Economic Policy Uncertainty and the Great Recession

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Abstract

I use Bayesian time-varying parameters structural VARs with stochastic volatility, and two alternative identification schemes, to explore the role played by policy uncertainty shocks within the context of the Great Recession in the United States, the Euro area, the United Kingdom, and Canada.

Shocks identified as being orthogonal to the state of the economy (except stock prices) within the month played a uniformly marginal role in either country. An alternative identification strategy in the spirit of Uhlig (2003, 2004) points instead towards a non-negligible role, with, e.g., (*i*) the fraction of 1-year ahead forecast error variance of U.S. industrial production growth explained by these shocks being around 20-30 per cent over the entire sample period; and (*ii*) the trough in median counterfactual industrial production growth in the aftermath of the collapse of Lehman Brothers being equal to -8.5 per cent, as opposed to the actual value of -16.3 per cent.

In either country, the period following the collapse of Lehman Brothers has been characterized by an increase in both the volatility of policy uncertainty shocks, and the fraction of draws from the posterior distribution for which they are estimated to have been positive (i.e., contractionary). Impulse-response functions, on the other hand, did not exhibit any peculiar pattern, during the Great Recession, compared to previous years.

Keywords: Economic policy uncertainty; structural VARs; Great Recession.

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1 Introduction

Following the influential work of Bloom (2009), the role played by economic policy uncertainty in macroeconomic fluctuations has been, in recent years, one of the most intensely discussed issues in either academia, policymaking circles, or the financial press.

Bloom (2009) used a model with a time-varying second moment estimated based on firm-level data in order to simulate the economic impact of a shock to aggregate uncertainty. His evidence suggests that uncertainty shocks generate sharp recessions, and subsequent swift rebounds, in both output and employment, due to the 'wait and see' attitude induced by higher uncertainty on firms' investment and hiring decisions. Baker, Bloom, and Davis (2013), based on fixed-coefficients structural VAR methods, have documented how, in the United States, innovations to their economic policy uncertainty index cause statistically significant declines in both employment and industrial production.

As pointed out by Bloom (2009, p. 624), *'[u]ncertainty is also a ubiquitous concern of policymakers.'*, with (e.g.) the Federal Reserve's *Federal Open Market Committee* (*FOMC*) openly worrying about the contractionary impact of heightened uncertainty both in the aftermath of 9/11, and during the most severe phase of the recent financial crisis.[1] By the same token, the April 2013 issue of the International Monetary Fund's *World Economic Outlook* contains an extensive discussion of the negative global macroeconomic spillovers from increases in economic policy uncertainty in the United States and the Euro area. One of its main findings is that

> 'U.S. policy-uncertainty shocks temporarily reduce GDP growth in other regions by up to $\frac{1}{2}$ percentage point in the year after the shock [...]. European policy-uncertainty shocks temporarily reduce GDP growth in other regions by a smaller amount [...].'

In the financial press, the macroeconomic impact of economic policy uncertainty has been mostly discussed with reference to the Great Recession.[2] In particular, several commentators have argued that the dramatic increases in policy uncertainty which have characterized the financial crisis and its aftermath have been a key factor holding back the recovery in both the United States and Europe.[3]

[1] On this, see the quotations from the FOMC's statements reported in Bloom (2009, p. 624).

[2] See, e.g., 'Dithering in the Dark', published on the issue of June 16, 2012 of *The Economist*, and 'Policy Uncertainty Paralyzes the Economy', by William Galston, published in the issue of September 24, 2013 of the *Wall Street Journal*.

[3] Informal evidence that this may have been the case was provided by a survey of the U.S. *National Association for Business Economics*, according to which the 'vast majority' of the polled economists believed that uncertainty about fiscal policy (debt ceiling negotiations, etc.) were 'holding back the pace of economic recovery.'.

1.1 This paper: methodology, and main results

In this paper I use Bayesian time-varying parameters structural VARs with stochastic volatility, and two alternative identification schemes, in order to explore the role played by policy uncertainty shocks within the context of the Great Recession in the United States, the Euro area, the United Kingdom, and Canada. Compared to previous studies (discussed below in Section 1.2), a key advantage of the model used herein is that, being entirely time-varying (specifically, allowing for time-variation in *both* the VAR's coefficients, *and* its covariance matrix) it allows me to explore the specific dimensions along which the role played by policy uncertainty shocks within the context of the Great Recession may have been different from the role they played in previous years.

My main results can be summarized as follows.

First, in all countries, shocks identified as being orthogonal to the state of the economy (except stock prices) within the month played a uniformly *marginal role* for either industrial production, inflation, or the *ex post* real monetary policy rate over the entire sample period, *including* the period since August 2007, which is traditionally taken to be the beginning of the financial crisis.[4] Beyond the policy uncertainty index, the only other macroeconomic variable for which such shocks played a non-negligible role was stock prices' growth, which, unsurprisingly, exhibits indeed a strong, negative reduced-form correlation with the uncertainty index in all countries.

Second, an alternative identification strategy in the spirit of Uhlig (2003, 2004) points instead towards an overall non-negligible role of policy uncertainty shocks. In the United States, for example, the fraction of 1-year ahead forecast error variance (henceforth, FEV) of industrial production explained by these shocks has systematically been around 20-30 per cent over the entire sample period, and it has exhibited a large, temporary spike immediately following the collapse of Lehman Brothers, as well as smaller spikes in correspondence to the 1997 Asian financial crisis, and around 9/11. Interestingly, however, following the temporary jumps after the collapse of Lehman, the fractions of FEV of either industrial production, inflation, or the *ex post* real rate explained by policy uncertainty shocks have fallen back to either pre-crisis levels, or even lower levels. This suggests that, in the United States, economic policy uncertainty has not played an especially important role within the context of the Great Recession, *compared* to previous years, in contrast to a quite common perception that its role has instead been unusually large. The same finding of a 'normal' role played by policy uncertainty shocks within the context of the financial crisis and its aftermath holds for Canada. In the Euro area, on the other hand, the fractions of FEV of either industrial production growth, inflation, or the *ex post* real rate explained by policy uncertainty shocks have exhibited, since the collapse of Lehman, a slow and steady increase. For industrial production growth, for example, the fraction

[4] On August 6, 2007, the European Central Bank, following widespread rumors of elevated levels of stress in Euro area money markets, intervened with a massive injection of 93 billion Euros.

has increased from about 15 per cent in August 2008 to 40-45 per cent at the end of the sample, in mid-2013. Finally, in the United Kingdom, for either of the three main macroeconomic indicators, the fractions of FEV have been, post-Lehman, uniformly greater than before, but such increases do not exhibit a common pattern across series. For industrial production growth, for example, beyond a large and quite persistent spike following September 2008, the fraction has exhibited, since the early 2011, a hump-shaped pattern with a peak around the end of 2012. For inflation, on the other hand, there has been a large and temporary increase between mid-2009 and mid-2011, and smaller increases over the subsequent period.

Third, for either the Euro area, the United Kingdom, or Canada, counterfactual simulations performed by killing off policy uncertainty shocks identified by combining inertial and sign restrictions generate minor-to-negligible differences with actual, historical series for either industrial production growth or inflation. As for the United States, the difference between counterfactual and actual series is often statistically significant, but the magnitudes involved are never very large. The alternative identification strategy, on the other hand, tends to produce much stronger results, especially for the United States and the Euro area. In particular, based on median estimates, the troughs of industrial production growth in the aftermath of the collapse of Lehman would have been equal to -8.5 and -12.2 per cent in the two economic areas, respectively, compared to the actual values of -16.3 and -24.1 per cent.

Fourth, in either country, and based on either identification strategy, the period following the collapse of Lehman Brothers has been characterized by an increase in both the volatility of policy uncertainty shocks, and the fraction of draws from the posterior distribution for which they are estimated to have been positive (i.e., contractionary).

Fifth, for either the Euro area, the United Kingdom, or Canada, and based on either identification strategy, impulse-response functions (henceforth, IRFs) to identified policy uncertainty shocks have exhibited, over the sample period, a negligible-to-minor extent of time-variation (which has never been statistically significant) for either of the five series. For the United States, IRFs to policy uncertainty shocks have exhibited, for several series, and based on either identification strategy, a non-negligible extent of variation since the early 1990s. In particular, the period following the collapse of Lehman has been characterized, for most series, by a decrease in the magnitudes of the responses to identified policy uncertainty shocks. Crucially, however, in no way such a decrease appears to have been *peculiar* to the financial crisis and its aftermath, as analogous, and often even larger declines took place during the very early years of the new millennium.

1.2 Related literature

To the very best of my knowledge, this paper is the first to explore the role played by policy uncertainty shocks within the context of the Great Recession based on time-

varying parameters structural VARs with stochastic volatility. As previously stressed, this is key in order to 'let the data speak' freely about the specific dimensions along which the role played by policy uncertainty shocks within the context of this episode may have been different from the role they played during previous years.

Beyond Bloom (2009) and Baker, Bloom, and Davis (2013), several recent papers have explored the role played by (different types of) economic policy uncertainty in macroeconomic fluctuations. Baker and Bloom (2013) have exploited the variation in natural catastrophes, terroristic attacks, etc. across countries in order to explore the macroeconomic impact of uncertainty shocks. Conceptually in line with Bloom (2009), they find that uncertainty has a negative impact on both output growth and its volatility.

In their exploration of the 2007-2009 U.S. recession based on a fixed-coefficients dynamic factor model with 200 variables, Stock and Watson (2012) identified a prominent role for financial disturbances and shocks associated with increased uncertainy, but no significant changes in the way such shocks were transmitted through the economy. Popescu and Smets (2010) explored the role of financial and uncertainty shocks for Germany based on recursive orderings of the variables. One of their main findings is that uncertainty shocks have a modest and temporary impact on real economic activity.

In terms of identification strategies, the paper closer to the present one is Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2013). Based on fixed-coefficients VARs, Caldara *et al.* (2013) use both recursive ordering, and Uhlig's (2003, 2004) approach, to explore the macroeconomic impact of financial and uncertainty shocks. Their main finding is that financial shocks *'generate slowly-building and economically significant recessions, followed by slow recoveries.'* Uncertainty shocks have similar effects when operating through the financial channel, but otherwise they have a much more muted impact. Another paper conceptually related to the present one is Mumtaz and Surico (2013), which estimates fixed-coefficients VARs with a stochastic volatility specification for the VAR's time-varying covariance matrix of reduced-form innovations in order to explore the macroeconomic impact on the U.S. economy of uncertainty pertaining to government spending and taxes, debt sustainability, and monetary policy. A main feature of Mumtaz and Surico's (2013) empirical specification is that the volatility of policy uncertainty shocks (which are identified based on a recursive scheme) is allowed to have an impact on the VAR's dynamics, thus introducing a link between second and first moments. Their main result is that the largest impact on real economic activity is associated with uncertainty shocks about debt sustainability, whereas shocks pertaining to the other three types of uncertainty have much smaller effects.

Finally, an alternative strand of literature has used either calibrated or estimated DSGE models in order to explore the role played by uncertainty shocks in macroeconomic fluctuations. The best-known example of this literature is probably Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez (2013), who

estimate stochastic processes with time-varying volatilities for U.S. government's tax and spending policies, and then feed the estimated processes into a calibrated standard New Keynesian model. Their main finding is that *'fiscal volatility shocks can have a sizable adverse effect on economic activity.'*.

The paper is organized as follows. The next section describes the main features of the time-varying VAR with stochastic volatility which is used throughout the paper; discusses advantages and limitations of alternative strategies for drawing the VAR's time-varying states (i.e., coefficients) imposing the restrictions that the VAR by stationary in each single month, and for each single draw; and describes the two identification strategies used herein. Section 3 discusses the evidence, whereas Section 4 concludes.

2 Methodology

In what follows I work with the following time-varying parameters VAR(p) model:

$$Y_t = B_{0,t} + B_{1,t}Y_{t-1} + ... + B_{p,t}Y_{t-p} + \epsilon_t \equiv X_t^{'}\theta_t + \epsilon_t \tag{1}$$

where the notation is obvious, and Y_t (which is an $N\times1$ vector) is defined as $Y_t \equiv [ip_t, \pi_t, R_t\text{-}\pi_t, sm_t, pu_t]'$, where ip_t is the log-difference of industrial production; π_t is inflation, computed as the log-difference of the relevant price index; R_t is the relevant short-term monetary policy rate (the Federal Funds rate for the United States; and the *ECB*, *Bank of England*, and *Bank of Canada* policy rates for the Euro area, the United Kingdom, and Canada, respectively), which I quote at the month-on-month non-annualized rate in order to make its scale comparable to that of inflation;[5] sm_t is the log-difference of a stock market index; and pu_t is Baker *et al.*'s (2013) policy uncertainty index for the relevant country. For a description of the data, see Appendix A. As I discuss below in Section 2.1, the number of series entering the VARs is uniquely dictated by reasons of computational feasibility: in a nutshell, for VARs featuring more than five series the Koop and Potter (2011) algorithm I use to draw the VAR's time-varying states (see Section 2.1.1 below) tended to perform poorly—most likely due to the proliferation of state variables[6]—and attempts to 'shrink' the

[5] So, to be clear, if r_t is the relevant short-term rate—with its scale such that, e.g., a ten per cent rate is represented as 10.0—R_t is computed as R_t=(1+r_t/100)$^{1/12}$-1.

[6] Evidence that the proliferation of state variables originating from expanding the number of series entering the VAR is indeed at the root of the problem is provided by following example for the Euro area, which is representative of analogous problems encountered for all other countries. Expanding the VAR considered herein by adding an additional series (either the unemployment rate, or credit growth), and setting the lag order to p=1, does not create any problem. However, when, for the same 6-variables VAR, the lag order is set according to the criterion adopted herein (as the maximum between the lag orders chosen by the AIC, SIC, and Hannan-Quinn criteria, resulting in p=4) the VAR's time-varying parameters become extremely volatile, as the posterior estimate of the extent of random-walk drift tends to 'blow up'.

state-space along the lines of Canova and Ciccarelli (2009), although 'mechanically' successful, were not fully satisfactory, as they exhibited problems of their own (which I discuss below).

The sample periods are January 1985-July 2013 for the United States; January 1991-July 2013 for the Euro area; January 1997-July 2013 for the United Kingdom; and January 1990-July 2013 for Canada. For all countries, the beginning of the sample period is dictated by the start of Baker *et al.*'s (2013) country-specific policy uncertainty index. For either VAR I set the lag order to the maximum between those chosen by the Akaike, Schwartz, and Hannan-Quinn criteria.

