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The Impact of Uncertainty Shocks under Measurement Error. A Proxy SVAR approach[1]

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Abstract

A growing literature considers the impact of uncertainty using SVAR models that include proxies for uncertainty shocks as endogenous variables. In this paper we consider the impact of measurement error in these proxies on the estimated impulse responses. We show via a Monte-Carlo experiment that measurement error can result in attenuation bias in impulse responses. In contrast, the proxy SVAR that uses the uncertainty shock proxy as an instrument does not suffer from this bias. Applying this latter method to the Bloom (2009) data-set results in impulse responses to uncertainty shocks that are larger in magnitude and more persistent than those obtained from a recursive SVAR.

JEL Classification: C15, C32, E32.

Keywords: Uncertainty Shocks, Proxy SVAR, Non-linear DSGE models.

1 Introduction

The recent financial crisis and ensuing recession has spurred a growing literature on the impact of uncertainty shocks on the economy. While a number of theoretical papers focus on modelling the channels of transmission of these shocks (see for example Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez and Uribe (2011), Fernandez-Villaverde, Guerron-Quintana, Kuester and Rubio-Ramirez (2011) and Basu and Bundick (2012)), a large strand of this literature is empirical and focusses on estimating the percentage change in real activity following a shock to a measure of uncertainty via empirical models such as structural VARs (SVARs).

A seminal paper that applies a SVAR model to this issue is Bloom (2009). The author builds a dummy variable indicator of volatility shocks for the US. The indicator takes a value of one when a measure of options implied stock market volatility (the Chicago board of options exchange VXO index) significantly exceeds its mean. This indicator is then added as an endogenous variable in a SVAR model containing standard macroeconomic variables. The author finds that a shock to the volatility indicator leads to a 1% decline in industrial production. Baker *et al.* (2012) build an index of US economic policy uncertainty by using a combination of textual analysis, data on tax code expiration and dispersion of economic forecasts. In a SVAR model, a 102 point increase in this uncertainty index reduces industrial production by 2.5% while aggregate employment declines by 2.3 million. Leduc and Liu (2012) use survey based measures of uncertainty in an SVAR model and find that an increase in uncertainty depresses economic activity. In recent contributions, Scotti (2013) builds a real-time measure of uncertainty while Jurado *et al.* (2013) propose a measure based on stochastic volatility models.

This strand of the literature on uncertainty has two common elements. First, these studies necessarily use proxies as measures of uncertainty as the true value is not directly observed. Second these proxies are entered directly into the VAR systems as endogenous variables.

In this paper we explore the consequences of these features for estimates of the impact of uncertainty. First, we use a simulation experiment to show that when the proxy for uncertainty differs from the true underlying measure, estimates of the impulse response from VARs that include the uncertainty measure are biased downwards.

In contrast, structural VARs that use this measure as an 'external instrument' (this proxy SVAR approach was proposed in Stock and Watson (2008) and Mertens and Ravn (2014)) to identify the uncertainty shock are less susceptible to this bias. Second we re-visit the empirical work in Bloom (2009) using this proxy SVAR approach and find important differences in the estimates of the impact of uncertainty shocks and their importance over the business cycle. Using the proxy SVAR, the estimated impact of these shocks is larger and more persistent.

The analysis in this paper contributes to the empirical literature on the impact of uncertainty shocks by highlighting the role played by the possibility of measurement error in the proxies for uncertainty, an issue that has received little attention so far. We show that failure to take measurement error into account can lead to researchers erroneously ascribing a small role for uncertainty over the business cycle and this can adversely influence policy decisions.

The paper is organised as follows: Section 2 describes how the impact of uncertainty shocks can be estimated using VAR models and applies the proxy VAR approach to this problem. Section 2.1 considers the performance of standard VAR models and the proxy VAR in estimating the response to uncertainty shocks under measurement error by conducting a simple Monte Carlo experiment. Section 3 applies these models to the Bloom (2009) dataset and shows how the results change when measurement error is taken into account. Section 4 concludes.

2 The SVAR approach to estimating the impact of uncertainty shocks

The existing empirical papers on the impact of uncertainty mentioned above consider the following SVAR model:

$$Y_t = c + \sum_{j=1}^{P} B_j Y_{t-p} + A_0 \varepsilon_t, \tag{1}$$

where Y_t is a matrix of endogenous variables which includes a measure of uncertainty $\hat{\sigma}_t$ and a set of macroeconomic variables of interest. The structural shocks ε_t are related to the VAR residuals u_t via the relation $A_0 \varepsilon_t = u_t$ where A_0 is a matrix such that $VAR(u_t) = \Omega = A_0 A_0'$. In applications to uncertainty A_0 is typically chosen to be the Cholesky decomposition of Ω with $\hat{\sigma}_t$ usually ordered before the macroeconomic variables. For example, the benchmark VAR in Bloom (2009) includes a stock price index, the dummy variable measure of uncertainty shocks, the federal funds rate, wages, CPI, hours, employment and industrial production.

Given that $\hat{\sigma}_t$ is a proxy for true underlying value for uncertainty, it is reasonable to assume a degree of measurement error. For example, the relationship between the constructed measure of uncertainty and its underlying value may be defined as $\hat{\sigma}_t = \sigma_t + \sigma_v v_t$ where v_t is a standard normal. It is easy to see that the presence of measurement error would bias the estimate of the structural shock of interest. In addition, it is well known that OLS estimates of the VAR coefficients would suffer from attenuation bias due to the correlation between the RHS variables and the residuals introduced by the measurement error.

In contrast, the proxy SVAR approach is less susceptible to the measurement error problem.[1] The underlying VAR model is given by the following equation:

$$\tilde{Y}_t = c + \sum_{j=1}^{P} B_j \tilde{Y}_{t-p} + \tilde{A}_0 \tilde{\varepsilon}_t. \tag{2}$$

The matrix of endogenous variables $\tilde{Y}_t$ does not contain the constructed measure of uncertainty shocks directly but, instead, this is used as an instrument to estimate the structural shock of interest. Denoting the structural shock related to uncertainty by $\tilde{\varepsilon}_t^{\sigma}$ and the remaining shocks by $\tilde{\varepsilon}_t^{\bullet}$, this approach requires the proxy for uncertainty $\hat{\sigma}_t$ to satisfy the following conditions:

$$\begin{aligned} E\left(\hat{\sigma}_t, \tilde{\varepsilon}_t^{\sigma}\right) &= \alpha \neq 0, \\ E\left(\hat{\sigma}_t, \tilde{\varepsilon}_t^{\bullet}\right) &= 0, \end{aligned} \tag{3}$$

where α denotes the covariance between $\hat{\sigma}_t$ and $\tilde{\varepsilon}_t^{\sigma}$. The first expression in equation 3 states the instrument $\hat{\sigma}_t$ is correlated with the structural shock to be estimated, while the second expression rules out a correlation between $\hat{\sigma}_t$ and the remaining structural shocks and establishes exogeneity of the instrument. As shown in Stock and Watson (2008), Mertens and Ravn (2014) and Mertens and Ravn (2013), these

[1] Mertens and Ravn (2014) show that the impact of measurement error in narrative measures of fiscal policy shocks is smaller when the Proxy VAR is used. In contrast, standard VAR models of fiscal policy can produce biased estimates when measurement error is present.

conditions along with the requirement that the structural shocks $\tilde{\varepsilon}_t$ are contemporaneously uncorrelated can be used to derive a GMM estimator for the column of $\tilde{A}_0$ that corresponds to $\tilde{\varepsilon}_t^{\sigma}$.[2] Mertens and Ravn (2013) also provide a measure of reliability of the instrument. The reliability statistic is a measure of the correlation between the instrument and the shock of interest and can be used to gauge the quality of the instrument.

