etc.). Such interest rate uncertainty, however, stayed at remarkably low levels for a sustained period in recent years during part of the binding ZLB episode post-GFC where the potential movements in the federal funds rate were truncated downward. Later on, monetary policy uncertainty began to steadily tick back upwards as the Federal Reserve signaled first and then started to implement its policy rate lift-off strategy.

This paper examines the causes and effects of these fluctuations in monetary policy uncertainty. Our empirical analysis augments the standard three variable VAR model with interest rate expectations and a survey-based measure of monetary policy uncertainty, while allowing the parameters and the volatility of the disturbances to vary over time to explicitly account for the potential shift in dynamics at the ZLB. First, we immediately see that what drives uncertainty shocks varies significantly over time, and has been dramatically shaped by the ZLB. Prior to 2008, a rise in interest rate expectations was associated with no measurable response in interest rate uncertainty. However, presumably due to the heightened scrutiny and media speculation of the Federal Reserve's decision regarding lift-off or from other circumstances that may have hindered the central bank's communication channels, in the post-2008 period, we find that a rise in interest rate expectations drives a corresponding spike in interest rate uncertainty. In light of current events, this is of particular note to policymakers as the perceived economic benefits of forward guidance can be undone (partly at least) whenever the central bank's attempts to signal the future path of the policy rate contribute to unintentionally increase the uncertainty and confusion around policy perceived by private agents.

At the same time, we consider what the actual direct impact of such a spike in interest rate uncertainty is. Using a benchmark TVP-VAR model with stochastic volatility, as well as a FAVAR model that focuses in on the more recent ZLB period but accounts for a wider set of variables, we find that a positive one standard deviation shock to interest rate uncertainty dampens economic activity, raising the unemployment rate by around 0.6 percentage points in the first few months after the initial shock, and remaining depressed for almost two years, while similarly lowering core inflation by 0.2 percentage points, although core inflation is shown to rebound more quickly than unemployment. The FAVAR model expands on these results, showing that not only does an exogenous shock to uncertainty increases unemployment and lowers core inflation, but also depresses financial markets, house prices, and lending activity, as well as measures of production such as construction.

We also extrapolate indirect policy-related effects of shocks to monetary policy uncertainty, recovering the time-varying IRFs of shocks to the federal funds rate and to interest rate expectations (forward guidance) from the TVP-VAR, and regress them on the level of monetary policy uncertainty and the other variables of the model itself in each time period. In short, we find confirmatory empirical evidence for our theoretical model with which we argue higher levels of monetary policy uncertainty cause firms subject to investment irreversibility to respond less on aggregate to policy actions. At higher levels of monetary policy uncertainty, both traditional monetary policy (a shock to the federal funds rate) as well as forward guidance shocks (or interest rate expectations shocks) are less effective at moving output and inflation in the desired direction. Indeed, we find empirical evidence showing that heightened monetary policy uncertainty and poor economic conditions actively dampen the effectiveness of monetary policy at stimulating the economy by weakening the magnitude, length, and shape of the responses of unemployment and core inflation to policy shocks.

Here stands the U.S. economy in 2021, again on the edge of interest rate lift-off and in an unprecedented situation after a severe recession at the height of the COVID19 pandemic. But there is much that can be learned from the previous experience at the ZLB. That starts by recognizing that dynamics regarding what drives monetary policy uncertainty movements are different at the ZLB—now, a rise in interest rate expectations or, put differently, expectations of lift-off can cause a concurrent (and negative) rise in uncertainty. And the effects of such a rise in interest rate uncertainty are two-pronged, both directly dampening economic activity as well as making any subsequent monetary policy actions less effective at managing the economy. Our theoretical model provides the structural backbone for these results, demonstrating that, a rise in interest rate uncertainty operates through an options-value-of-waiting channel effect, as firms prefer to postpone investment decisions on the aggregate until the policy path becomes less uncertain.

This paper highlights the trade-off for policymakers between being “right” and being decisive. The indirect effects of monetary policy uncertainty are such that allowing the economy to endure a higher level of interest rate uncertainty may make any subsequent “right”

policy decisions less effective. This is not to say that policymakers should throw caution out the window when considering interest rate policy; however, at the very least, our findings can be said to provide evidence in support of clearly communicating the central bank's intentions in as specific a manner as possible under the given circumstances.

An area of fruitful future research would be to go beyond the domestic U.S. experience and explore the international spillovers from monetary policy uncertainty and how policy uncertainty propagates across countries. There is increasing evidence such as that reported in [Kumar *et al.* \(2021\)](#) suggesting that uncertainty may behave differently in emerging than in advanced economies which, naturally, also can influence monetary policy responses differently. More research on this area can contribute to further understand the domestic and foreign transmission mechanisms of monetary policy.