Following, e.g., Cogley and Sargent (2002), Cogley and Sargent (2005), Primiceri (2005), and Gambetti, Pappa, and Canova (2006) the VAR's time-varying parameters, collected in the vector θ_t, are postulated to evolve according to

$$p(\theta_t \mid \theta_{t-1},\, Q) = I(\theta_t)\ f(\theta_t \mid \theta_{t-1},\, Q) \tag{2}$$

with $I(\theta_t)$ being an indicator function rejecting unstable draws—thus enforcing a stationarity constraint on the VAR—and with $f(\theta_t \mid \theta_{t-1},\, Q)$ given by

$$\theta_t = \theta_{t-1} + \eta_t \tag{3}$$

with $\eta_t \sim N(0,\, Q)$. The VAR's reduced-form innovations in (1) are postulated to be zero-mean normally distributed, with time-varying covariance matrix Ω_t which, following established practice, I factor as

$$\mathrm{Var}(\epsilon_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})' \tag{4}$$

The time-varying matrices H_t and A_t are defined as:

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 \\ 0 & 0 & 0 & 0 & h_{5,t} \end{bmatrix} \qquad A_t \equiv \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{2,1,t} & 1 & 0 & 0 & 0 \\ \alpha_{3,1,t} & \alpha_{3,2,t} & 1 & 0 & 0 \\ \alpha_{4,1,t} & \alpha_{4,2,t} & \alpha_{4,3,t} & 1 & 0 \\ \alpha_{5,1,t} & \alpha_{5,2,t} & \alpha_{5,3,t} & \alpha_{5,4,t} & 1 \end{bmatrix} \tag{5}$$

with the $h_{i,t}$ evolving as geometric random walks,

$$\ln h_{i,t} = \ln h_{i,t-1} + \nu_{i,t} \tag{6}$$

For future reference, I define $h_t \equiv [h_{1,t},\, h_{2,t},\, \ldots\, ,h_{N,t}]'$. Following Primiceri (2005), I postulate the non-zero and non-one elements of the matrix A_t—which I collect in the vector $\alpha_t \equiv [\alpha_{2,1,t},\, \alpha_{3,1,t},\, \ldots,\, \alpha_{5,4,t}]'$—to evolve as driftless random walks,

$$\alpha_t = \alpha_{t-1} + \tau_t\ , \tag{7}$$

and I assume the vector $[u_t', \eta_t', \tau_t', \nu_t']'$ to be distributed as

$$\begin{bmatrix} u_t \\ \eta_t \\ \tau_t \\ \nu_t \end{bmatrix} \sim N(0, V), \text{ with } V = \begin{bmatrix} I_4 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & Z \end{bmatrix} \text{ and } Z = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_4^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_5^2 \end{bmatrix} \tag{8}$$

where u_t is such that $\epsilon_t \equiv A_t^{-1} H_t^{\frac{1}{2}} u_t$.[7] Finally, following, again, Primiceri (2005) I adopt the additional simplifying assumption of postulating a block-diagonal structure for S, too—namely

$$S \equiv \text{Var}(\tau_t) = \begin{bmatrix} S_1 & 0_{1\times 2} & 0_{1\times 3} & 0_{1\times 4} \\ 0_{2\times 1} & S_2 & 0_{2\times 3} & 0_{2\times 4} \\ 0_{3\times 1} & 0_{3\times 2} & S_3 & 0_{3\times 4} \\ 0_{4\times 1} & 0_{4\times 2} & 0_{4\times 3} & S_4 \end{bmatrix} \tag{9}$$

with $S_1 \equiv \text{Var}(\tau_{21,t})$, $S_2 \equiv \text{Var}([\tau_{31,t}, \tau_{32,t}]')$, $S_3 \equiv \text{Var}([\tau_{4,1,t}, \tau_{4,2,t}, \tau_{4,3,t}]')$, $S_4 \equiv \text{Var}([\tau_{5,1,t}, \tau_{5,2,t}, \tau_{5,3,t}, \tau_{5,4,t}]')$, thus implying that the non-zero and non-one elements of A_t belonging to different rows evolve independently. As discussed in Primiceri (2005, Appendix A.2), this assumption drastically simplifies inference, as it allows to do Gibbs sampling on the non-zero and non-one elements of A_t equation by equation.

2.1 Estimation

I estimate (1)-(9) *via* Bayesian methods. Appendix B discusses my choices for the priors (which are based on standard priors in the literature on estimating Bayesian time-varying VARs at the quarterly frequency, which I rescaled, when necessary, in order to take into account of the fact that I am here working at the monthly frequency); and the Markov-Chain Monte Carlo algorithm (specifically, Gibbs-sampling) I use in order to simulate the posterior distribution of the hyperparameters and the states conditional on the data. In a nutshell, this is the same used by Primiceri (2005) along all dimensions, with the single exception of the algorithm I use in order to draw the time-varying parameters (that is, the θ_t's) imposing the costraint that the VAR be stationary on a month-by-month basis.

[7] As discussed in Primiceri (2005, pp. 6-7), there are two justifications for assuming a block-diagonal structure for V. First, parsimony, as the model is already quite heavily parameterized. Second, 'allowing for a completely generic correlation structure among different sources of uncertainty would preclude any structural interpretation of the innovations'.

2.1.1 Drawing the θ_t's *via* Koop and Potter's (2011) 'single-move' algorithm

In the literature on Bayesian time-varying parameters VARs—see, first and foremost, Cogley and Sargent (2005), Primiceri (2005), and Gambetti, Pappa, and Canova (2006)—researchers typically use Carter and Kohn (2004)'s multi-move algorithm to jointly draw all of the states for $t = 1, 2, ..., T$. Then, in case they want to impose a stationarity constraint on a period-by-period basis, they check for the stationarity of the VAR at each single date, and they retain the joint draw if and only if the VAR is stationary for all periods. As discussed, e.g., by DelNegro (2003) and Koop and Potter (2011), however, this strategy becomes progressively more difficult to implement as the number of series entering the VAR increases. As Koop and Potter (2011, p. 1127) point out, *'[i]n such cases, the algorithm of Cogley and Sargent (2005)* [that is: Carter and Kohn (2004)'s *cum ex post* rejection of the unstable draws] *will discard nearly every draw. It is not hard to find empirical problems where such an algorithm can take billions and billions of draws without accepting even a single one.'*[8] Because of this, in this paper I use Koop and Potter's (2011) single-move algorithm in order to draw the θ_t's imposing the costraint that the VAR be stationary on a month-by-month basis. (The algorithm is briefly described in Appendix B.)

2.1.2 An alternative strategy: shrinking the state-space

As discussed, e.g., by Canova and Ciccarelli (2009) and Canova and Pérez-Forero (2013), under these circumstances a possible alternative strategy is to 'shrink the state-space', by making the elements of θ_t functions of a small number of time-varying 'factors', and then to keep using Carter and Kohn's algorithm, which, *ceteris paribus*, is significantly faster than Koop and Potter's. The rationale for this is that, since the problem discussed by DelNegro (2003) and Koop and Potter (2011) crucially depends on the dimension of the state space, by drastically shrinking it the problem is eliminated at the root.

I tried this approach within the present context for both larger VARs,[9] and—in order to check the approach's reliability—for the same 5-variables systems I am using herein. Following Canova and Ciccarelli (2009),[10] I postulated that the vectorized θ_t's evolve as an exact linear function[11] of four random-walk factors: a factor which

[8] Indeed, for either country, I initially tried to estimate the VAR *via* Carter and Kohn's algorithm, which is significantly faster than Koop and Potter's (2011) single-move one. In all cases the algorithm got 'stuck' and it could not proceed, as it could not get stable draws.

[9] For the United States the VAR featured ten series; for the United Kingdom and Canada it featured eight series; and for the Euro area it contained six series.

[10] See their general overview of the approach in Section 2 of the paper, and their specific application to the transmission of shocks in G7 countries in Section 8.

[11] By 'exact' I mean that, in line with the application in Section 8 of their paper, the linear relationship betwen the factors and the θ_t's does not feature any error term (that is: u_t in their equation 2 is equal to zero).

is common to all of the elements of the θ_t's; an equation-specific factor; a variable-specific factor; and a lag-specific factor. In all cases the problem of getting stable draws *via* Carter and Kohn's algorithm disappeared, and estimation was quite fast. This is due to the dramatic extent of shrinkage of the dimension of the state-space which is obtained *via* Canova and Ciccarelli's factorization of the vectorized θ_t's: for the 10-variables VAR I estimated for the United States, for example, the dimension of the state-space went (with $p = 6$) from 610 to 28.

Although, from a strictly 'mechanical' point of view, Canova and Ciccarelli's approach proved successful at solving the problem of the 'curse of dimensionality' associated with Carter and Kohn's algorithm, the results based on the 5-variables 'factorized' VARs often turned out to be different, and sometimes markedly so, from those produced by the standard VARs estimated *via* Koop and Potter's (2011) algorithm.[12] Since the key difference between the two approaches is that the former imposes a specific, and strong form of restriction—in terms of *common dynamics*—on the evolution of the elements of θ_t, whereas the latter does not impose any such restriction, the contrast between the two sets of results raises questions about the extent to which imposing such restriction is, within the present context, appropriate, as opposed to instead distorting the inference.

Because of this, in what follows I will uniquely report and discuss the results based on the 5-variables VARs estimated *via* Koop and Potter's algorithm. Ideally, I would have wanted to include in the VARs a larger extent of information, in order to achieve a better identification of the shocks.[13] However, given (*i*) the potential distortion of the inference resulting from shrinking the dimension of the state space and (*ii*) the fact that, as I previously mentioned, estimation of standard, non-factorized VARs featuring more than five variables *via* Koop and Potter's (2011) algorithm typically proved unfeasible because of computational problems, I ultimately decided to simply limit myself to five-variables VARs.[14] As an (admittedly limited) defense of this decision, it has to be stressed that, beyond the policy uncertainty index, the VARs I am using herein contain information about three of the main features characterizing macroeconomic fluctuations: price developements (π_t), the level of economic activ-

[12] I am not showing here any of these results for reasons of space, but they are all available upon request.

[13] On the need for VARs to be 'informationally sufficient'—that is, to include information about all of the key economy's key driving forces—see Forni and Gambetti (2011).

[14] An alternative approach would have been to use a dynamic factor model along the lines of DelNegro and Otrok (2008). An important point to stress however, is that although this would have allowed me to use a significantly larger amount of information than I am using herein, the extent to which this approach would have suffered from some version of the previously-discussed problem plaguing the 'shrinkage of the state space' is an entirely open question. Intuitively, the reason for this is that both approaches are based on the notion of postulating a common time-varying dynamics for objects which may instead be characterized by a quite significant extent of idiosyncratic time-variation. As a result, dynamic factor models with time.varying parameters may well turn out to suffer from exactly the same problems plaguing, within the present context, the approach based on shrinking the state space.

ity (ip_t), and the stance of monetary policy (R_t-π_t). Further, the inclusion of stock prices—which, as I discuss in the next section, under both identification strategies are allowed to react to policy uncertainty shocks within the month—should be of significant help in identifying such shocks for two reasons.

First, for all countries considered herein, stock market growth exhibits a remarkably strong negative correlation with the economic policy uncertainty index.[15] Although, from a strictly logical point of view, this by no means represents a hard proof that stock prices possess a strong informational content for policy uncertainty shocks, such a strong reduced-form correlation provides, at the very least, informal, *prima facie* evidence that this may indeed be the case. Indeed, *second*, consistent with this interpretation, for either country both identification schemes clearly suggest that policy uncertainty shocks do indeed explain comparatively large fractions of the FEV of stock prices growth at all horizons. Overall this suggests that, although being far from ideal, the approach adopted in this paper—beyond being the most reasonable one within the present context—should be regarded as sufficiently reliable.

Finally, an intrinsic limitation of this paper is represented by the fact that, in line with most of the literature, I exclusively focus on Baker *et al.*'s (2013) *aggregate* indices of policy uncertainty.[16] Although, in principle, an extension of the approach adopted herein to the analysis of individual types of policy uncertainty (fiscal, monetary, ...) is straightforward, for reasons of space I have decided to uniquely focus on aggregate policy uncertainty, and to leave the analysis of the time-varying relevance and impact of individual types of uncertainty to future research.

2.2 Identification strategies

2.2.1 Combining zero and sign restrictions

The first identification strategy I use combines inertial restrictions and sign restrictions. Specifically, policy uncertainty shocks are identified by imposing the restrictions that

- within the month, they only impact upon the policy uncertainty index and stock prices, whereas they do not have any impact on either prices, industrial production, or the central bank's monetary policy rate (and therefore, the *ex post* real rate). (Following the month of impact, on the other hand, all variables' responses are left entirely unrestricted.) Such restrictions are conceptually in line with (e.g.) the way researchers such as Sims and Zha (2006) and Leeper and Roush (2003) have identified monetary policy shocks: in the same way as it is reasonable to assume that such shocks do not affect prices and economic activity within the month, it is equally reasonable to assume that—with the

[15] I am not reporting this evidence for reasons of space, but it is available upon request.

[16] An exception is represented by Mumtaz and Surico (2013), who focus on fiscal uncertainty.

single exception of stock prices—the same holds true for policy uncertainty shocks.[17]

- The second restriction I impose—once again, conceptually in line with Sims and Zha (2006)—is that a non-negative policy uncertainty shock induces, within the month, a non-positive response in stock prices.[18] The key motivation for imposing this restriction is that, just as a matter of simple logic, positive innovations to economic policy uncertainty should not be expected to lead to an increase in stock prices.

I jointly impose the zero and sign restrictions *via* the algorithm proposed by Arias, Rubio-Ramirez, and Waggoner (2013), which allows imposition of sign restrictions conditional on zero restrictions. The two sign restrictions on the policy uncertainty index and on stock prices are only imposed on impact, whereas for all months after impact IRFs are left entirely unrestricted.

2.2.2 Uhlig's (2003, 2004) 'maximum fraction of forecast error variance' approach

The second identification strategy is based on the 'maximum fraction of FEV' approach to identification pioneered by Uhlig (2003) and Uhlig (2004). I consider two alternative horizons—3- and 6-months after the initial impact—and for each month in the sample period, and each draw from the posterior distribution, I identify the policy uncertainty shock as the single shock which explains the largest fraction of the FEV of the policy uncertainty index at that horizon.[19] For either country, results based on the two alternative horizons are very similar, and in what follows I will therefore exclusively report results for the 6-months ahead horizon, but the entire set of results is available upon request.

3 Evidence

Figures 1-13 report the evidence. The two vertical lines reported in either figure mark the beginning of the financial crisis, which I take to be August 2007, when the

[17] Further, since (exactly as the two previously-mentioned papers) I am here working at the monthly frequency, the problems plaguing inertial restriction discussed by Canova and Pina (2005) most likely do not apply here, or are drastically reduced. It is important to keep in mind that the problems highlighted by Canova and Pina (2005) have been systematically illustrated based on DSGE models estimated (or calibrated) at the quarterly frequency. Whereas it is quite implausible to assume that a shock does not have any impact on some variables for an entire quarter, the assumption of no impact within the month is much more reasonable.

[18] The corresponding restriction imposed by Sims and Zha (2006) is that a non-negative monetary policy shock induces, within the month, a non-positive response in Divisia M2.