Equation 3 imposes less stringent conditions on the quality of $\hat{\sigma}_t$. In particular, the only requirements are that $\hat{\sigma}_t$ is correlated with the shock of interest and uncorrelated with other shocks. These conditions can be satisfied even if $\hat{\sigma}_t$ is measured with error.

2.1 A simple Monte Carlo experiment

To gauge the possible impact of measurement error on VAR estimates of responses to uncertainty shocks we conduct a simple simulation experiment. In particular we generate data from a simple non-linear DSGE model where the variance of a structural shock of interest is characterised by stochastic volatility. We use the generated data to estimate the standard recursive VAR and the proxy SVAR. Using these VAR estimates, we check if the DSGE responses can be recovered using the empirical models.

2.1.1 The data generating process

The data is generated from a standard model of the monetary transmission mechanism. The model is derived in detail in the on-line appendix to the paper.[3] Here we present an overview of the key characteristics.

The household side of the model consists of a continuum of households that consume, save in bonds, work and pay taxes. On the firms side, there is continuum of intermediate good producers that sell differentiated goods to final output producers. Intermediate good producers face a quadratic cost of adjusting prices (see Rotemberg (1982))–there is full indexation to either steady state value added inflation or to a lagged measure of inflation. The government purchases units of final output and finances its expenditure using lump-sum taxes.

Finally, the monetary policy authority follows a rule for the nominal interest rate

[2] See the online appendix to the paper for details of the estimation procedure.

[3] See https://sites.google.com/site/hmumtaz77/Onlineappendix.pdf?attredirects=0&d=1.

(R_t) that responds to deviations of CPI inflation (π_t) from its target (π), and to deviations of output (y_t) from its steady-state value. This gives the following rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\phi_R} \left(\frac{\pi_t}{\Pi}\right)^{(1-\phi_R)\phi_\pi} \left(\frac{y_t}{y}\right)^{(1-\phi_R)\phi_Y} \varepsilon_t^R. \tag{4}$$

R is the steady state nominal interest rate that ensures that CPI inflation is at target in the long run. We assume that ε_t^R is a *heteroscedastic* interest rate shock, given by

$$\log \varepsilon_t^R = \rho_{\varepsilon^R} \log \varepsilon_{t-1}^R + \sigma_t^R \eta_t^R. \tag{5}$$

The evolution of policy uncertainty is given by

$$\log \sigma_t^R = (1 - \rho_{\sigma^R})\,\sigma_{\varepsilon^R} + \rho_{\sigma^R} \log \sigma_{t-1}^R + \sigma_{\sigma^R} \eta_t^{\sigma^R}. \tag{6}$$

The model, therefore, incorporates uncertainty in the monetary policy rule and this is the focus of the estimation on the generated data described below.[4]

The model is solved using third-order perturbation methods (see Judd (1998)) since for any order below three, stochastic volatility shocks that we are interested in do not enter into the decision rule as independent components. The calibration of the parameters is standard and is described in the on-line appendix.

We use artificial data for $\sigma_t^R, y_t, \pi_t, R_t$ and the structural shock to volatility $M_t = \sigma_{\sigma^R} \eta_t^{\sigma^R} + v_t$, with $v_t \sim N(0, \sigma_v^2)$. Note that v_t is assumed to be a measurement error, and when this equals zero, the structural shock is measured perfectly. In the experiment below we assume that σ_v^2 varies between 0 and 5. Note that the calibrated value σ_{σ^R} equals 1 and therefore these values for the variance of the measurement error cover a large range.

The data is generated for 2200 periods with the first 2000 observations discarded to remove the impact of starting values. The final 200 observations are used to estimate the following two VAR models. First we estimate the standard recursive SVAR:

$$Y_t^{(1)} = c + \sum_{j=1}^{P} B_j Y_{t-j}^{(1)} + A_0^{(1)} \varepsilon_t^{(1)}, \tag{7}$$

where $Y_t^{(1)} = \{M_t, y_t, \pi_t, R_t\}$ and $A_0^{(1)}$ is obtained via a Cholesky decomposition with the ordering of the variables as in $Y_t^{(1)}$. This mimics the kind of SVAR models

[4] We show in the on-line appendix that if uncertainty is incorporated in the preference shock or the productivity shock the conclusions of the Monte Carlo experiment remain unchanged.

considered for example in Bloom (2009) where a measure of the uncertainty shock enters the VAR system directly.

The second empirical model is the proxy SVAR that takes the following form[5]:

$$Y_t^{(2)} = d + \sum_{j=1}^{P} D_j Y_{t-j}^{(2)} + A_0^{(2)} \varepsilon_t^{(2)}, \tag{8}$$

where $Y_t^{(2)} = \{\sigma_t^R, y_t, \pi_t, R_t\}$. The first shock in $\varepsilon_t^{(2)}$ is the volatility shock and is identified by using the following moment restrictions:

$$E\left(M_t, \varepsilon_{1,t}^{(2)}\right) = \alpha \neq 0, \tag{9}$$

$$E\left(M_t, \varepsilon_{i,t}^{(2)}\right) = 0, i = 2, 3, 4. \tag{10}$$

In Figure 1 we consider the scenario where measurement error equals zero and $M_t = \sigma_{\sigma^R} \eta_t^{\sigma^R}$. The dotted lines in the figure present the response of the macroeconomic variables to a one unit increase in policy uncertainty in the DSGE model. The blue line and the shaded area present the median and the 90% error band (based on 1000 replications) of the same response estimated using the proxy and recursive SVARs. When the uncertainty shock is observed without error, the two SVAR models deliver a similar performance. The median response of Y and R from the SVAR models tracks the true response closely. While the contemporaneous SVAR response of π is close to the DSGE response, there appears to be a slight downward bias at medium horizons. This probably reflects the fact that the linear VAR models abstract from the non-linear dynamics present in the reduced form of the DSGE model obtained via third order perturbation.

Figure 2 presents the results of the simulation when measurement error is present. Each panel of the figure reports the median bias in the SVAR impulse responses (Z-axis) as the variance of the measurement error increases in importance relative to σ_{σ^R}. The bias is defined as the difference between the point estimate of the VAR response and the DSGE response with a positive bias indicating that the VAR response is estimated to be less negative than the DSGE response.

The impact of the measurement error on the estimated responses from the proxy

[5] We use a modified version of the Matlab code provided by Mertens and Ravn (2013) to estimate the proxy SVAR model.