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Appendix. Data Sources

Table A1. Data Used with all TVP-VARs with Stochastic Volatility

Notation	Variable	Notes	Source(s)
$uncert_{t,t+4}^{10,90}$	Interest rate uncertainty	Interest rate uncertainty, measured as the difference between the panel-level 90 th and 10 th percentile expected yield on the 3-month Treasury Bill, 4 quarters ahead	<ul style="list-style-type: none"> • Blue Chip Economic Indicators • Survey of Professional Forecasters (FRB.P)
$uncert_{t,t+4}^{\sigma}$	Interest rate uncertainty	Interest rate uncertainty, measured as the standard deviation of the panel's expected yield on the 3-month Treasury Bill, 4 quarters ahead	<ul style="list-style-type: none"> • Survey of Professional Forecasters (FRB.P)
$uncert_{t,t+4}^{\Delta}$	Interest rate uncertainty	Interest rate uncertainty, measured as the sum of the absolute value of the quarterly revisions to the expected yield on the 3-month Treasury Bill over the forecast horizon	<ul style="list-style-type: none"> • Survey of Professional Forecasters (FRB.P)
$E_t(i_{t+4})$	Interest rate expectations	Panel-level median expected yield on the 3-month Treasury Bill, 4 quarters ahead (annualized rates, %)	<ul style="list-style-type: none"> • Blue Chip Economic Indicators: "tbill6bc" • Survey of Professional Forecasters: "tbill6" (FRB.P)
FFR_t	Federal funds rate	Effective overnight federal funds rate (annualized rate, %)	<ul style="list-style-type: none"> • FRB.SL
UR_t	Unemployment	Seasonally-adjusted civilian unemployment rate (%)	<ul style="list-style-type: none"> • FRB.SL
$\pi_t^{Core_CPI}$	Inflation	Core inflation (CPI), quarter-over-quarter (annualized rate, %), seasonally-adjusted	<ul style="list-style-type: none"> • FRB.SL

Note: All data collected or calculated by the authors are available upon request. FRB.P stands for Federal Reserve Bank of Philadelphia (<https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters>); and FRB.SL stands for the Federal Reserve Economic Database (FRED) of the Federal Reserve Bank of St. Louis (<https://research.stlouisfed.org/fred2/>). Blue Chip Economic Indicators (BCEI) is a monthly survey (<http://www.aspenpublishers.com/blue-chip-publications.htm>); all data used in models with BCEI expectations data is similarly monthly. The acronym SPF stands for the Survey of Professional Forecasters; SPF is a quarterly survey from FRB.P; all data used in models with SPF expectations data is quarterly.

Note: Our novel measure of uncertainty can be calculated as follows:

$$uncert_{t,t+4}^{\Delta} = |E_t(i_{t+4}) - E_{t-1}(i_{t+4})| + |E_t(i_{t+3}) - E_{t-1}(i_{t+3})| + |E_t(i_{t+2}) - E_{t-1}(i_{t+2})| + |E_t(i_{t+1}) - E_{t-1}(i_{t+1})|.$$

Table A2. Additional Data Used with the FAVAR Model

Notation	Variable	Notes	Source(s)
$uncert_{t,t+4}^{10,90}$	Interest rate uncertainty	Interest rate uncertainty, measured as the difference between the panel-level 90 th and 10 th percentile expected yield on the 3-month Treasury Bill, 4 quarters ahead	Blue Chip Economic Indicators
$E_t(i_{t+4})$	Interest rate expectations	Panel-level median expected yield on the 3-month Treasury Bill, 4 quarters ahead (annualized rates, %)	Blue Chip Economic Indicators: "tbill6bc"
FFR_t	Federal funds rate	Effective overnight federal funds rate, Annualized Rate	FRB.SL
UR_t	Unemployment	Civilian Unemployment Rate, Percent, Quarterly, Seasonally Adjusted	FRB.SL
$\pi_t^{Core_CPI}$	Core CPI	Consumer Price Index for All Urban Consumers: All Items Less Food and Energy, Index 1982-1984=100, Quarterly, Seasonally Adjusted	FRB.SL
π_t^{CPI}	CPI	Consumer Price Index for All Urban Consumers: All Items, Index 1982-1984=100, Quarterly, Seasonally Adjusted	FRB.SL
$\pi_t^{Food_PPI}$	Food PPI	Producer Price Index by Commodity for Processed Foods and Feeds, Index 1982=100, Quarterly, Not Seasonally Adjusted	FRB.SL
$\pi_t^{Core_PPI}$	Core PPI	Producer Price Index by Commodity for Final Demand: Finished Goods Less Foods and Energy, Index 1982=100, Quarterly, Seasonally Adjusted	FRB.SL
π_t^{PPI}	PPI	Producer Price Index for All Commodities, Index 1982=100, Quarterly, Seasonally Adjusted	FRB.SL
$\pi_t^{GDP_Defl}$	GDP Deflator	Gross Domestic Product: Implicit Price Deflator, Index 2009=100, Quarterly, Seasonally Adjusted	FRB.SL
ω_t	Wages	Gross domestic income: Compensation of employees, paid: Wages and salaries, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate	FRB.SL