[19] As discussed in Section 1.1, this is broadly conceptually in line with one of the identification strategies used by Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2013).

European Central Bank (henceforth, ECB), following reports of widespread stress in Euro area money markets, stepped in by injecting 93 billion Euros; and the collapse of Lehman Brothers, in September 2008, which marked the start of the most virulent phase of the crisis.

3.1 The volatility of policy uncertainty shocks

Figure 1 shows the medians and the 1- and 2-standard deviations percentiles of the posterior distributions of the standard deviations of estimated policy uncertainty shocks. For either identification strategy, standard deviations have been normalized on the policy uncertainty index, which represents the natural normalization.[20]

For the United States, evidence produced by either identification strategy points towards an increase in the volatility of policy uncertainty shocks around August 2007, when the ECB first intervened in Euro area money markets. Evidence is comparatively stronger based on Uhlig's approach, and it is instead weaker, with a greater extent of econometric uncertainty across the board, based on inertial restrictions. *From now on, the expression 'inertial restrictions' will be used as a shorthand for 'the identification strategy based on a combination of inertial and sign restictions'.* Uhlig's approach also points towards a temporary spike in volatility immediately following 9/11 and the collapse of Lehman Brothers, and a hump-shaped temporary increase during the Summer of 2011, the period leading up to the introduction of 'Operation Twist'. Whereas the strategy based on inertial restrictions also identifies this last increase, it points towards a *decrease* following the collapse of Lehman Brothers, and provides no clear evidence of an increase following 9/11. Such a failure to clearly identify increases in the volatility of policy uncertainty shocks following either 9/11 or the collapse of Lehman might be interpreted as evidence of a comparatively lower extent of reliability of this identification strategy, compared to Uhlig's approach. This is the case especially for the latter episode, whereas for 9/11 the argument is much less clear-cut. Because of this, in what follows I will tend to emphasize results based on Uhlig's approach, and to give instead less weight to those based on inertial restrictions.

For the Euro area Uhlig's approach points towards two volatility increases post-August 2007, both following the collapse of Lehman, and around the end of 2011-beginning of 2012, when the Greek government revealed the true extent of the country's fiscal predicament. Either of the two increases is also captured by the inertial restrictions approach, but with a much greater extent of uncertainty. Finally, and somehow puzzlingly, both approaches identify modest increases in volatility following the ECB's August 2007 intervention in Euro area money markets. One possible interpretation of this finding is that the very decisiveness and dimension of the ECB's

[20] So, to be clear, for each month t in the sample, and for each draw j from the posterior distribution, the standard deviation of policy uncertainty shocks has been computed as the square root of the last element of the column corresponding to the policy uncertainty shock in the structural impact matrix $A_{0,t,j}$.

intervention 'nipped policy uncertainty in the bud'—albeit temporarily—by providing reassurance that the central bank was ready to take unprecedented, and massive steps in order to calm money markets.

Turning to the United Kingdom, Uhlig's methodology points towards a modest increase in the volatility of policy uncertainty shocks following August 2007; a small upwards jump following the collapse of Lehman; and a steady, and ultimately sizeable increase after that. Based on the alternative identification strategy, the pattern is very broadly similar based on the median estimates, but the extent of uncertainty is, once again, vastly superior.

Finally, evidence for Canada is consistent across the two identification strategies, and points towards the overall stability of the volatility of policy uncertainty shocks up until the collapse of Lehman; a non-negligible increase after September 2008; and some fluctuations after that, with a sizeable increase towards the end of 2011.

Let's now turn to the evolution of the sign pattern of the identified policy uncertainty shocks.

3.2 The evolution of the sign pattern of policy uncertainty shocks

Figure 2 shows the smoothed fractions of draws from the posterior distribution for which policy uncertainty shocks are estimated to have been positive. Smoothing has been performed *via* a Bartlett window of dimension 12+1+12=25 months.[21] Based on Uhlig's methodology, the period following the outbreak of the crisis, in August 2007, has been characterized for either country by a significant increase in the fraction of draws for which policy uncertainty shocks are estimated to have been positive. This is very clear for the United States, the Euro area, and the United Kingdom, and only to a slightly lesser extent for Canada. As for the two-to-three years leading up to the crisis, in either the United States, the Euro area, or Canada policy uncertainty shocks are estimated to have been predominantly negative, whereas for the United Kingdom no clear-cut pattern is discernible. Results based on inertial restrictions are broadly in line with those based on Uhlig's methodology, with the main difference being that the fluctuations in the smoothed fractions of positive draws are much less wide, and results are therefore uniformly weaker.

Although evidence clearly suggests that policy uncertainty shocks have been predominantly positive during the period following the outbreak of the crisis, this, by itself, by no means represents a hard proof that such shocks played an important role in this episode. In order to explore the role played by policy uncertainty shocks within the context of the Great Recession, we therefore now analyze the fractions of

[21] 'Killing off' all of the components of the raw fraction of draws with a frequency of oscillation faster than one year and a half *via* Christiano and Fitzgerald (2003)'s band-pass filter produces qualitatively similar results. This evidence is available upon request.

the series' FEV explained by such shocks, and we perform counterfactual simulations in which we re-run history by killing off such shocks.

3.3 The fractions of forecast error variance explained by policy uncertainty shocks

Figures 3 to 6 show, for either country, the medians and the 1- and 2-standard deviations percentiles of the posterior distributions of the fractions of the 1-year ahead FEV (henceforth, FEV) of either series explained by policy uncertainty shocks.[22] A key finding emerging from the figures is the stark and systematic contrast between the results produced by the two identification schemes.

3.3.1 Results based on the strategy combining zero and sign restrictions

Results based on the strategy combining zero and sign restrictions point towards a uniformly negligible role of policy uncertainty shocks in explaining fluctuations in either industrial production growth, inflation, or the *ex post* real rate. This is especially apparent for the United Kingdom and Canada, for which the 95th percentiles of the posterior distributions for either of the three series have been uniformly below 10 per cent—and most of the time even below 5 per cent—for the entire sample periods; it is just slightly less so for the Euro area, for which the fractions of explained FEV have exhibited modest increases following the collapse of Lehman; finally, for the United States the role played by policy uncertainty shocks is uniformly negligible only for inflation, whereas for the other two series it is non-negligible, but uniformly modest, with (based on median estimates) the maximum values of the fractions of FEVs explained by policy uncertainty shocks being around 15 per cent. Further, and puzzlingly, the period following August 2007 does not exhibit any clear-cut, systematic difference compared to the pre-crisis period. On the other hand, results are completely different for stock prices growth and policy uncertainty. Unsurprisingly, policy uncertainty shocks play an important role (although, based on median estimates, not a dominant one) in driving the evolution of Baker *et al.*'s policy uncertainty indices. It is to be noticed, however, that—with the possible exception of the United States during the months between the outbreak of the crisis and the collapse of Lehman, and of Canada immediately after the collapse of Lehman—the fractions of FEV of the policy uncertainty indices explained by policy uncertainty shocks do not exhibit any obvious difference between the pre- and post-August 2007 sub-periods. As for stock prices, conceptually in line with the previously mentioned strong, negative reduced-form correlation between policy uncertainty indices and stock prices growth, policy

[22] Results for other forecast horizons are qualitatively in line with those discussed herein, and are not reported for reasons of space, but they are available upon request. Further, results for the overall fractions of the *variances* of the series explained by policy uncertainty shocks are also qualitatively in line with the evidence reported in Figures 3-6, and are available upon request.

uncertainty shocks are also estimated to explain large fractions of their FEV. In the United States, for example, based on median estimates the fraction had been oscillating between 20 and 50 per cent between the mid-1990s and the summer of 2007; it significantly increased following the beginning of the crisis, in August 2007; and it has been oscillating between 35 and 55 per cent ever since. In either the Euro area or the United Kingdom the fraction of FEV of stock prices growth explained by policy uncertainty shocks has been oscillating around 30 per cent during the entire sample period. Interestingly—and in marked contrast with the United States—the period following the outbreak of the crisis does not exhibit any difference whatsoever with respect to previous years. Finally, for Canada the fraction of FEV of stock prices growth explained by policy uncertainty shocks had exhibited a large, temporary spike around the time of the collapse of Lehman, and it has significantly declined during subsequent years.

Summing up, based on the set of results produced by the inertial restrictions approach we would conclude that, in either country,

(i) policy uncertainty shocks have played a uniformly negligible-to-minor role in the evolution of either real economic activity, prices, or the stance of monetary policy, and

(ii) quite strikingly, the period following the outbreak of the financial crisis does not exhibit any obvious, clear-cut difference compared to the pre-crisis years.

3.3.2 Results based on Uhlig's approach

Results based on Uhlig's approach paint a completely different picture, in which policy uncertainty shocks played a definitely non-negligible, and sometimes important role in the evolution of real activity, prices, and the monetary policy stance.

In the United States their role is estimated to have been uniformly minor only for inflation, with the median estimate of its fraction of FEV explained by policy uncertainty shocks oscillating around 10 per cent over the entire sample period. For either industrial production growth or the *ex post* real FED Funds rate, on the other hand, the median estimates of the fractions have oscillated around 30 per cent, and between 20 and 50 per cent, respectively, and in both cases they have exhibited a clear spike immediately following the collapse of Lehman. The role of policy uncertainty shocks in the evolution of stock prices growth is estimated to have been markedly smaller than the corresponding estimate produced by the approach based on inertial restrictions. Finally—and again in marked contrast with the results produced by the alternative identification strategy—policy uncertainty shocks are estimated to have explained *close to all* of the FEV of the policy uncertainty index. In fact, as Figures 4-6 show, this result holds for all countries.

Turning to the Euro area, a consistent finding for either industrial production growth, inflation, or the *ex post* real ECB policy rate is that the fractions of their FEVs explained by policy uncertainty shocks, which had been uniformly modest up

until the collapse of Lehman, have systematically increased over the following period. For industrial production growth, for example, the fraction temporarily spiked (based on median estimates) to almost 50 per cent in the months immediately after the collapse of Lehman, and since then it has been gradually increasing, reaching about 45 per cent at the end of the sample. For inflation and the *ex post* real rate the broad pattern is the same, with increases (based on median estimates) from about 10-20 per cent immediately before the collapse of Lehman to about 40-50 per cent at the end of the sample. Finally, as for stock prices two findings stand out: first, in contrast to the results produced by the alternative identification scheme, the fraction of FEV explained by policy uncertainty shocks has been uniformly modest (based on median estimates, around 10-15 per cent) over the entire sample period; second, with the exception of a minor, temporary upward blip following the collapse of Lehman, the period of the financial crisis does not exhibit any difference whatsoever compared to previous years.

In the United Kingdom the period following the collapse of Lehman has been characterized by systematically higher values of the fractions of FEV explained by policy uncertainty shocks, compared to the previous period, for either industrial production growth, inflation, the *ex post* real rate, or stock prices growth. Only for the latter variable, however, the fraction has exhibited a consistent upward trend: for either of the other three series, indeed, the fraction of FEV has exhibited repeated fluctuations, but without any consistently increasing or decreasing pattern.

Finally, results for Canada stand out, compared to those for the other three countries, along several dimensions: first, based on median estimates, the fractions of FEV of either industrial production growth, inflation, or the *ex post* real rate are typically estimated to have been modest (with the exception of industrial production growth during the years immediately before the outbreak of the crisis); second, the period following the collapse of Lehman does not exhibit any clear-cut difference compared to previous years, and in particular it does not exhibit any systematic increase for in the fraction of FEV for any series.

3.3.3 Which of the two sets of results should be regarded as more reliable?

Given the contrast between the sets of results produced by the two alternative identification schemes, an obvious question arises: *'Which of the two sets of results should be regarded as the more reliable?'* Although, as I previously mentioned in Section 3.1, results based on Uhlig's methodology appear overall to better capture key events in recent economic history, in my own view the case against the alternative approach, and in favor of Uhlig's, is not watertight. The reason is that the identification strategy combining inertial and sign restrictions does not produce a manifestly implausible overall set of result. As a consequence, although some (such as myself) may tend to give more weight to the results produced by Uhlig's approach, those produced by the

alternative strategy cannot be dismissed straight away.

Although the evolution of the fractions of FEV of individual series explained by policy uncertainty shocks provides crucial information about the role played by these disturbances within the context of the Great Recession, it does not provide any indication about what would have happened if such shocks had not been present. In order to answer this question, we therefore turn to results from counterfactual simulations.

3.4 Counterfactual simulations 'killing off' policy uncertainty shocks

Figure 7 shows, for the United States, the actual, historical paths of the Federal Funds rate, Baker *et al.*'s policy uncertainty index, and annual[23] inflation, stock prices growth, and industrial production growth, together with the medians and the 2-standard deviations percentiles[24] of the posterior distributions of the counterfactual simulations performed by 'killing off', for each draw from the posterior, the identified policy uncertainty shocks over the entire sample period. Figures 8 to 11, on the other hand, show, for either of the four countries, the actual series, together with the medians and the 1- and 2-standard deviations percentiles of the posterior distributions of the counterfactual simulations performed by 'killing off' policy uncertainty shocks only over the period following August 2007.

3.4.1 The United States since the early 1990s

Starting from the longer counterfactual simulation for the United States, results based on the identification strategy combining inertial and sign restrictions point towards an overall modest, although often non-negligible role of identified policy uncertainty shocks for all series. This is especially apparent for stock market growth, which, based on median estimates, would have been higher—although, most of the time, not significantly so—both during the early years of the new millennium, and during the months immediately following the collapse of Lehman. Much weaker results (in the sense of smaller differences between actual and counterfactual paths) obtain for industrial production growth, inflation, and the FED Funds rate. In particular, during both the early millennium recession, and the Great Recession, killing off policy uncertainty shocks would have increased industrial production growth by just a few percentage points, which, compared to the actual magnitude of the downturns, represent only marginal improvements. As for inflation, the difference between actual

[23] For prices, industrial production, and stock prices I am showing annual rates of growth in order to make the figures more intelligible. Since in the estimated VARs rates of growth are computed as log-differences, for each draw from the posterior counterfactual annual rates of growth for prices, industrial production, and stock prices are computed based on the relevant counterfactual month-on-month log-difference.

[24] I do not report 1-standard deviations percentiles in order to avoid cluttering the figure.

and counterfactual paths is uniformly negligible. As for the FED Funds rate, the difference between actual and counterfactual paths is again mostly negligible, with the notable exceptions of the years 2002-2004, and especially of the period following the collapse of Lehman, when the counterfactual rate would have been higher, and statistically significantly so, by about 1-1.5 percentage points. This suggests that a non-negligible portion of the dramatic cut in the FED Funds rate following the collapse of Lehman was a response to the equally dramatic increase in the extent of policy uncertainty. Finally, in line with the evidence reported in the last panel of the top row of Figure 3, the counterfactual path for the policy uncertainty index is also, most of the time, not significantly different from the actual historical path, thus confirming, once again, that the policy uncertainty shocks identified by combining inertial and sign restrictions do not play a dominant role in explaining the evolution of policy uncertainty.