SVAR is muted.[6] As discussed above, this is because the mis-measured uncertainty shock does not enter the VAR system directly but is used as an instrument. In contrast to these results, there is a clear attenuation bias evident in the responses estimated using the recursive SVAR model. Even for relatively small values of $\sigma_v/\sigma_{\sigma^R}$ the estimated impulse response is less negative than the DSGE response, with this difference much more pronounced than the proxy SVAR. Note that this bias is present both at horizon 0 and beyond indicating that the estimates of the contemporaneous impact matrix and the VAR coefficients are affected by the measurement error problem.

3 Empirical results: The Bloom (2009) VAR model re-visited

In this section, we re-estimate the VAR model in Bloom (2009) and consider the possible role of measurement error. Bloom (2009) estimate a variety of VAR models that contain the following variables (in this order): (1) log S&P500 stock market index, (2) an indicator of shocks to stock-market volatility, (3) Federal Funds Rate, (4) log average hourly earnings, (5) log consumer price index, (6) hours, (7) log employment, and (8) log industrial production. The benchmark volatility shock indicator is constructed by the author to correspond to periods when stock market volatility is above a given threshold. As shown in Figure 1 of Bloom (2009), the constructed shocks correspond closely to periods of economic and/or political turbulence. The different VAR specifications in Bloom (2009) correspond to different measures of stock market volatility shocks constructed by the author. The author shows, however, that the key results remain unchanged across the different measures. In particular, all the VARs that include the different measures result in very similar responses for industrial production.

In the left panel of Figure 3 we produce the results in Bloom (2009) using the benchmark volatility shock measure employed in Bloom (2009)[7]. The panel shows the response to 1 unit volatility shock as in Bloom (2009). Note that Bloom (2009)

[6] There is a slight positive bias in the responses that stays constant as the variance of the measurement error increases. As mentioned above, this possibly reflects the fact the data generating process (DGP) is non-linear while the VAR model is linear.

[7] We use the data and data transformations employed by Bloom (2009). The data can be down-

shows that a one unit shock to the dummy variable corresponds to a 15 unit shock to the actual VXO index which the author uses in an additional VAR specification to show that the results are not sensitive to the choice of volatility indicator.

As in Bloom (2009), both industrial production and employment decline by 1% and 0.6% at the one year horizon. Bloom (2009) shows that this decline is fairly similar to the fall in these variables in response to a 1% increase in the Federal Funds rate. Both variables increase subsequently, with the rise in industrial production statistically significant. Notably the response of the stock price index shows a similar pattern – there is an initial decline and a subsequent bounceback. The shock also results in a fall in hours, the federal funds rate, wages and CPI, with the decline in these variables lasting for less than a year.

The right panel of Figure 3 shows the impulse responses to a volatility shock from a version of the VAR that uses the benchmark Bloom volatility shock measure as an instrument. In particular, we estimate the following VAR(12) model:

$$Z_t = d + \sum_{j=1}^{12} D_j Z_{t-j} + A_0 \varepsilon_t, \tag{11}$$

where Z_t contains the VXO stock market volatility index and the 7 macroeconomic and financial variables included in the Bloom (2009) VAR model above. For convenience, the VXO is ordered first in the proxy SVAR model.[8] The shock to volatility is identified using the following moment conditions:

$$E\left(M_t, \varepsilon_{1,t}\right) = \alpha \neq 0, \tag{12}$$

$$E\left(M_t, \varepsilon_{i,t}\right) = 0, i = 2, 3, ..8, \tag{13}$$

where M_t is the benchmark volatility shock measure employed by Bloom (2009) in their VAR model.[9] Thus unlike the VAR model in Bloom (2009), M_t does not enter directly into the VAR, but is used as an instrument to estimate the first column of the A_0 matrix and the volatility shock $\varepsilon_{1,t}$. The reliability statistic is estimated to be 0.6, suggesting a high correlation between M_t and the shock of interest.

loaded at http://www.stanford.edu/~nbloom/replication.zip. The data is monthly and available from 1962M7 to 2008M6. Following Bloom (2009) we employ a lag length of 12.

[8] As no zero restrictions are placed on the contemporaneous impact of the shock in the proxy VAR model, the ordering of the variables has no impact on the impulse responses.

[9] We show in the sensitivity analysis that similar results are obtained using the alternative definitions of the volatility shock employed by Bloom (2009).

The responses shown in the right panel of Figure 3 are scaled so that the shock corresponds to a 15 unit increase in the VXO in order to be consistent with a unit increase in the uncertainty dummy variable indicator used in the benchmark VAR model in Bloom (2009).

The estimated impulse responses using the proxy VAR model suggest a larger response to the volatility shock. For instance, while the stock market index declines by 3% in Bloom's SVAR, the estimated response is more than 10% in the proxy SVAR. Note also that this response in the proxy SVAR is persistent and lasts for about two years. Similarly, the responses of employment, CPI, Federal Funds rate and industrial production from the proxy SVAR are estimated to be larger and more persistent. Note that the bounceback in industrial production occurs at around the 20 month horizon, rather than after 6 months in the Cholesky case. We show in the sensitivity analysis below that if the recursive VAR is estimated using the VXO index instead of the dummy variable indicator and a 15 unit shock is considered, the estimated responses are significantly smaller in magnitude than those obtained from the proxy SVAR implying that the difference across models is robust to specification of the recursive VAR and scaling of the shock.

The results in Figure 3 match those obtained in the Monte-Carlo simulation described above. In particular, the responses to the volatility shock appear to be smaller in size when the shock measure is included directly into the VAR system. In contrast, when the shock measure is used as an instrument to identify the volatility shock in the proxy SVAR, the estimated impulse responses are larger in size and more persistent. This is consistent with the attenuation bias revealed by the Monte-Carlo experiment.

Figure 4 plots the contribution of the estimated volatility shock to the main variables using the two VAR models. The black lines in the figure represent the de-trended data for each variable. The blue and the red lines are the counterfactual estimates of these series assuming the presence of only the volatility shock, where the two VAR models are used, respectively, to identify the volatility shock. The volatility shock estimated using the proxy SVAR appears to be more important. For instance, the contribution of this shock in the benchmark VAR model to fluctuations in the stock market index is relatively small. In contrast, the results from the proxy SVAR imply that this shock accounts for a large proportion of the movement in this variable. This feature is especially apparent during the large troughs in the stock market index in the early and mid-1970s, the early 1980s and during the recession in the early 2000s. Similarly, the proxy VAR suggests that the volatility shock makes a more important contribution to employment and industrial production, especially during the recession in the early years of the last decade. This estimated contribution is smaller when the benchmark VAR model is used. The first and second columns of Table 1 quantify these contributions by showing the proportion of the unconditional variance of each series explained by the uncertainty shock estimated via the two models. It is evident from the table that the uncertainty shock accounts for a larger proportion of the variance of each series when the proxy SVAR is used and this feature is especially apparent for stock prices, employment and industrial production.