GDP_t	GDP	Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate	FRB.SL
φ_t	Productivity	Business Sector: Real Output Per Hour of All Persons, Index 2009=100, Quarterly, Seasonally Adjusted	FRB.SL
λ_t	Capacity Utilization	Capacity Utilization: Total index, Percent of Capacity, Quarterly, Seasonally Adjusted	FRB.SL
M_t	Capacity Utilization: Manufacturing	Capacity Utilization: Manufacturing (NAICS), Percent of Capacity, Quarterly, Seasonally Adjusted	FRB.SL
E_t	Capacity Utilization: Electricity & Gas	Capacity Utilization: Electric and gas utilities, Percent of Capacity, Quarterly, Seasonally Adjusted	FRB.SL
C_t	Consumption	Real Personal Consumption Expenditures, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate	FRB.SL
G_t	Government Expenditures	Federal government current expenditures, Billions of Dollars, Quarterly, Seasonally Adjusted	FRB.SL
EX_t	Exports	Real Exports of Goods and Services, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate	FRB.SL
IM_t	Imports	Real imports of goods and services, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate	FRB.SL
ζ_t	Inventories	Total Business Inventories, Millions of Dollars, End of Period, Quarterly, Seasonally Adjusted	FRB.SL
χ_t	Construction	Total Construction Expenditures, Index 2007:Q4=100, Quarterly, Seasonally Adjusted Annual Rate	FRB.SL
\perp_t	Transportation	Total Transportation Services Index, Chain-type Index 2000=100, Quarterly, Seasonally Adjusted	FRB.SL
$TRN_t^{freight}$	Freight Transportation	Freight Transportation Services Index, Chain-type Index 2000=100, Quarterly, Seasonally Adjusted	FRB.SL

η_t	Industrial Production: Food, Beverage & Tobacco	Industrial Production: Nondurable manufacturing: Food, beverage, and tobacco, Index 2012=100, Quarterly, Seasonally Adjusted	FRB.SL
ρ_t	Industrial Production: Petroleum & Coal	Industrial Production: Nondurable manufacturing: Petroleum and coal products, Index 2012=100, Quarterly, Seasonally Adjusted	FRB.SL
ξ_t	Industrial Production: Chemicals	Industrial Production: Nondurable manufacturing: Chemical, Index 2012=100, Quarterly, Seasonally Adjusted	FRB.SL
M_t^1	M1	M1 Money Stock, Billions of Dollars, Quarterly, Seasonally Adjusted	FRB.SL
M_t^2	M2	M2 Money Stock, Billions of Dollars, Quarterly, Seasonally Adjusted	FRB.SL
M_t^{Base}	Monetary Base	St. Louis Adjusted Monetary Base, Billions of Dollars, Quarterly, Seasonally Adjusted	FRB.SL
$M_t^{Currency}$	Currency	Currency Component of M1, Billions of Dollars, Quarterly, Seasonally Adjusted	FRB.SL
K_t	Reserves	Total Reserve Balances Maintained with Federal Reserve Banks, Billions of Dollars, Quarterly, Seasonally Adjusted	FRB.SL
Γ_t	Lending	Loans and Leases in Bank Credit, All Commercial Banks, Billions of U.S. Dollars, Quarterly, Seasonally Adjusted	FRB.SL
Γ_t^{HH-NP}	Household & Nonprofit Lending	Households and Nonprofit Organizations; Credit Market Instruments; Liability, Level, Billions of Dollars, Quarterly, Seasonally Adjusted	FRB.SL
Γ_t^{CC}	Credit Card Lending	Consumer Loans: Credit Cards and Other Revolving Plans, All Commercial Banks, Billions of U.S. Dollars, Quarterly, Seasonally Adjusted	FRB.SL
$House_t$	House Prices	All-Transactions House Price Index for the United States, Index 1980:Q1=100, Quarterly, Seasonally Adjusted	Mack and Martínez-García (2011)
$P_t^{Shiller}$	P/E Ratio	Cyclically-adjusted price to earnings ratio for the S&P 500 index	Shiller (2016)

$\Psi_t^{Shiller}$	Dividend Yield	Ratio of dividends over stock price for the S&P 500 index	Shiller (2016)
Ω_t	Market Capitalization	Russell 2000 Price Index, Seasonally Adjusted	FRB.SL
γ_t	VIX Equity Volatility	CBOE Volatility Index, Seasonally Adjusted	FRB.SL
e_t	Nominal Exchange Rate	Trade-Weighted U.S. Dollar Index against broad group of U.S. trading partners, Seasonally Adjusted	Grossman et al. (2014)

Note: All data collected or calculated by the authors are available upon request. FRB.SL stands for the Federal Reserve Economic Database (FRED) of the Federal Reserve Bank of St. Louis (<https://research.stlouisfed.org/fred2/>). Blue Chip Economic Indicators (BCEI) is a monthly survey (<http://www.aspenpublishers.com/blue-chip-publications.htm>). All data in the FAVAR model is quarterly, given the difficult nature of obtaining such a large vector of variables at monthly frequency (GDP, Construction, Government Expenditures, etc.). The BCEI expectations and uncertainty data (<http://www.aspenpublishers.com/blue-chip-publications.htm>) were converted into quarterly frequency using simple averaging. All data was transformed to be stationary where necessary.