Results based on Uhlig's procedure point towards a more important role played by policy uncertainty shocks in shaping U.S. macroeconomic fluctuations since the early 1990s. This is especially apparent for the Federal Funds rate, which, absent these shocks, would have been (based on median estimates) between 1 and 2 percentage points lower, and significantly so, during the second half of the 1990s; it would have been higher, by about the same amount, between 2002 and 2004; it would have been lower by about 2 and a half percentage points during the months before the collapse of Lehman; and, most notably, it would have been higher by about 2 to 3 percentage points following the collapse of Lehman. Taken at face value, these results would imply that *about half* of the fall in the FED Funds rate between the peak immediately before the outbreak of the crisis and the end of the sample is to be interpreted as the FED's reaction to the dramatic increase in policy uncertainty associated with the financial crisis. Equally important has been the role played by policy uncertainty shocks for industrial production, with the counterfactual path being significantly lower during the second half of the 1990s and during the period leading up to the collapse of Lehman; reaching (based on median estimates) a trough equal to to -8.5 per cent in the aftermath of the collapse of Lehman, as opposed to the actual trough of -16.3 per cent; and about 4 percentage points higher than actual industrial production growth during subsequent years. As for inflation, the difference between counterfactual and actual paths is most of the time not statistically significant, with the exception of the last years of the sample, when, based on median estimates, the counterfactual path has been about 1 percentage points higher than the actual one. Stock prices growth is the only variable for which Uhlig's methodology delivers counterfactual paths which are, most of the time, closer to the actual historical paths than those produced by the alternative identification strategy. The difference between the results produced by the two approaches is especially apparent during the early years of the new millennium, when the median counterfactual path produced by Uhlig's methodology is nearly indistinguishable from the actual historical path. The starkest difference between the results produced by the two approaches pertains however to

the policy uncertainty index itself, with the counterfactual paths generated by Uhlig's approach being broadly flat over the entire sample period, thus clearly suggesting that, in line with the evidence reported in the last panel of the second row of Figure 3, policy uncertainty shocks identified based on Uhlig's method explain nearly all of the variation in Baker *et al.*'s policy uncertainty index.

3.4.2 The Great Recession

Turning to the counterfactuals for the Great Recession, for the United States the results reported in Figure 8 are in line with those shown in Figure 7 for the period after August 2007, and will not therefore discussed further.

For the Euro area, results based on the identification strategy combining inertial and sign restrictions point towards a negligible impact for industrial production, inflation, and the policy uncertainty index; a sizeable impact for stock prices, with the median counterfactual path being uniformly and markedly higher than the actual historical path, and in 2011-2012 significantly so; and a counterfactual path for the ECB policy rate which would have been uniformly *lower* than the actual path—even going into negative territory—and most of the time significantly so. I would argue that this is a further reason (beyond those I previously discussed in Section 3.1) to look with some skepticism at the results produced by this approach. The results produced by Uhlig's approach appear almost uniformly more sensible: the counterfactual path for stock prices growth is again, based on median estimates, uniformly higher than the actual historical one, although never significantly so at the 10 per cent level; the counterfactual path for inflation has been, since the early 2011, uniformly lower than the actual path, and often significantly so; counterfactual industrial production growth would have been markedly higher, and significantly so, both during the dramatic downturn following the collapse of Lehman, and since the early 2001; and the policy uncertainty index would have been essentially flat between 8 and 10 over the entire sample period. In particular, based on median estimates, the trough of industrial production growth in the aftermath of the collapse of Lehman would have been equal to -12.2 per cent compared to the actual trough of -24.1 per cent. As for the ECB policy rate, in marked contrast with the results produced by the alternative identification scheme, here it would have been significantly *higher* than the actual path, increasing (based on median estimates) from about 3 per cent around the time of the collapse of Lehman, to about 4.2 per cent at the end of the sample. This, together with the just-discussed results for industrial production growth, clearly point towards a major role played by policy uncertainty shocks in the Euro area within the context of the Great Recession.

In the United Kingdom, the first identification strategy suggests that policy uncertainty shocks played essentially no role for inflation and industrial production, a minor role for stock prices and policy uncertainty, and some non-negligible role for the *Bank of England*'s policy rate, especially since early 2012, when the rate would

have been (based on median estimates) about 1.4-1.5 percentage points higher than the actual rate. Based on Uhlig's approach, the *Bank*'s counterfactual policy rate would instead have been broadly similar to the actual path; counterfactual inflation would have been between 1 and 2 percentage points lower than the actual historical path since the first half of 2010; industrial production growth would have been somehow higher, although not significantly so, during the recession following the collapse of Lehman, and towards the end of the sample; and stock prices growth would have been *lower*, although not significantly so, since the early 2010. All in all, results based on either identification strategy point towards a negligible-to-minor role played by policy uncertainty shocks within the context of the Great Recession in the United Kingdom.

Finally, turning to Canada, counterfactual industrial production growth would have been nearly indistinguishable from the actual path based on the identification strategy combining inertial and sign restrictions, and it would have been only marginally different, and not significantly so, based on Uhlig's methodology; both inflation and the *Bank of Canada*'s policy rate would have been mostly higher, but never significantly so, based on the first identification strategy, and would instead have been markedly higher, and mostly significantly so, based on Uhlig's (this is especially apparent for the monetary policy rate); and counterfactual stock market growth would have been, based on median estimates, broadly similar based on the two alternative identification strategies—and in particular, markedly higher during the period immediately following the collapse of Lehman—but the difference with the actual path would have been statistically significant only based on Uhlig's approach. Overall, results for Canada are therefore mixed: in particular, for the real activity indicator, industrial production, thes do not point towards much of a role played by policy uncertainty shocks.

3.5 Impulse-response functions

Figure 12 shows, for the United States, the medians and the 1- and 2-standard deviations percentiles of the posterior distributions of the IRFs of either series to a normalized policy uncertainty shock at the 1-year ahead horizon. (The evolution of the IRFs at alternative horizons is broadly similar to the one at the 1-year horizon, and is not reported here for reasons of space, but the entire set of results is available upon request.) For each month, all IRFs have been normalized by setting the median of the posterior distribution of the impact of policy uncertainty shocks on the policy uncertainty index at t=0 equal to 25, which is roughly equal to the standard deviation of policy uncertainty shocks identified based on Uhlig's methodology around the time of the collapse of Lehman Brothers. IRFs for either of the other three countries are not reported here for reasons of space, as they exhibit a negligible-to-minor extent of time-variation—which is never statistically significant—for either of the five series, and based on either of the two identification strategies (all of these results are however

available upon request).

Results based on either of the two identification strategies consistently point towards modest changes in U.S. IRFs over the sample period only for inflation, whereas such changes are much more sizeable for other variables, in particular for industrial production and stock prices growth. For all series except inflation, the broad pattern of variation points towards a stronger responsiveness of the economy to policy uncertainty shocks towards the end of the 1990s and, to a lesser extent, immediately before the outbreak of the financial crisis. An important point to stress is that, although, since the Summer of 2007, IRFs to policy uncertainty shocks appear to have been uniformly more muted than during the years leading up to the crisis, this specific pattern clearly does *not* represent a feature *peculiar* to the financial crisis *per se*, as a very similar weakening of the responses to policy uncertainty shocks also pertained, e.g., the early years of the new millennium (with the single exception of inflation, for which the estimated extent of time-variation is uniformly small). Rather, the evidence reported in Figure 12 is compatible with the notion that the response of the economy to policy unertainty shocks is (very broadly speaking) comparatively stronger during periods of expansion, and it is instead weaker during periods of recession. Finally, it is to be stressed how, for all series, the responses to policy uncertainty shocks are in line with what basic intuition would induce us to expect, with negative impacts for either industrial production, inflation, stock prices growth, or the *ex post* real FED Funds rate.

4 Conclusions

In this paper I have used Bayesian time-varying parameters structural VARs with stochastic volatility, and two alternative identification schemes, to explore the role played by policy uncertainty shocks within the context of the Great Recession in the United States, the Euro area, the United Kingdom, and Canada. Shocks identified as being orthogonal to the state of the economy (except stock prices) within the month played a uniformly marginal role in either country. An alternative identification strategy in the spirit of Uhlig (2003, 2004) points instead towards a non-negligible role, with, e.g., (*i*) the fraction of 1-year ahead forecast error variance of U.S. industrial production growth explained by these shocks being around 20-30 per cent over the entire sample period; and (*ii*) the trough in median counterfactual industrial production growth in the aftermath of the collapse of Lehman Brothers being equal to -8.5 per cent, as opposed to the actual value of -16.3 per cent. In either country, the period following the collapse of Lehman Brothers has been characterized by an increase in both the volatility of policy uncertainty shocks, and the fraction of draws from the posterior distribution for which they are estimated to have been positive (i.e., contractionary). Impulse-response functions, on the other hand, did not exhibit any peculiar pattern, during the Great Recession, compared to previous years.

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A The Data

Here follows a detailed description of the dataset.

A.1 Indices of overall economic policy uncertainty

All indices of overall economic policy uncertainty are from Baker, Bloom, and Davis (2013), and they have downloaded from http://www.policyuncertainty.com. The website contains country-specific policy uncertainty indices for the United States (since January 1985), the United Kingdom (since January 1997), and Canada (since January 1990). As for the Euro area, it contains country-specific indices for Germany , France, and Italy (all of them since January 1997), and Spain (since January 2001). In order to construct a synthetic policy uncertainty index for the Euro area I have therefore proceeded as follows. For the period between January 1997 and December 2000, I have taken the 'aggregate' of Germany, France, and Italy as a proxy for the entire Euro area, and I have aggregated the three respective country-specific indices into a synthetic Euro-area index using as weights the fractions of each country's nominal GDP (expressed in Euros) in the three-countries aggregate nominal GDP. In order to do this, I used country-specific series for quarterly, seasonally adjusted nominal GDP expressed in Euros from the *OECD*'s *Main Economic Indicators* database—specifically, DEUGDPNQDSMEI ('Current Price Gross Domestic Product in Germany, Billions of Euros'), FRAGDPNQDSMEI ('Current Price Gross Domestic Product in France, Billions of Euros'). and ITAGDPNQDSMEI ('Current Price Gross Domestic Product in Italy, Billions of Euros'). As for the period since January 2001, I have used exactly the same methodology, but this time I have applied it to the 'aggregate' of Germany, France, Italy and Spain (as for Spain, the corresponding series is ESPGDPNQDSMEI, 'Current Price Gross Domestic Product in Spain, Billions of Euros'). An important point to stress is that, for the Euro area, data up until August 2001 are uniquely used to calibrate the priors. This means that the entire estimation step here is being performed based on a policy uncertainty index which has been constructed in a consistent way, by aggregating all of the four countries' indices. As a result, although sub-optimal—ideally, I would have preferred to use a proper policy uncertainty index for the entire Euro area, computed by aggregating country-specific indices for all individual member countries—the solution adopted herein (*i*) has been constructed in a consistent way along the estimation sample, which is what ultimately matters, and (*ii*) since it pertains to the four largest countries, accounting for about 70 per cent of Euro area GDP, it should be regarded as a good proxy for policy uncertainty at the level of the entire Euro area.

A.2 Macroeconomic data

A.2.1 United States

A monthly seasonally adjusted industrial production index (acronym is 'INDPRO') is from the Board of Governors of the Federal Reserve System. A monthly seasonally adjusted chain-type price index for personal consumption expenditures excluding food and energy ('PCEPILFE') is from U.S. Department of Commerce: Bureau of Economic Analysis. A monthly series for the effective Federal Funds rate ('FEDFUNDS') is form the Board of Governors of the Federal Reserve System. A monthly series for the Standard and Poor's composite price index is from Robert Shiller's website.

A.2.2 Euro area

A monthly seasonally adjusted industrial production index ('STS.M.I6.Y.PROD.NS0020.4.000', Euro area 17, industrial production index, total industry, excluding construction) is from *Eurostat*, and has been downloaded from the *European Central Bank*'s website. A monthly seasonally adjusted harmonized index of consumer prices ('ICP.M.U2.S.000000.3.INX', Euro area, HICP, overall index) is from the *ECB*'s database. The *ECB*'s policy rate is from the *ECB*'s website. Before January 1999, I took, as proxy for an 'average' monetary policy rate at the level of the entire Euro area, the short rate from the *ECB*'s dataset (once again, it is important to keep in mind data data before August 2001 are here uniquely used ion oredr to compute the priors). A monthly series for stock prices ('FM.M.U2.EUR.DS.EI.DJEURST.HSTA', Euro area, Dow Jones Euro Stoxx Price Index) is from the *ECB*'s database.

A.2.3 United Kingdom

A seasonally adjusted series for monthly interpolated real GDP is from the *National Institute of Economic and Social Research*. A monthly seasonally unadjusted series for the consumer price index ('GBRCPIALLMINMEI', consumer price index of all items in the United Kingdom) is from the *OECD*'s Main Economic Indicators dataset, and it has been seasonally adjusted *via* the *ARIMA* X-12 procedure as implemented in *EViews*. A monthly series for the *Bank of England*'s monetary policy rate ('INTDSRGBM193N', discount rate for United Kingdom) is from the *International Monetary Fund*'s *International Financial Statistics* database. A monthly series for stock prices ('SPASTT01GBM661N', total share prices for all shares for the United Kingdom) is from the *OECD*'s Main Economic Indicators dataset.

A.2.4 Canada

Monthly indices for industrial production ('CANPROINDMISMEI', production of total industry), consumer prices ('CANCPICORMINMEI', consumer price index: all items excluding food and energy), and stock prices ('SPASTT01CAM661N', total

share prices for all shares) are from the *OECD*'s Main Economic Indicators dataset. The industrial production and stock prices indices are seasonally adjusted. The consumer prices index, on the other hand, is seasonally unadjusted, and it has been seasonally adjusted *via* the *ARIMA* X-12 procedure as implemented in *EViews*. A monthly series for the *Bank of Canada*'s monetary policy rate ('INTDSRCAM193N', discount rate for Canada) is from the *International Monetary Fund*'s *International Financial Statistics* database.

B Details of the Markov-Chain Monte Carlo Procedure

We estimate (1)-(9) *via* Bayesian methods. The next two subsections describe our choices for the priors, and the Markov-Chain Monte Carlo algorithm we use to simulate the posterior distribution of the hyperparameters and the states conditional on the data, while the third section discusses how we check for convergence of the Markov chain to the ergodic distribution.