3.1 The impact of uncertainty during the recession of 2008/2009

In this section we consider the estimated contribution of the uncertainty shock during the recent recession and investigate if the recursive VAR and the proxy VAR suggest different conclusions with regards to the contribution of uncertainty to the recent data. For this purpose we extend the dataset in Bloom (2009) to June 2014.[10]

Figure 5 shows the estimated historical decomposition and the final two columns of Table 1 present the contribution of the uncertainty shock to the unconditional variance using the extended dataset. As in the benchmark case, the contribution of uncertainty shocks estimated using the proxy VAR is larger over the recent recession (see Figure 5). This difference is especially apparent in the case of the stock price index where the negative contribution of the uncertainty shock using the proxy VAR is estimated to be substantial during 2009. In contrast, this contribution is smaller when the recursive VAR is used. A similar result can also be seen for employment and industrial production where the proxy VAR estimates indicate a larger contribution of uncertainty to a fall in these variables. It is also interesting to note that as in Leduc and Liu (2012), the proxy VAR estimates suggest that the contribution of uncertainty to fluctuations in real activity was larger during the recession of 2008/2009 relative to the recession during the early 1980s. Note also that the overall contribution of the uncertainty shock to the variance of each series is estimated to be larger when the Proxy VAR is used.

[10] The on-line appendix to the paper shows the impulse responses using the extended sample. These are very similar to the benchmark responses presented in Figure 3.

3.2 Sensitivity Analysis

We test the robustness of the empirical results along two dimensions. First, we re-estimate the proxy SVAR using the additional volatility shock measures considered by Bloom (2009). Second, we consider alternatives to the VXO index included in the proxy SVAR.

Figure 6 shows the impact of a 15 unit volatility shock from the benchmark VAR model and uses the additional volatility shock measures constructed by Bloom (2009) as instruments. The figure shows that the impulse response of the key variables are similar in magnitude and persistence across the different instruments when different shock measures are used.

Figure 7 shows the impulse response to a volatility shock using two alternatives to the VXO measure of volatility.[11] First, we employ a non-parametric estimate of stock market volatility where the monthly standard deviation is estimated as the sample standard deviation of the daily observations within that month. Second, we use a stochastic volatility model to estimate the volatility. This model is defined as $\Delta S_t = h_t^{1/2} e_t$ where $e_t \tilde{} N(0,1)$, $h_t = \alpha + \vartheta h_{t-1} + g^{1/2} v_t$, $v_t \tilde{} N(0,1)$ and S_t denotes the monthly S&P500 stock price index.[12] Figure 7 shows that the impulse responses using alternative measures of volatility are similar to the benchmark case.

In Figure 8 we show the response of employment and industrial production using the two VAR models considered in Figure 3. In addition, we show the response from a version of the recursive VAR where the uncertainty shock dummy is replaced by the actual VXO index and a 15 unit shock to the index is considered (red line). The responses from this model are slightly more persistent than the benchmark recursive VAR. However, it is clear that these responses are still significantly smaller in magnitude and persistence from those obtained using the proxy VAR model. This shows that the difference in the responses across models is robust to specification of the recursive VAR and scaling of the shock.

[11] The benchmark shock measure is used as an instrument for each model.

[12] The model is estimated using the MCMC algorithm described in Jacquier *et al.* (1994).

4 Conclusions

This paper re-considers the SVAR approach to estimating the impact of volatility shocks and investigates the role played by measurement error. First, by estimating VAR models on data simulated from a DSGE model with stochastic volatility, we show that estimates of impulse responses to volatility shocks from a recursive SVAR suffer from a downward bias in the presence of measurement error. In contrast, the proxy SVAR produces impulse responses close to the underlying DSGE responses. This is because the proxy SVAR uses the volatility shock as an instrument rather than an endogenous variable, thus ameliorating the effect of measurement error.

An application of the proxy SVAR to the Bloom (2009) data-set results in responses to the volatility shock that are larger in magnitude to those obtained using the recursive SVAR employed in Bloom (2009). Similarly, a historical decomposition exercise using the volatility shock estimated from the proxy SVAR suggests a larger role for this shock than implied by the recursive SVAR. These results suggest that it may be important to account for measurement error when considering the impact of volatility using VAR models that include a proxy for volatility shocks.

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5 Tables and Figures

Table 1: Percentage of unconditional variance explained by the uncertainty shock.

	Recursive VAR	Proxy VAR	Recursive VAR	Proxy VAR
		Original Sample	Including recession of 2008/2009	
Stock Price Index	5.3	37.4	2.0	34.7
FFR	4.1	15.6	2.7	5.4
Wage	2.0	4.8	1.9	3.0
CPI	1.4	9.1	3.7	3.9
Hours	4.5	9.7	2.5	8.8
Employment	2.2	14.9	2.4	14.3
Industrial Production	3.3	13.4	2.3	9.4

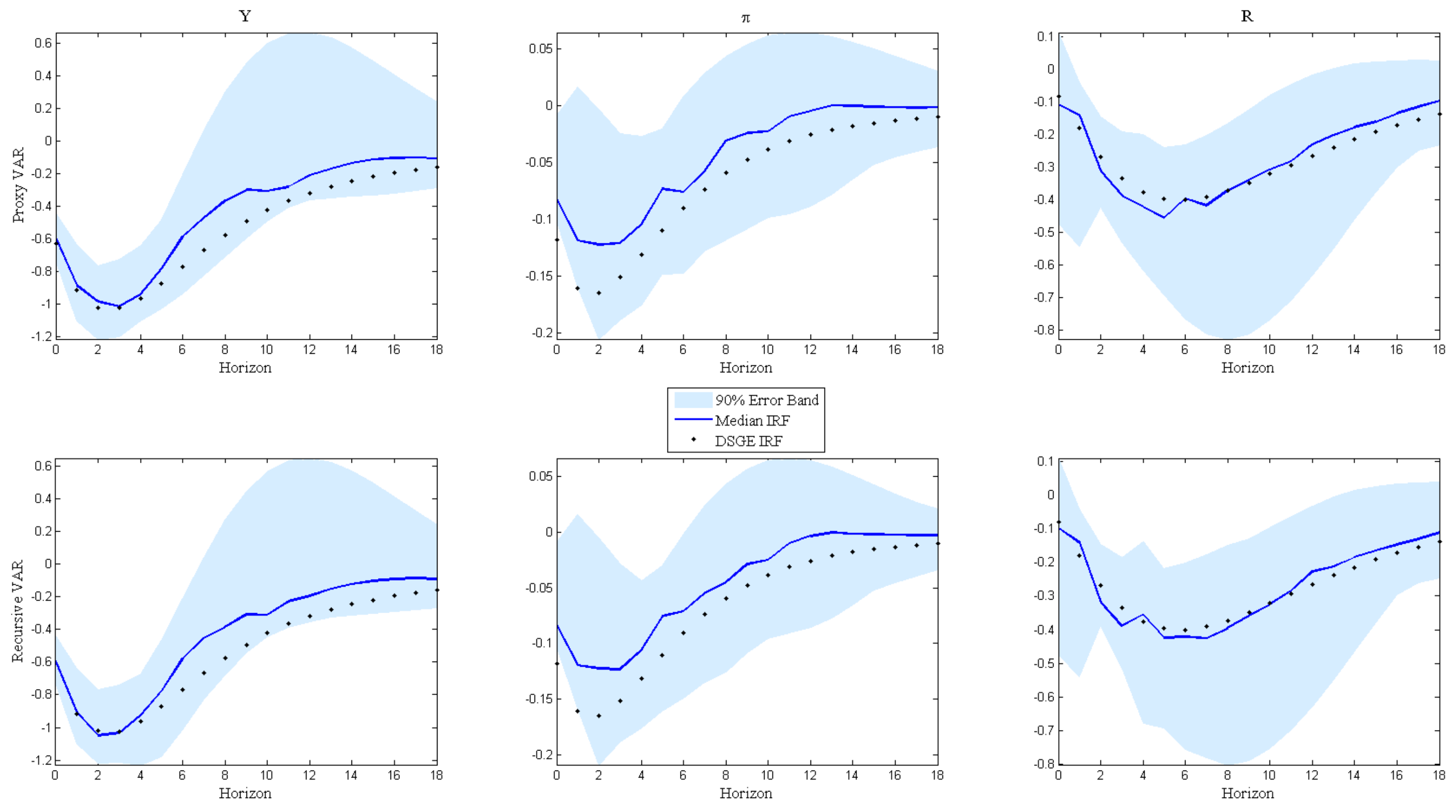

Figure 1: A comparison of SVAR and DSGE impulse responses to policy uncertainty shocks in the absence of measurement error.

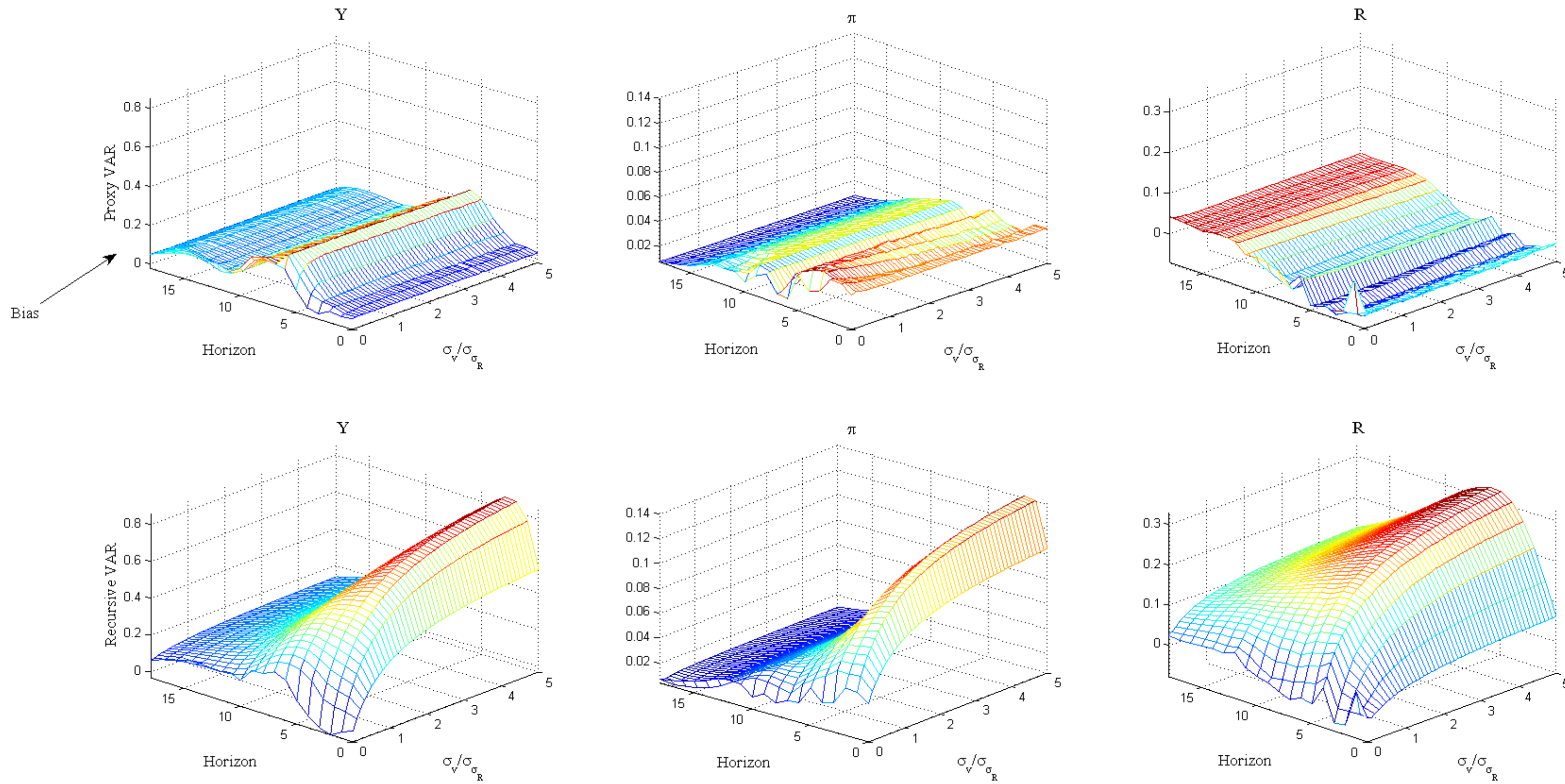

Figure 2: Bias in SVAR impulse responses to policy uncertainty shocks under measurement error. The bias is calculated as the median impulse response from the VAR models minus the impulse response from the DSGE model.