B.1 Priors

For the sake of simplicity, the prior distributions for the initial values of the states—θ_0, α_0, and h_0—which we postulate all to be normal, are assumed to be independent both from one another, and from the distribution of the hyperparameters. In order to calibrate the prior distributions for θ_0, α_0 and h_0 we estimate a time-invariant version of (1) based on the first 8 years of data, and we set

$$\theta_0 \sim N\left[\hat{\theta}_{OLS}, 4 \cdot \hat{V}(\hat{\theta}_{OLS})\right] \tag{B1}$$

As for α_0 and h_0 we proceed as follows. Let $\hat{\Sigma}_{OLS}$ be the estimated covariance matrix of ϵ_t from the time-invariant VAR, and let C be the lower-triangular Choleski factor of $\hat{\Sigma}_{OLS}$—i.e., $CC' = \hat{\Sigma}_{OLS}$. We set

$$\ln h_0 \sim N(\ln \mu_0, 10 \times I_4) \tag{B2}$$

where μ_0 is a vector collecting the logarithms of the squared elements on the diagonal of C. We then divide each column of C by the corresponding element on the diagonal—let's call the matrix we thus obtain $\tilde{C}$—and we set

$$\alpha_0 \sim N[\tilde{\alpha}_0, \tilde{V}(\tilde{\alpha}_0)] \tag{B3}$$

where $\tilde{\alpha}_0$—which, for future reference, we define as $\tilde{\alpha}_0 \equiv [\tilde{\alpha}_{0,11}, \tilde{\alpha}_{0,21}, ..., \tilde{\alpha}_{0,61}]'$—is a vector collecting all the non-zero and non-one elements of $\tilde{C}^{-1}$ (i.e, the elements below the diagonal), and its covariance matrix, $\tilde{V}(\tilde{\alpha}_0)$, is postulated to be diagonal, with

each individual (j,j) element equal to 10 times the absolute value of the corresponding j-th element of $\tilde{\alpha}_0$. Such a choice for the covariance matrix of α_0 is clearly arbitrary, but is motivated by our goal to scale the variance of each individual element of α_0 in such a way as to take into account of the element's magnitude.

Turning to the hyperparameters, we postulate independence between the parameters corresponding to the three matrices Q, S, and Z—an assumption we adopt uniquely for reasons of convenience—and we make the following, standard assumptions. The matrix Q is postulated to follow an inverted Wishart distribution,

$$Q \sim IW\left(Q_0^{-1}, T_0\right) \tag{B4}$$

with prior degrees of freedom T_0 and scale matrix $T_0\bar{Q}$. In order to minimize the impact of the prior, thus maximizing the influence of sample information, we set T_0 equal to the minimum value allowed, the length of θ_t plus one. As for $\bar{Q}$, we calibrate it as $\bar{Q}= \gamma \times \hat{\Sigma}_{OLS}$, setting γ to a value which is equivalent, at the monthly frequency, to the value used by Cogley and Sargent (2005) at the quarterly frequency. Since Cogley and Sargent (2005) set γ to γ=3.5$\times 10^{-4}$, here I set it to $\gamma=(3.5^{1/2}\times 10^{-2}/3)^2=(3.5/9)\times 10^{-4}$.

The three blocks of S are assumed to follow inverted Wishart distributions, with prior degrees of freedom set, again, equal to the minimum allowed, respectively, 2, 3 and 4:

$$S_1 \sim IW\left(\bar{S}_1^{-1}, 2\right) \tag{B5}$$

$$S_2 \sim IW\left(\bar{S}_2^{-1}, 3\right) \tag{B6}$$

$$S_3 \sim IW\left(\bar{S}_3^{-1}, 4\right) \tag{B7}$$

As for $\bar{S}_1$, $\bar{S}_2$ and $\bar{S}_3$, we calibrate them based on $\tilde{\alpha}_0$ in (B3) as $\bar{S}_1=\lambda \times |\tilde{\alpha}_{0,11}|$, $\bar{S}_2=\lambda\times\text{diag}([|\tilde{\alpha}_{0,21}|, |\tilde{\alpha}_{0,31}|]')$ and $\bar{S}_3=\lambda\times\text{diag}([|\tilde{\alpha}_{0,41}|, |\tilde{\alpha}_{0,51}|, |\tilde{\alpha}_{0,61}|]')$, with λ =1.1111$\times 10^{-4}$. Such a calibration is consistent with the one we adopted for Q, as it is equivalent to setting $\bar{S}_1$, $\bar{S}_2$ and $\bar{S}_3$ equal to $(0.01/3)^2$ times the relevant diagonal block of $\tilde{V}(\tilde{\alpha}_0)$ in (B3), and it is the monthly equivalent of the calibration for λ at the quarterly frequency I have previously used, e.g., in Benati (2008) and Benati and Goodhart (2011). Finally, as for the variances of the stochastic volatility innovations, I adapt to the monthly frequency the calibration used by Cogley and Sargent (2002, 2005) for the quarterly frequency, and I postulate an inverse-Gamma distribution for the elements of Z,

$$\sigma_i^2 \sim IG\left(\frac{(0.01/3)^2}{2}, \frac{1}{2}\right) \tag{B8}$$

B.2 Simulating the posterior distribution

I simulate the posterior distribution of the hyperparameters and the states conditional on the data *via* the following MCMC algorithm, combining elements of Primiceri (2005), Cogley and Sargent (2002, 2005), and Koop and Potter (2011). In what

follows, x^t denotes the entire history of the vector x up to time t—i.e. $x^t \equiv [x_1', x_2', , x_t']'$—while T is the sample length.

(a) Drawing the elements of θ_t Conditional on Y^T, α^T, and H^T, the observation equation (1) is linear, with Gaussian innovations and a known covariance matrix. Following Koop and Potter (2011), I sample the elements of θ^T, for all t≥1, as follows.[25]

- I start by drawing a candidate $\theta_t^c \sim N(\mu_t, \Psi_t)$, where

$$\mu_t = \frac{\theta_{t-1,i} + \theta_{t+1,i-1}}{2} + G_t \left[Y_t - X_t' \left(\frac{\theta_{t-1,i} + \theta_{t+1,i-1}}{2} \right) \right] \tag{B9}$$

$$G_t = \frac{1}{2} Q_{i-1} X_t \left(X_t' Q_{i-1} X_t + \Omega_t \right)^{-1} \tag{B10}$$

$$\Psi_t = \frac{1}{2} \left(I_K - G_t X_t' \right) Q_{i-1} \tag{B11}$$

  for $t < T$, and

$$\mu_t = \theta_{t-1,i} + G_t \left[Y_t - X_t' \theta_{t-1,i} \right] \tag{B12}$$

$$G_t = Q_{i-1} X_t \left(X_t' Q_{i-1} X_t + \Omega_t \right)^{-1} \tag{B13}$$

$$\Psi_t = \left(I_K - G_t X_t' \right) Q_{i-1} \tag{B14}$$

  for $t = T$.

- Based on the companion form for θ_t^c, I assess whether the candidate draw is stable. Let $I(\theta_t^c)$ be an indicator function taking the value of 1 if the draw is stable, and 0 otherwise.

- The acceptance rate for θ_t^c is equal to

$$\omega_{\theta,t} = \min \left[\frac{I(\theta_t^c) \lambda \left(\theta_{t,i-1}, Q_{i-1} \right)}{\lambda \left(\theta_t^c, Q_{i-1} \right)}, 1 \right] \tag{B15}$$

  where $\lambda(\cdot)$ is an integrating constant which measures the fractions of draws satsfying the stability constraint. To compute $\lambda(\cdot)$, I draw, for $k = 1, 2, ..., 100$, $\theta_t^{c,k} \sim N(\theta_t^c, Q_{i-1})$, and I evaluate $\lambda_k = I(\theta_t^{c,k})$. Then, I evaluate $\lambda(\theta_t^c, Q_{i-1}) = 100^{-1} \sum_{k=1}^{100} \lambda_k$ and $\lambda(\theta_{t,i-1}, Q_{i-1})$, and I compute the acceptance probability. For $t = T$, the probability is $\omega_{\theta,T} = I(\theta_T^c)$. Then, I draw $\nu \sim U(0,1)$, and I set $\theta_{t,i} = \theta_t^c$ if $\nu < \omega_{\theta,t}$, and $\theta_{t,i} = \theta_{t,i-1}$ otherwise.

[25] The following description of the Koop and Potter (2011) single-move algorithm has been taken from Canova and Perez-Forero (2013).

- Finally, as for Q, since we postulated that $Q \sim IW\left(Q_0^{-1}, T_0\right)$, the unrestricted posterior is $Q \sim IW\left(Q_1^{-1}, T_1\right)$, where $T_1 = T_0 + T$, and

$$Q_1 = \left[Q_0 + \sum_{t=1}^{T} \left(\theta_{t,i} - \theta_{t-1,i}\right)\left(\theta_{t,i} - \theta_{t-1,i}\right)'\right]^{-1} \tag{B16}$$

Conceptually in line with the way θ_t was drawn, I start by drawing a candidate $Q^c \sim IW\left(Q_1^{-1}, T_1\right)$. Then, for $t = 1, 2, 3, ..., T$ I evaluate $\lambda\left(\theta_{t,i}, Q^c\right)$ and $\lambda\left(\theta_{t,i}, Q_{i-1}\right)$ and compute the acceptance probability

$$\omega_Q = \min\left[\prod_{t=1}^{T} \frac{\lambda\left(\theta_{t,i}, Q_{i-1}\right)}{\lambda\left(\theta_{t,i}, Q^c\right)}, 1\right] \tag{B17}$$

Finally, I draw $\nu \sim U(0,1)$, and I set $Q_i = Q^c$ if $\nu < \omega_Q$, and $Q_i = Q_{i-1}$ otherwise.

(b) Drawing the elements of α_t Conditional on Y^T, θ^T, and H^T, following Primiceri (2005), we draw the elements of α_t as follows. Equation (1) can be rewritten as $A_t\tilde{Y}_t \equiv A_t(Y_t\text{-}X_t'\theta_t)\text{=}A_t\epsilon_t \equiv u_t$, with Var($u_t$)=$H_t$, namely

$$\tilde{Y}_{2,t} = -\alpha_{21,t}\tilde{Y}_{1,t} + u_{2,t} \tag{B18}$$

$$\tilde{Y}_{3,t} = -\alpha_{31,t}\tilde{Y}_{1,t} - \alpha_{32,t}\tilde{Y}_{2,t} + u_{3,t} \tag{B19}$$

$$\tilde{Y}_{4,t} = -\alpha_{41,t}\tilde{Y}_{1,t} - \alpha_{42,t}\tilde{Y}_{2,t} - \alpha_{43,t}\tilde{Y}_{3,t} + u_{4,t} \tag{B20}$$

—plus the identity $\tilde{Y}_{1,t} = u_{1,t}$—where $[\tilde{Y}_{1,t}, \tilde{Y}_{2,t}, \tilde{Y}_{3,t}, \tilde{Y}_{4,t}]' \equiv \tilde{Y}_t$. Based on the observation equations (B18)-(B20), and the transition equation (7), the elements of α_t can then be drawn by applying the same algorithm we described in the previous paragraph separately to (B18), (B19) and (B20). The assumption that S has the block-diagonal structure (9) is in this respect crucial, although, as stressed by Primiceri (2005, Appendix D), it could in principle be relaxed.

(c) Drawing the elements of H_t Conditional on Y^T, θ^T, and α^T, the orthogonalised innovations $u_t \equiv A_t(Y_t\text{-}X_t'\theta_t)$, with Var($u_t$)=$H_t$, are observable. Following Cogley and Sargent (2002), we then sample the $h_{i,t}$'s by applying the univariate algorithm of Jacquier, Polson, and Rossi (1994) element by element.[26]

(d) Drawing the hyperparameters Finally, conditional on Y^T, θ^T, H^T, and α^T, the innovations to θ_t, α_t, the $h_{i,t}$'s are observable, which allows us to draw the hyperparameters—the elements of Q, S_1, S_2 S_3, and the σ_i^2—from their respective distributions.

Summing up, the MCMC algorithm simulates the posterior distribution of the states and the hyperparameters, conditional on the data, by iterating on (a)-(d). I use a burn-in period of 50,000 iterations to converge to the ergodic distribution, and after that I run 10,000 more iterations sampling every 10th draw in order to reduce the autocorrelation across draws.[27]

[26] For details, see Cogley and Sargent (2005, Appendix B.2.5).

[27] In this we follow Cogley and Sargent (2005). As stressed by Cogley and Sargent (2005), however,

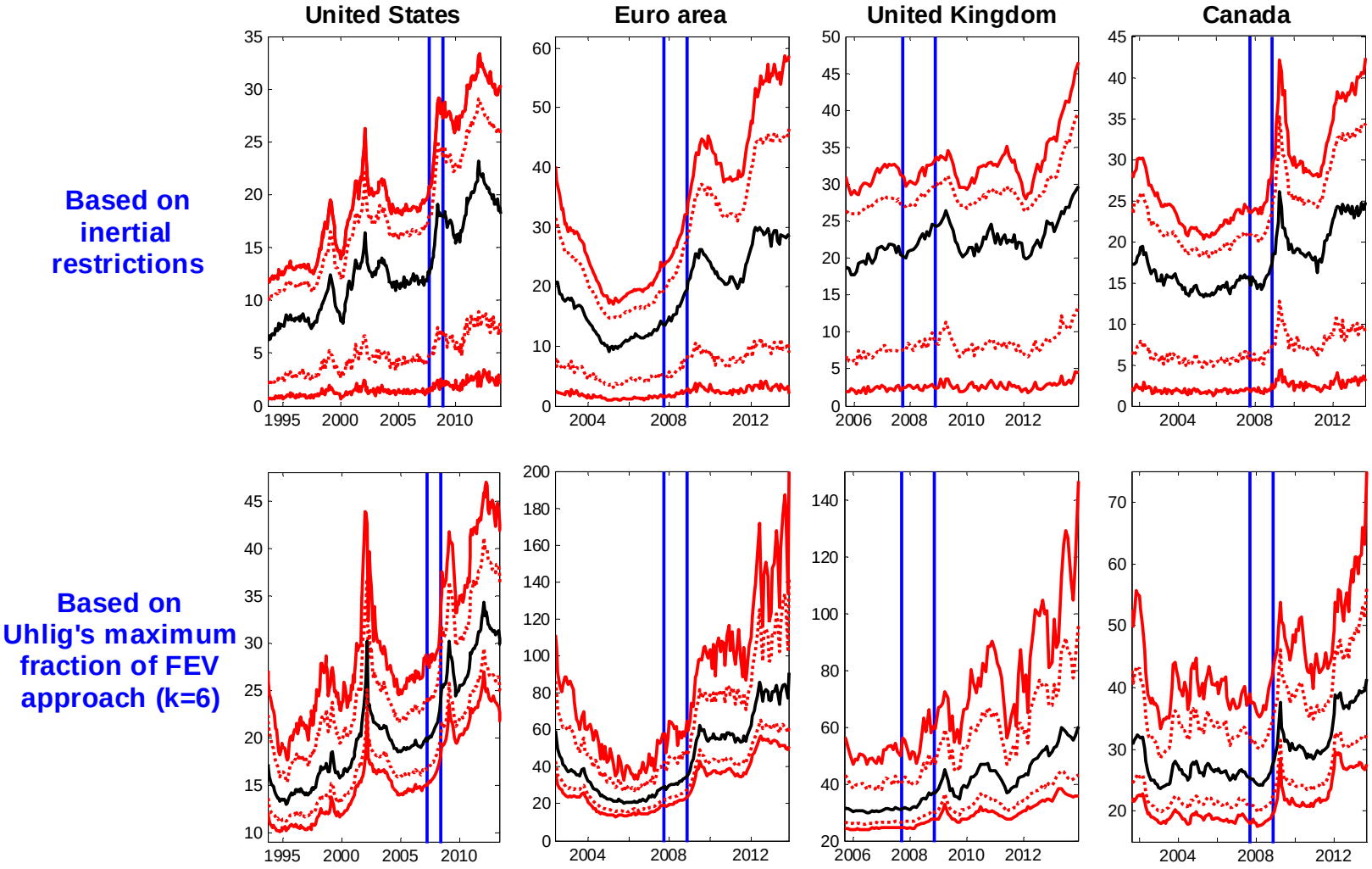

Figure 1 Estimated standard deviations of policy uncertainty shocks, medians and 1- and 2-standard deviation percentiles

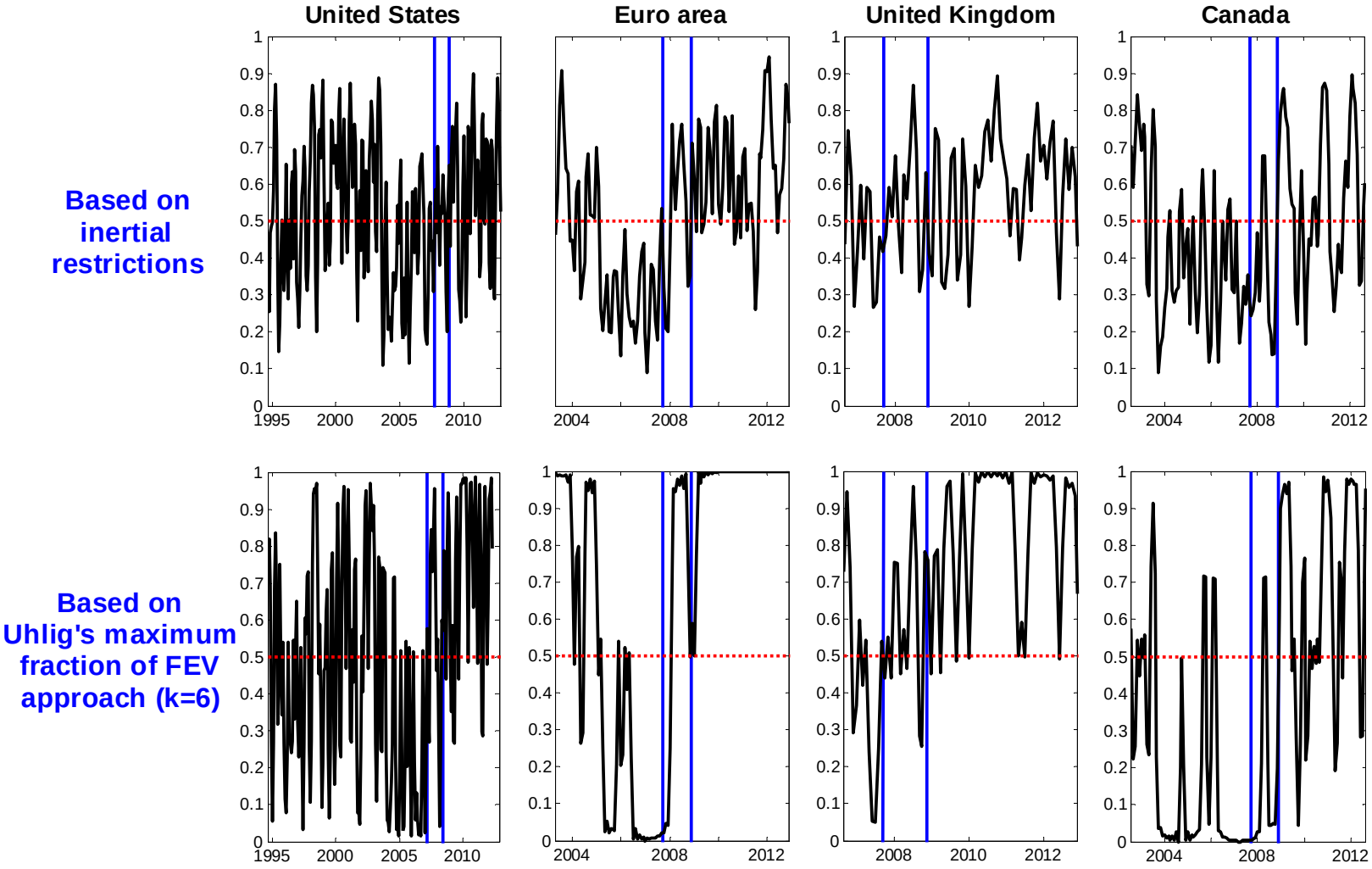

Figure 2 Smoothed fractions of positive policy uncertainty shocks (smoothing performed *via* a Bartlett window)

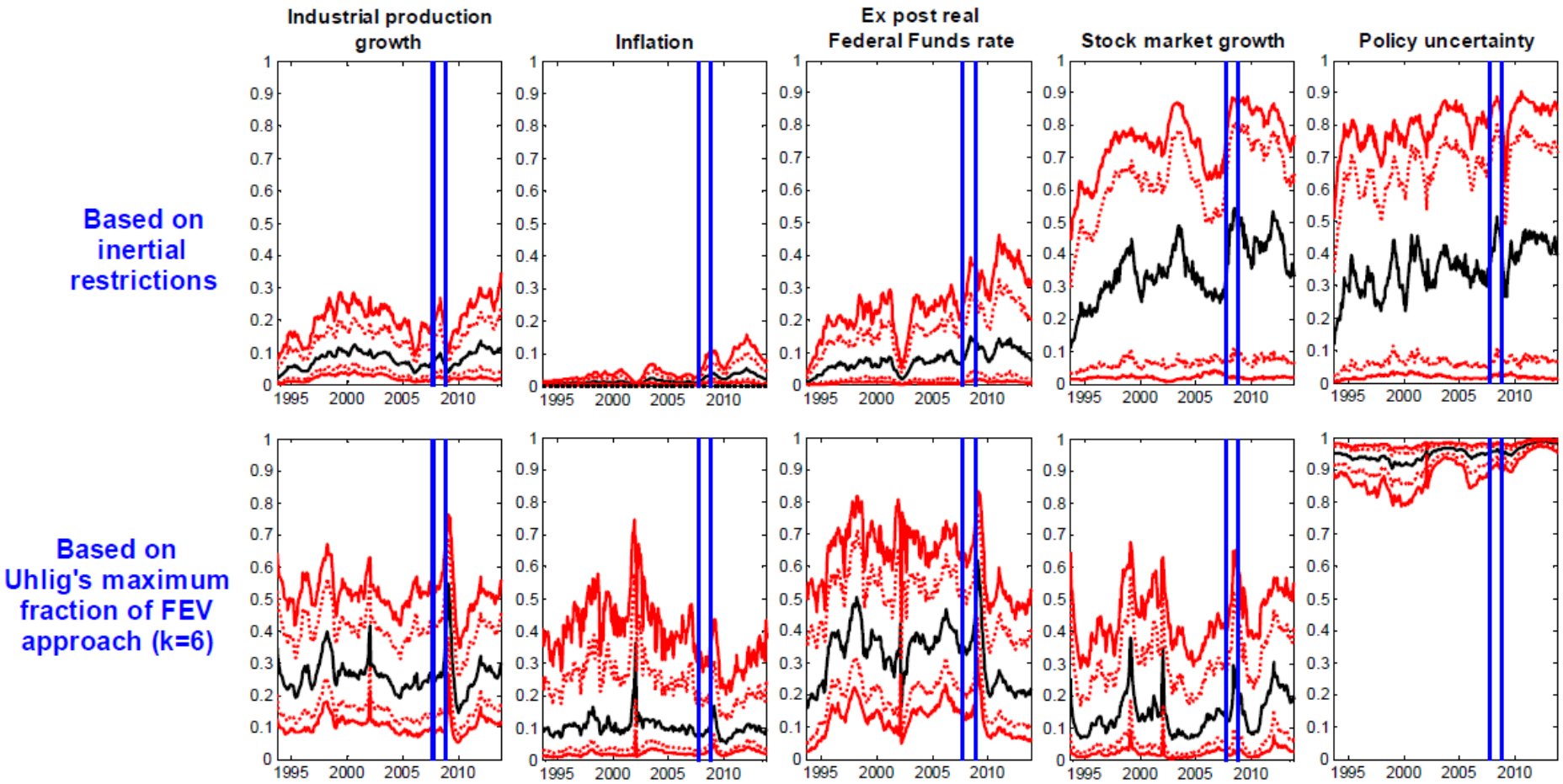

Figure 3 United States: fractions of 1-year ahead forecast error variance explained by policy uncertainty shocks

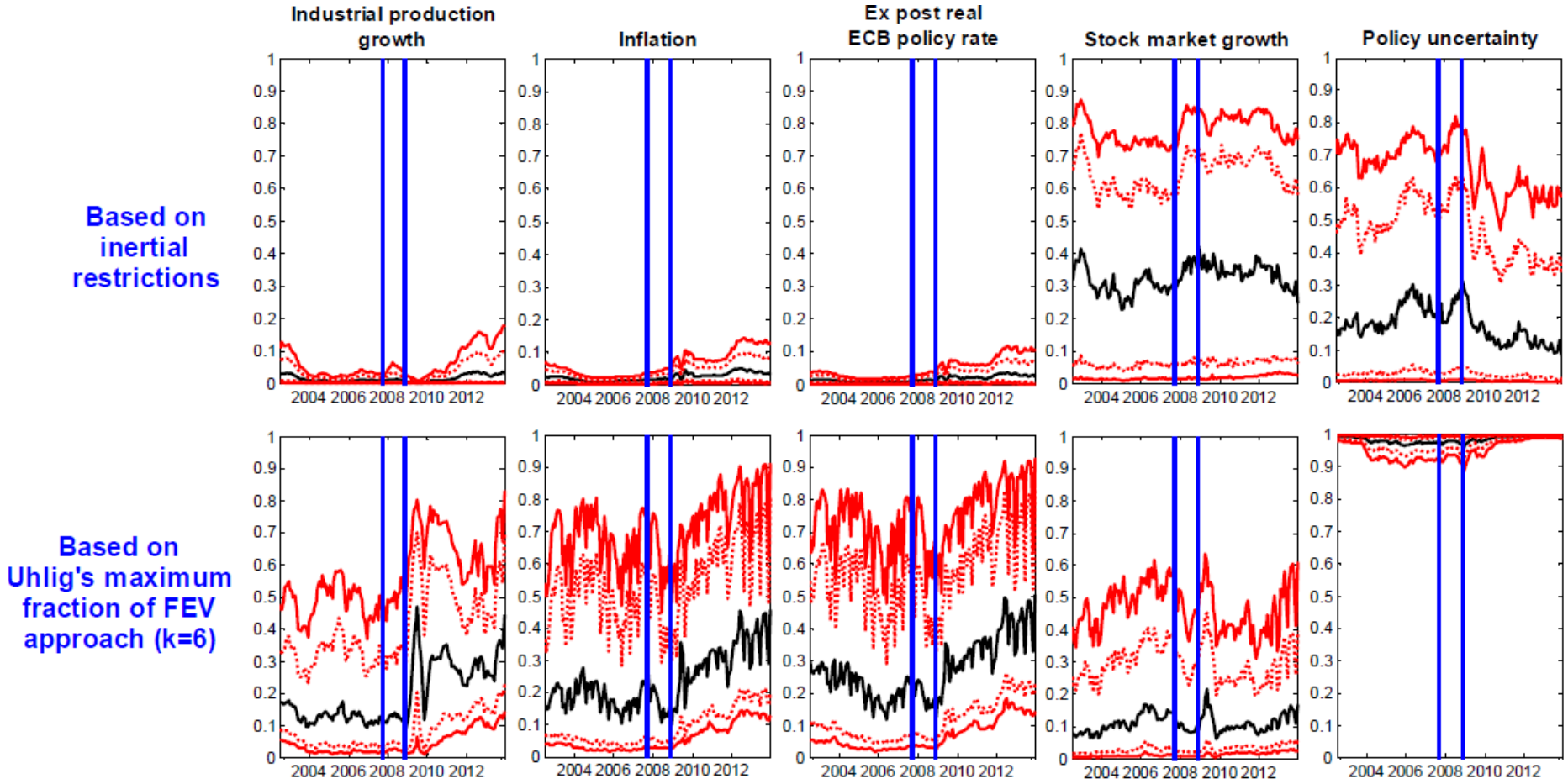

Figure 4 Euro area: fractions of 1-year ahead forecast error variance explained by policy uncertainty shocks