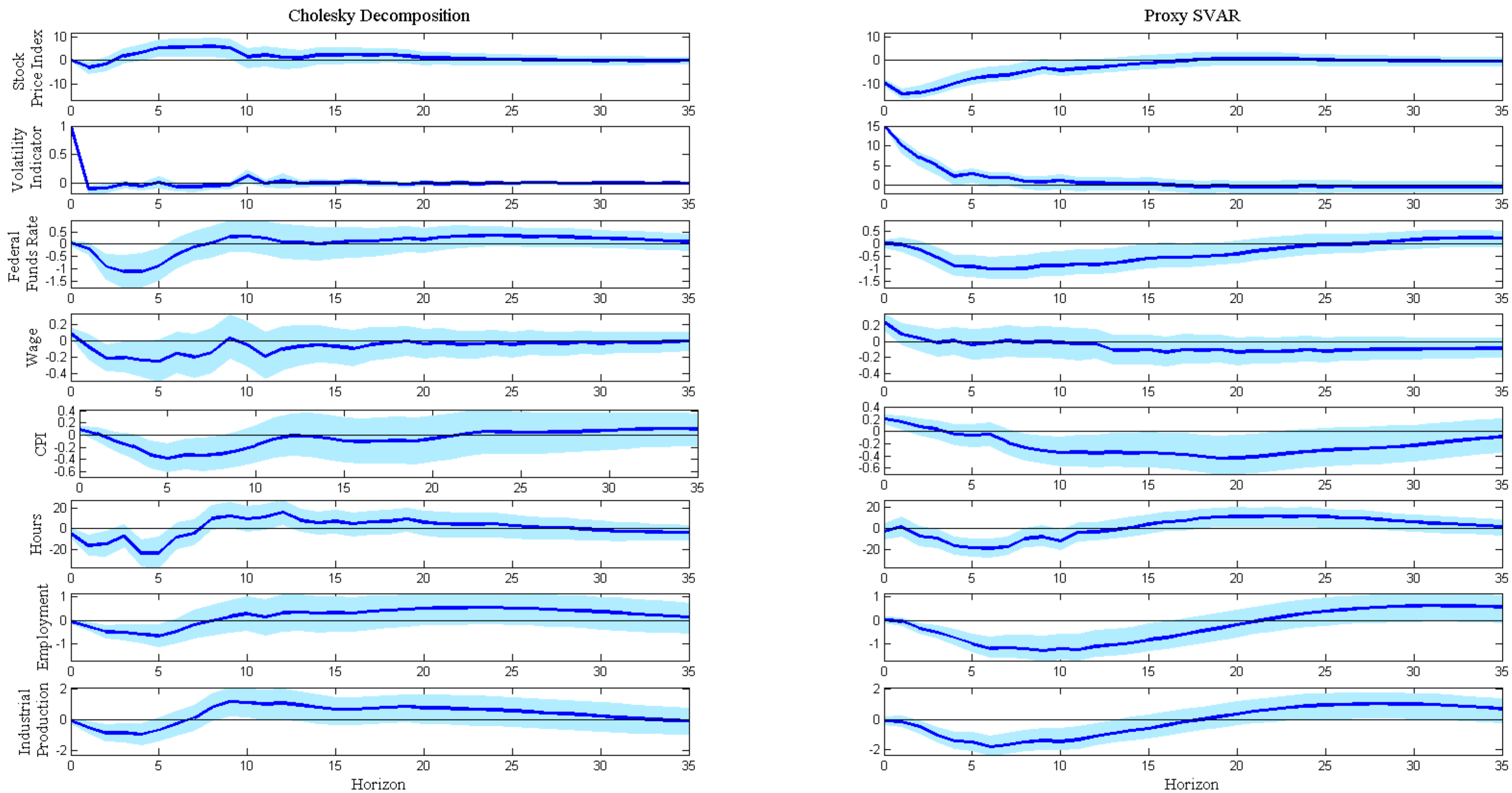

Figure 3: Impulse response to a volatility shock using a recursive VAR and the Proxy SVAR. The shaded area represents the 90% confidence interval estimated using a wild bootstrap with 10,000 replications.

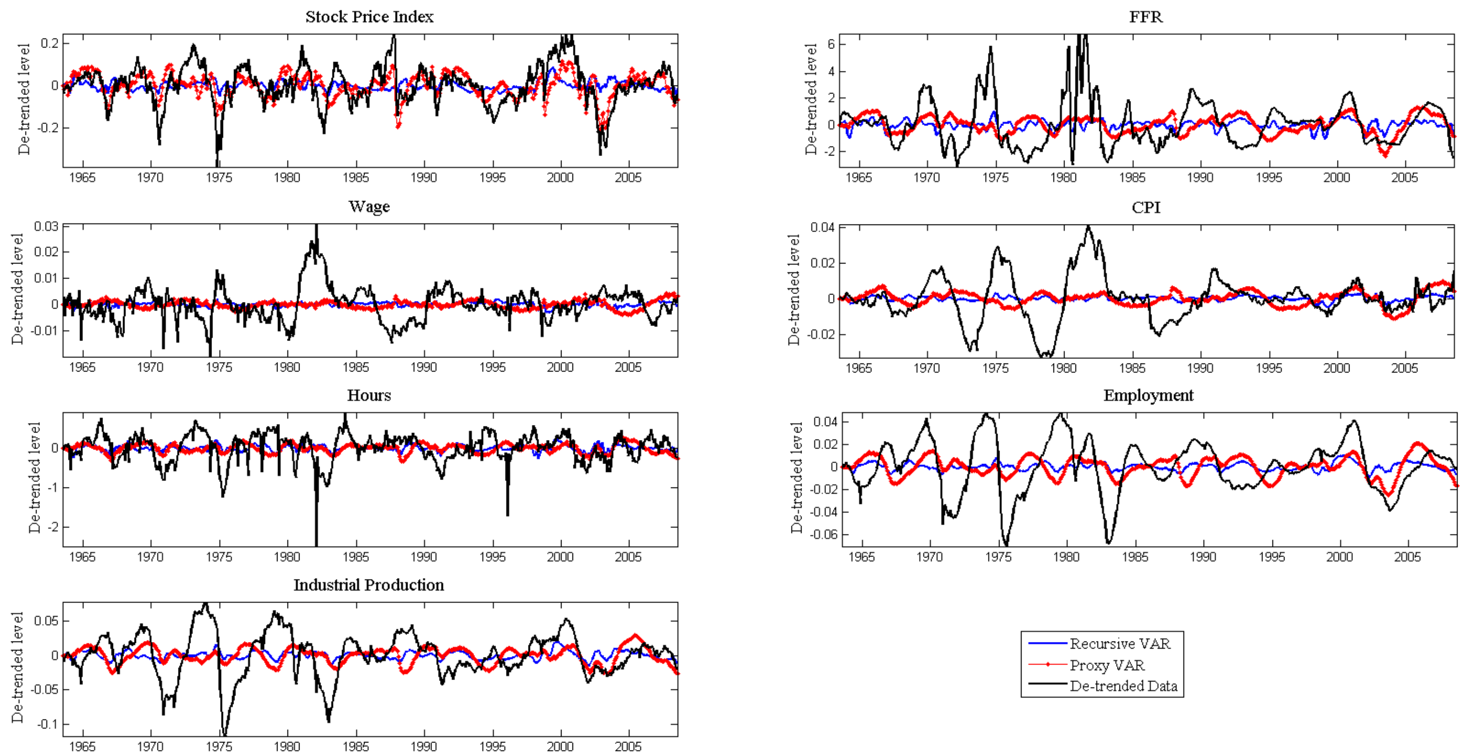

Figure 4: Historical Decomposition: The contribution of the volatility shock using the recursive VAR and the Proxy SVAR.

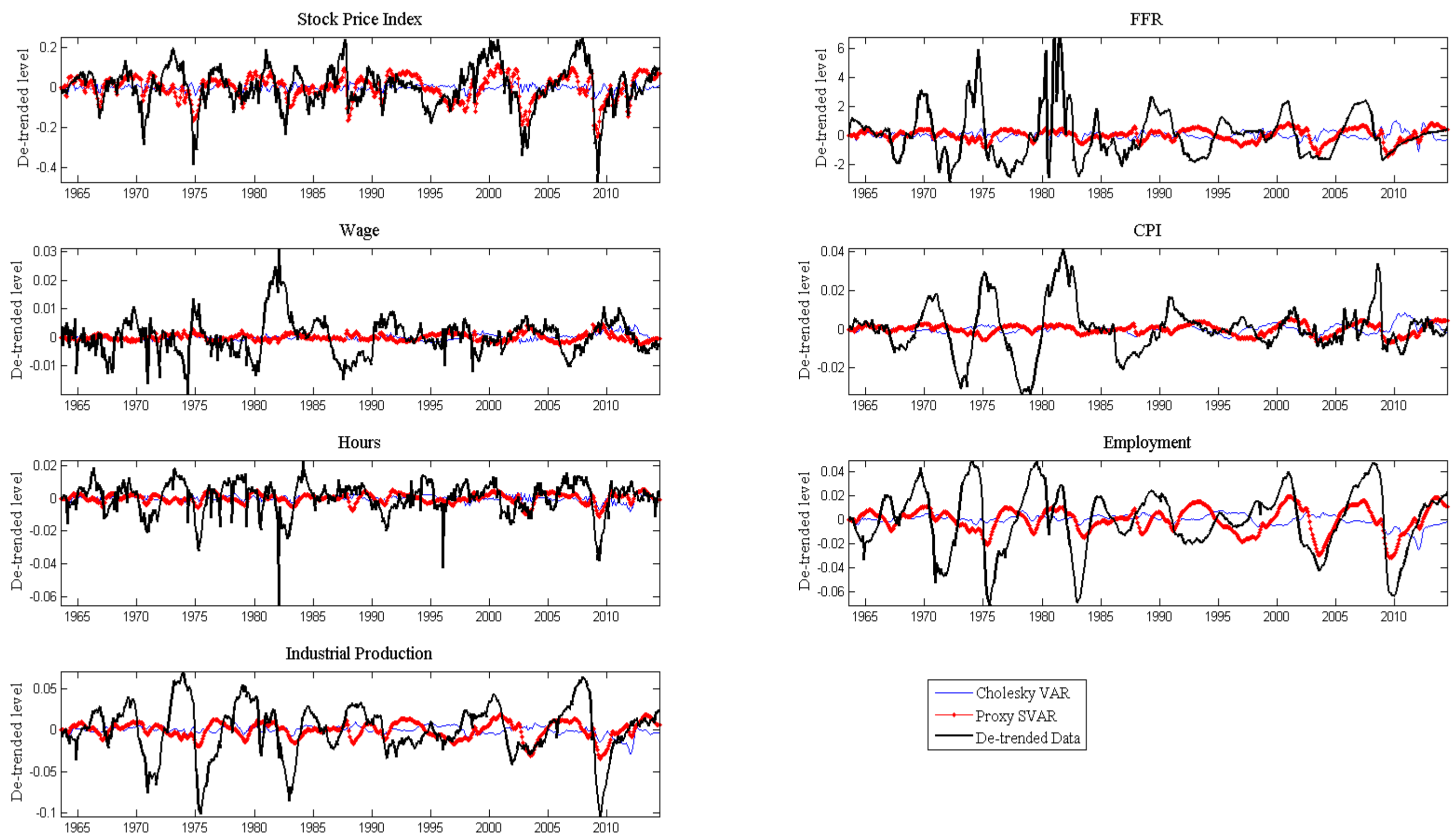

Figure 5: Historical Decomposition using the sample extended to 2014: The contribution of the volatility shock using the recursive VAR and the Proxy SVAR.

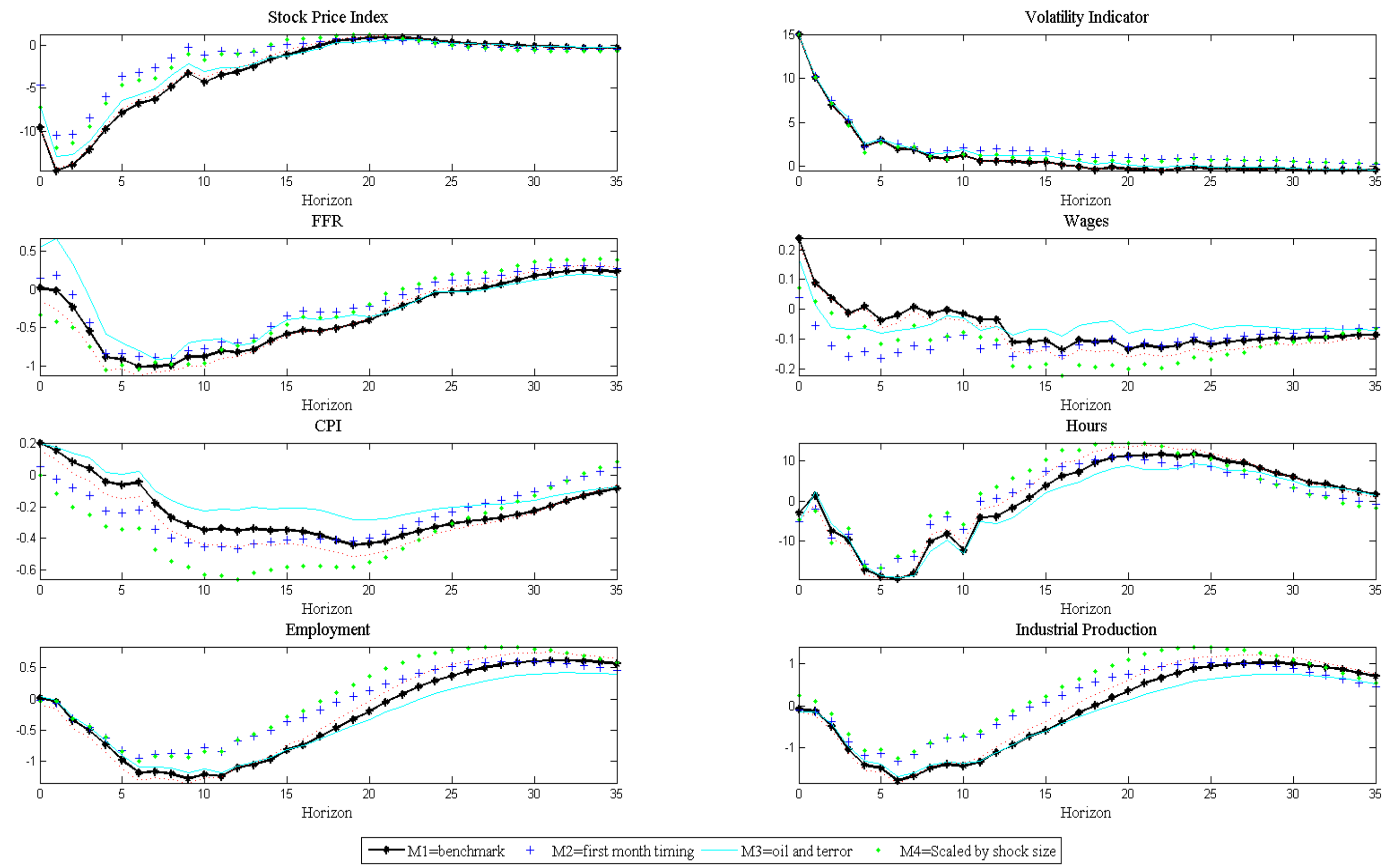

Figure 6: The impact of a volatility shock from the proxy SVAR using different shock measures. ‘First month timing’ refers to the indicator where shocks are dated by first month rather than the highest month. ‘Oil and Terror’ refers to shocks associated with war, terrorism and oil. The final measure is the benchmark shock scaled by the size of movement in stock market volatility. These different shock measures are described in appendix A1 of Bloom (2009).