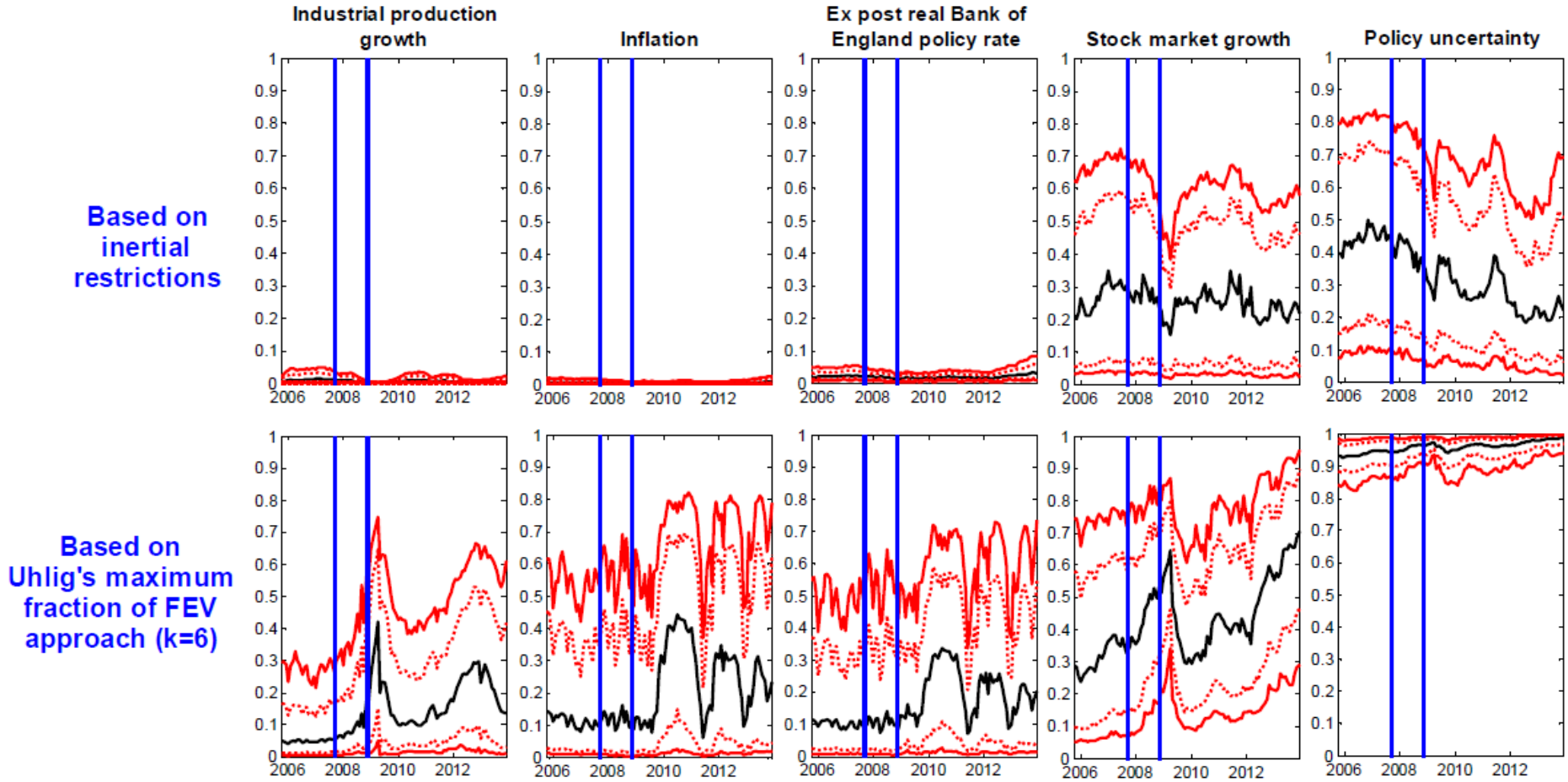

Figure 5 United Kingdom: fractions of 1-year ahead forecast error variance explained by policy uncertainty shocks

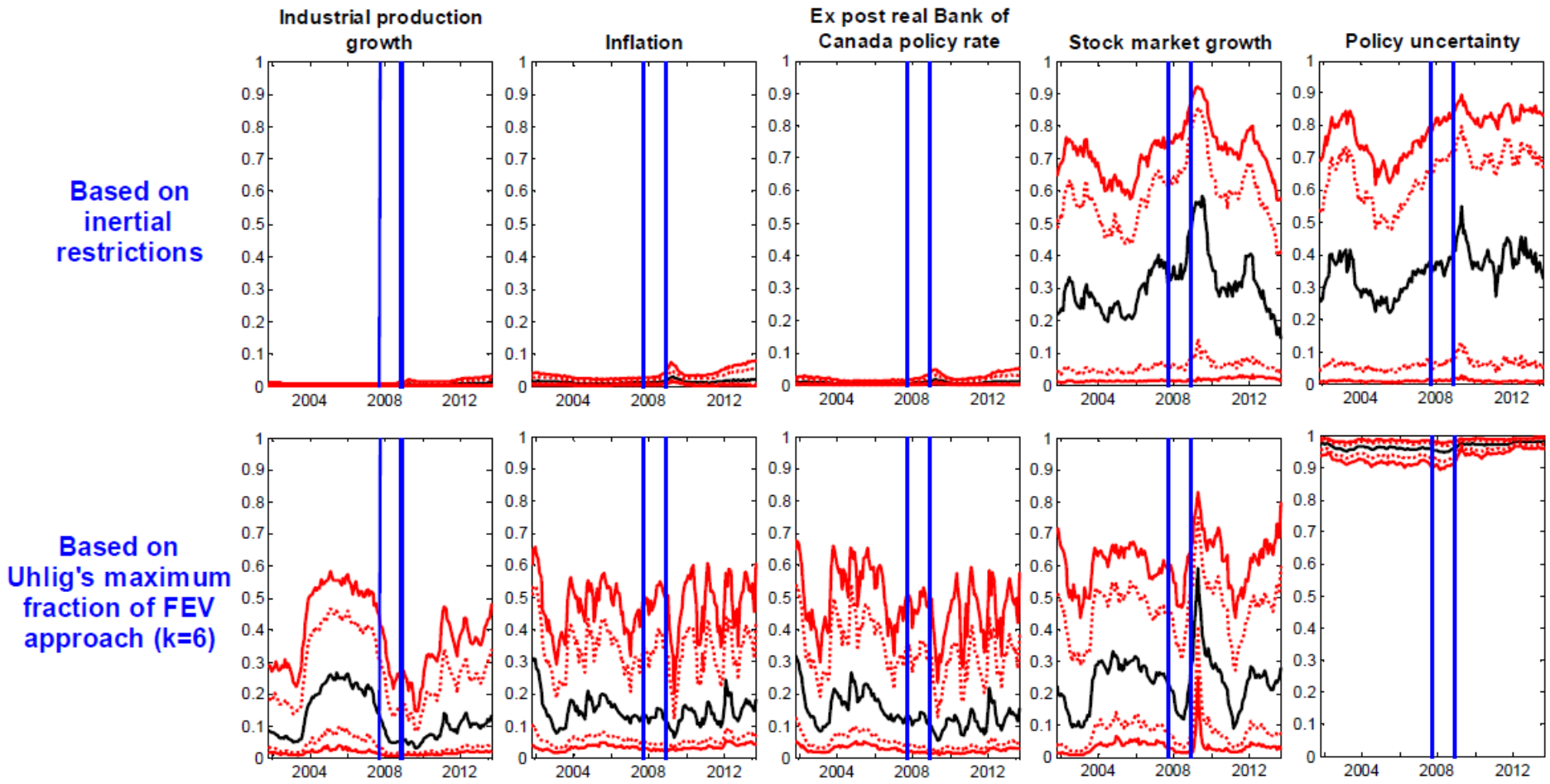

Figure 6 Canada: fractions of 1-year ahead forecast error variance explained by policy uncertainty shocks

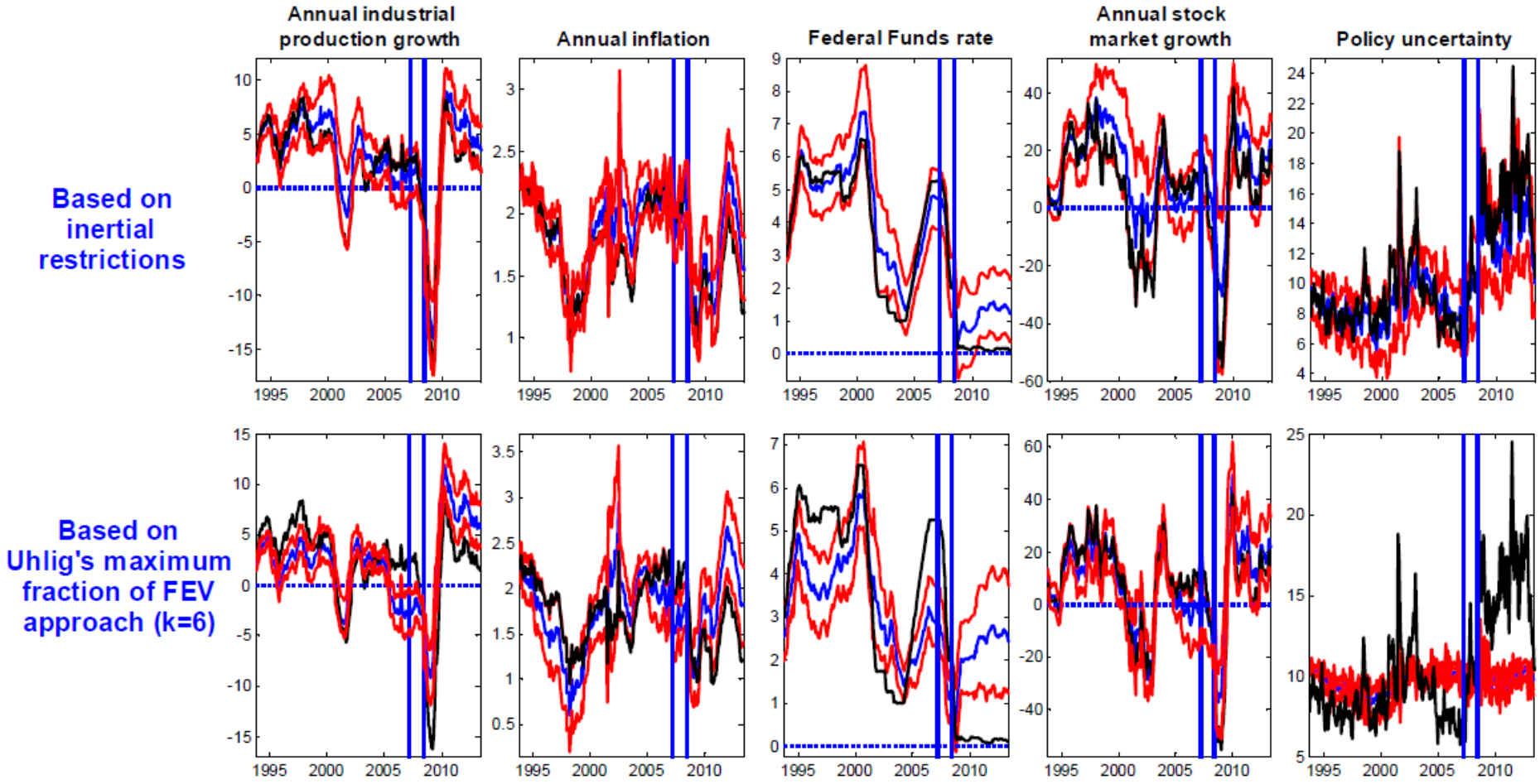

Figure 7 United States: counterfactual simulations performed by 'killing off' estimated policy uncertainty shocks (full sample)

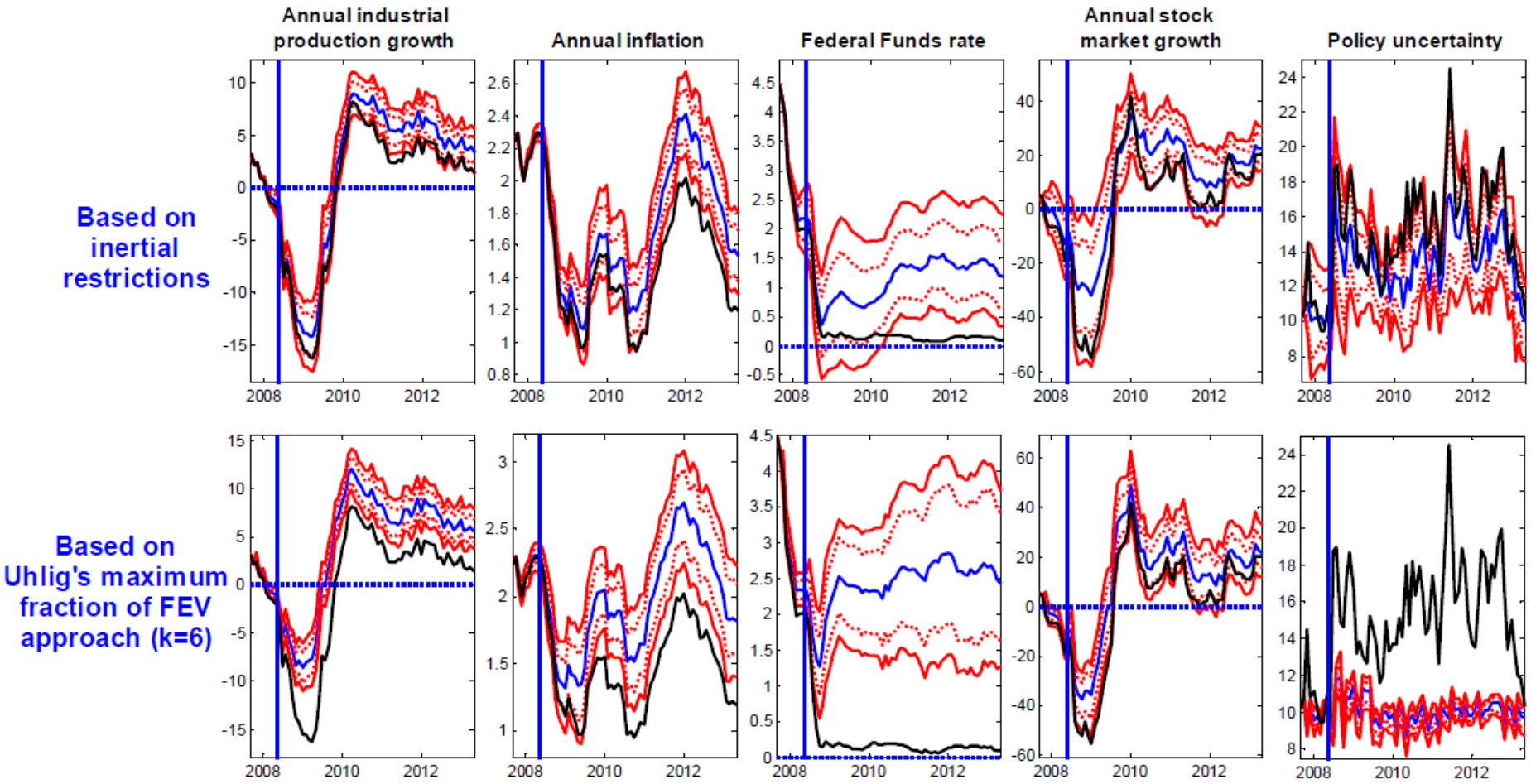

Figure 8 United States: counterfactual simulations performed by 'killing off' estimated policy uncertainty shocks (Great Recession)