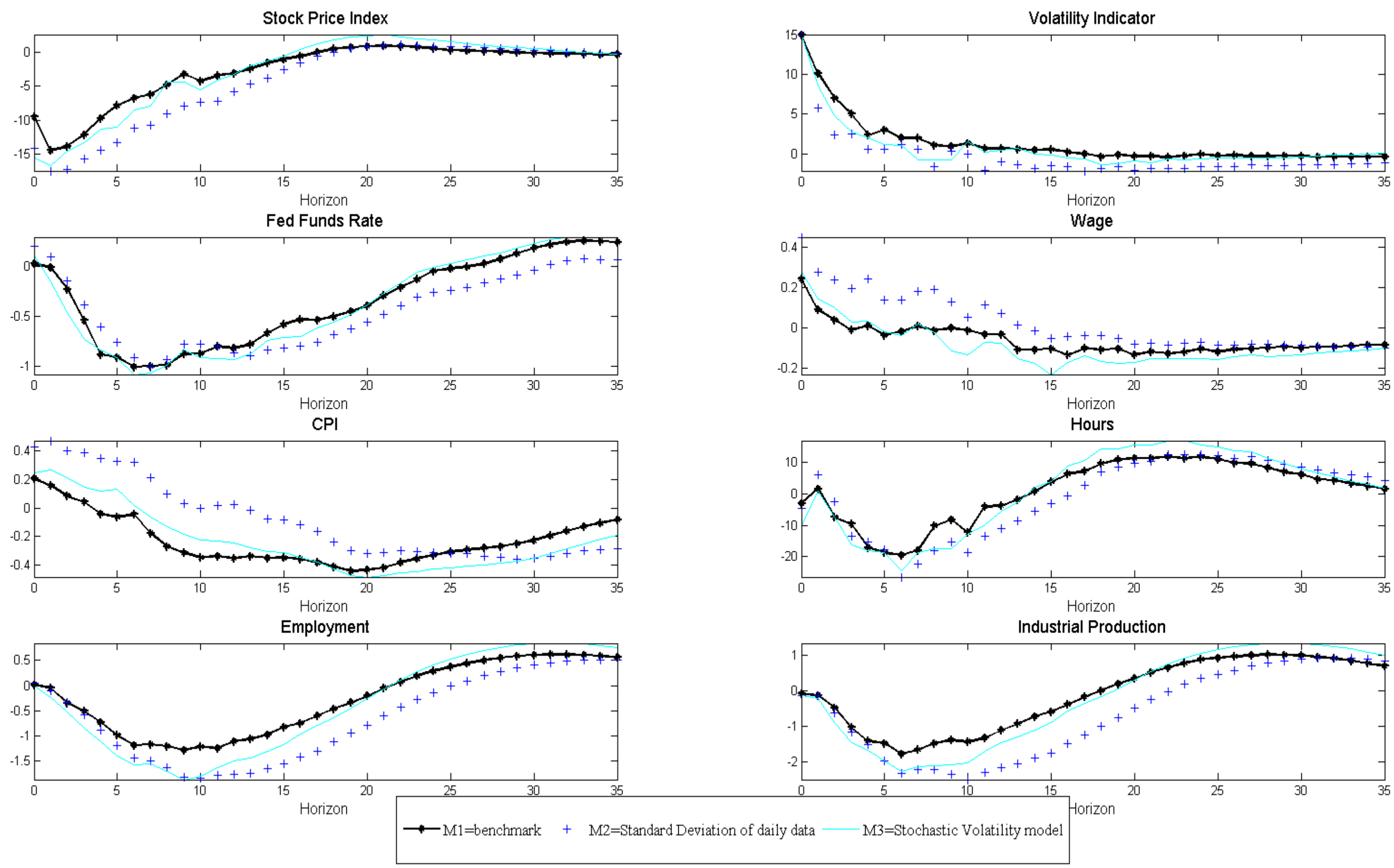

Figure 7: Impulse responses to the volatility shock from the proxy SVAR using different measures of stock market volatility. Model M2 uses a monthly volatility measure based on standard deviation of daily stock returns. Model M3 uses a measure estimated via a stochastic volatility model.

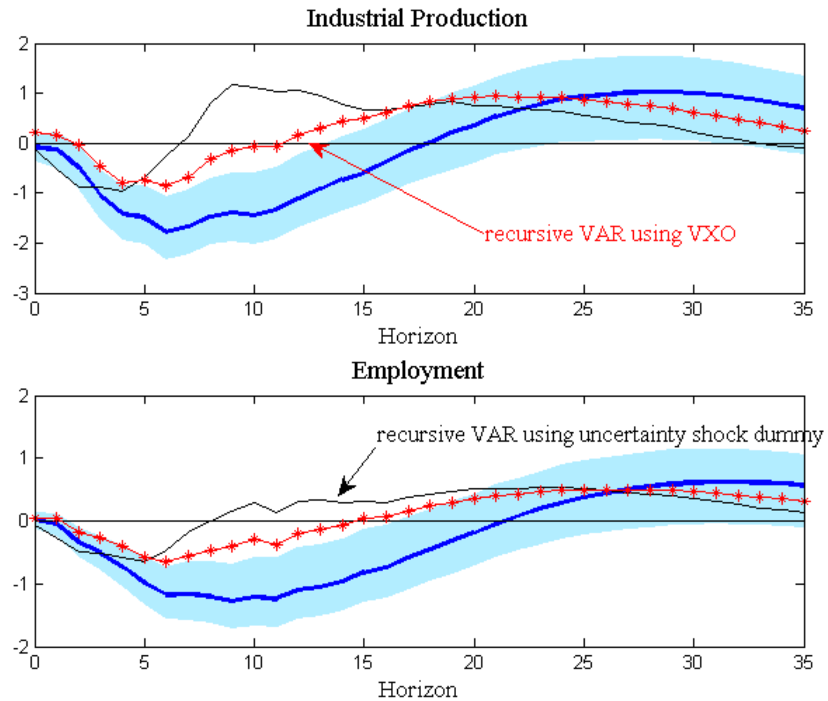

Figure 8: The response of industrial production and employment to uncertainty shocks. The blue line and shaded area show the response from the proxy VAR to a 1 unit shock. The black line shows the response to a 1 unit shock using a recursive VAR that includes the uncertainty shock dummy variable. The red line shows the response to 15 unit shock using a recursive VAR that includes the VXO index.