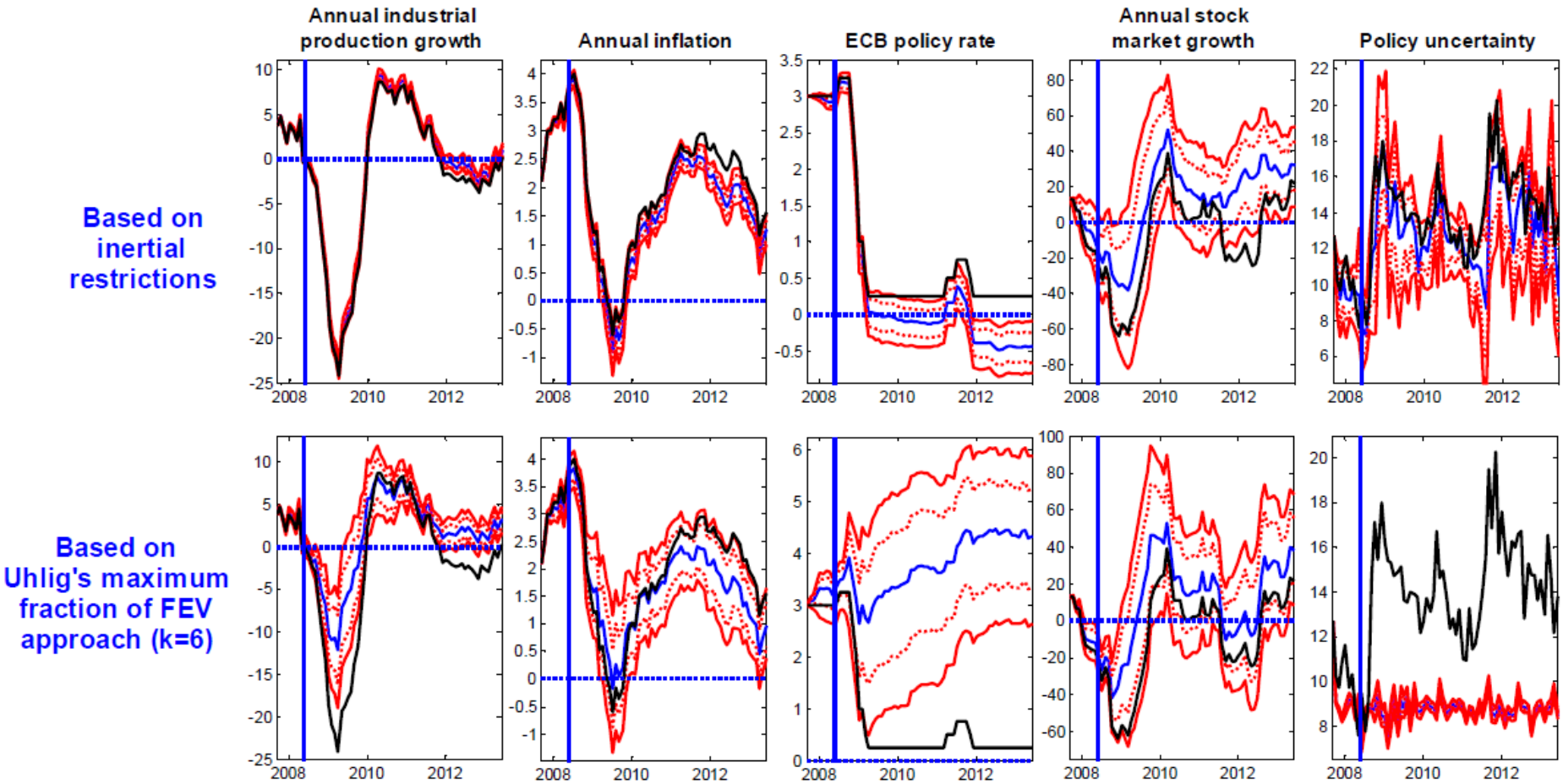

Figure 9 Euro area: counterfactual simulations performed by 'killing off' estimated policy uncertainty shocks (Great Recession)

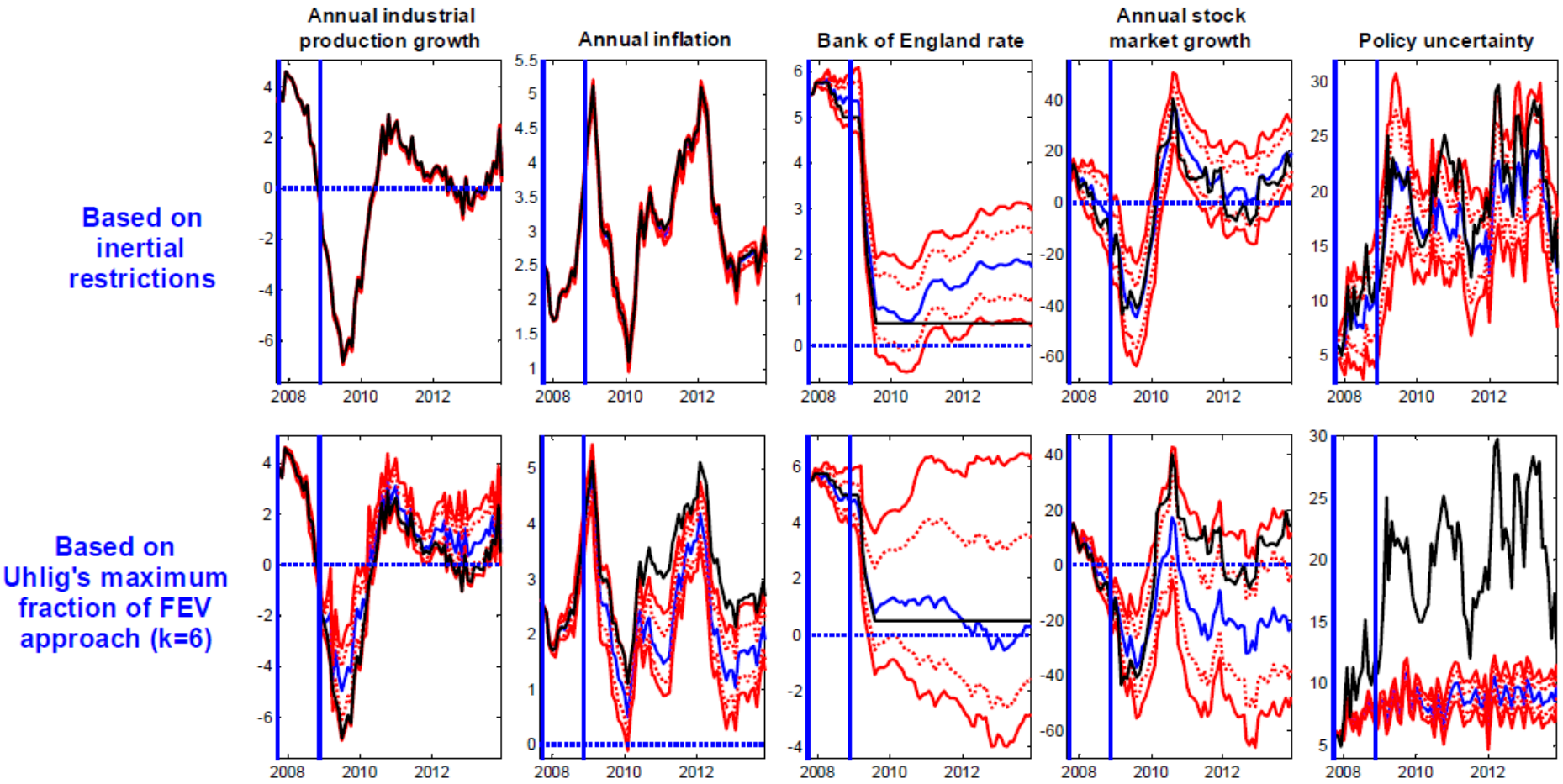

Figure 10 United Kingdom: counterfactual simulations performed by 'killing off' estimated policy uncertainty shocks (Great Recession)

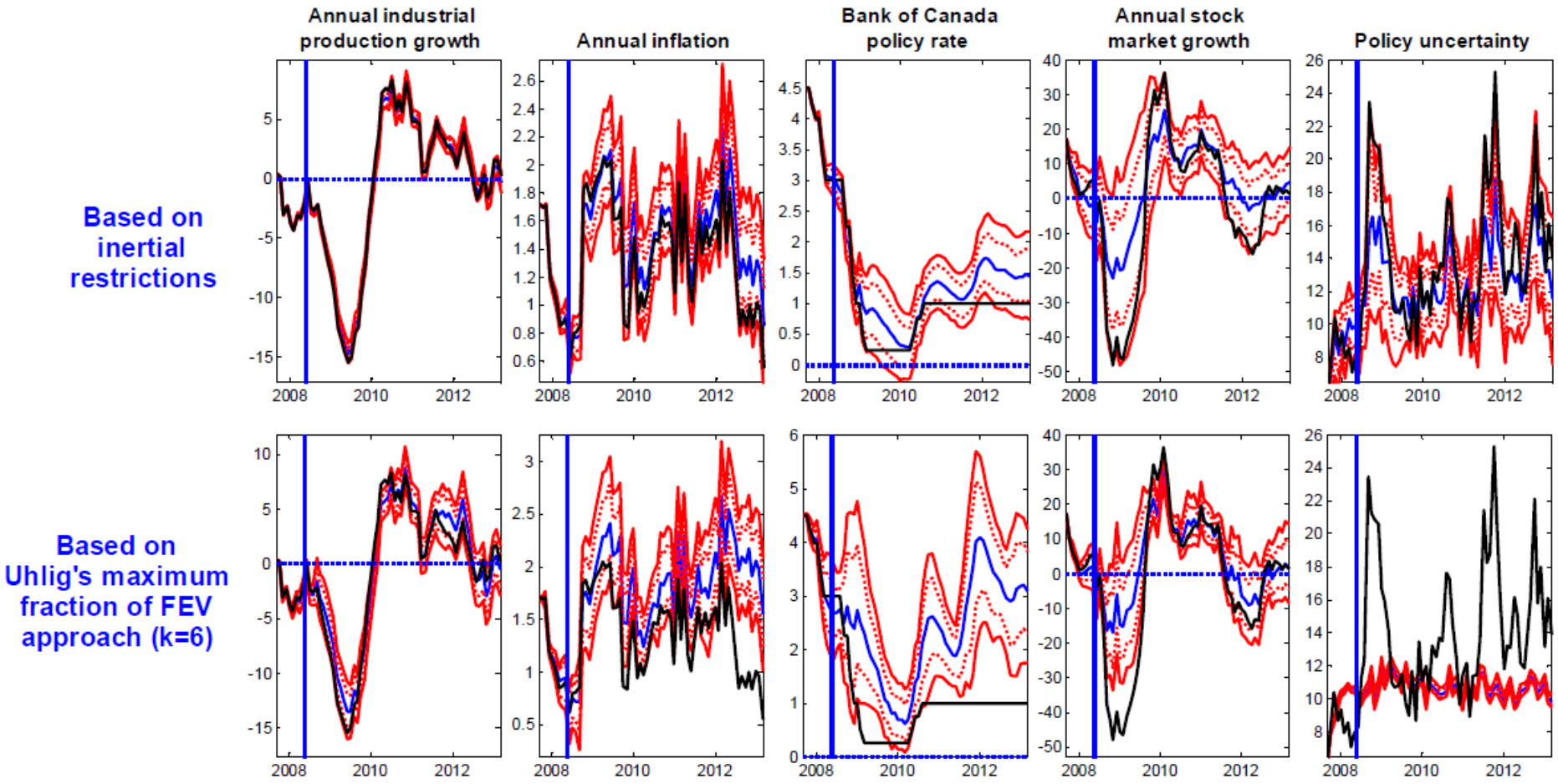

Figure 11 Canada: counterfactual simulations performed by 'killing off' estimated policy uncertainty shocks (Great Recession)

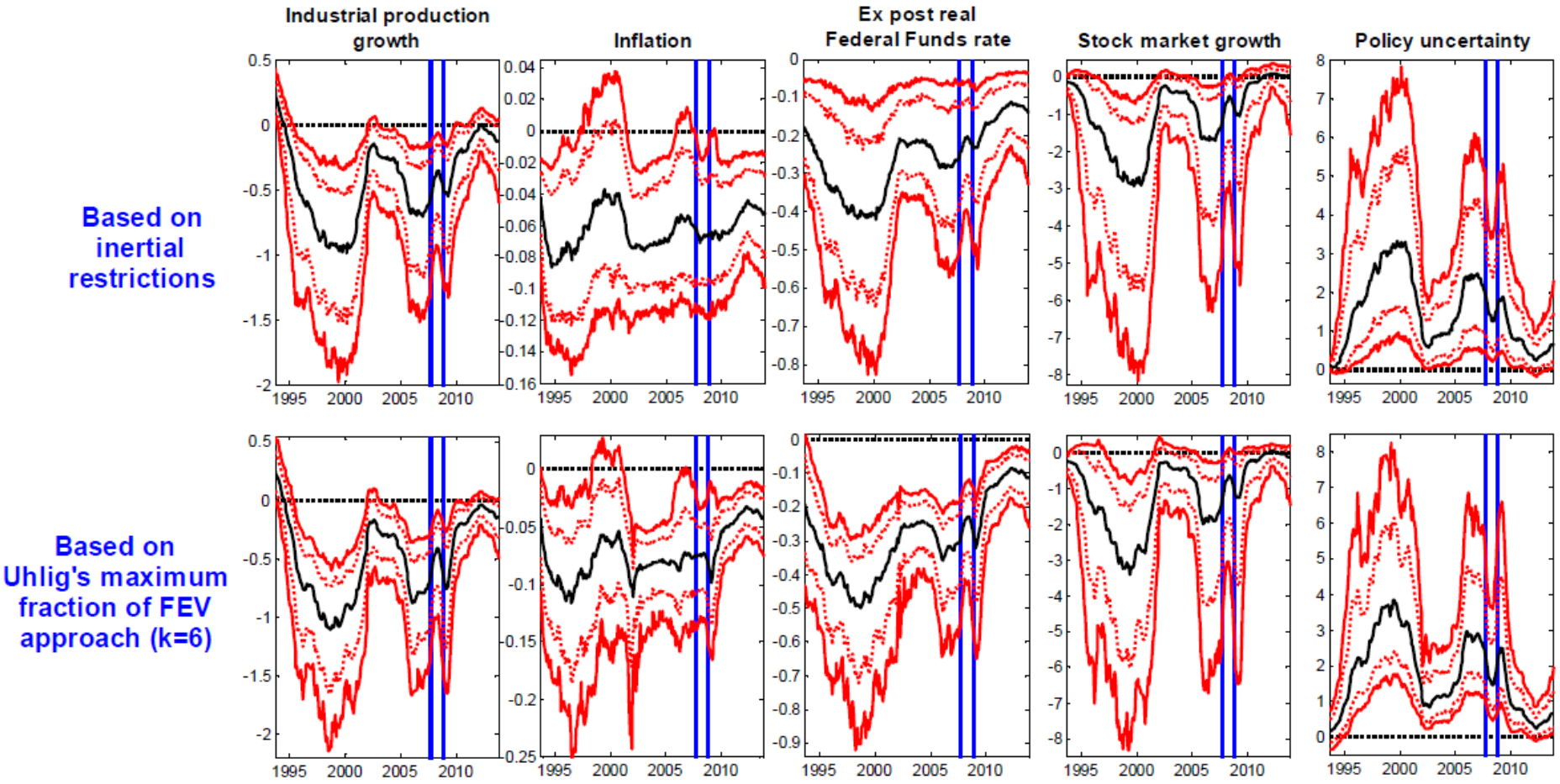

Figure 12 United States: impulse-response functions to a normalized policy uncertainty shock at the 1-year horizon