Online appendix for "What Are The Macroeconomic Effects of High-Frequency Uncertainty Shocks?"

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This online appendix includes the following elements:

- Appendix A reports results for the Baker et al. (2016) VAR estimated at two different frequencies: monthly and quarterly.
- Appendix B provides a detailed description of the Monte Carlo experiment.
- Appendix C details the block wild bootstrapping procedure we use to calculate confidence bands for the impulse responses obtained from MIDAS models.
- Appendix D shows the responses of all macroeconomic variables to an uncertainty shock obtained from the mixed-frequency VAR models.
- Appendix E compares responses from a MIDAS model with those from a single frequency VAR model when the uncertainty shock is defined along the lines of Bloom (2009).
- Appendix F reports results when using the economic policy uncertainty index as a measure of uncertainty.
- Appendix G compares MIDAS impulse responses with those obtained from mixed-frequency VAR models.

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A The Baker et al. (2016) VAR estimated at monthly and quarterly frequencies

To motivate the use of data sampled at different frequencies in the context of the evaluation of the macroeconomic effects of uncertainty shocks, we estimate the baseline VAR model from Baker et al. (2016) at two separate data frequencies: monthly and quarterly. Finding that the impulse response analysis differs depending on the frequency of analysis would suggest that using mixed-frequency data to study the effects of high-frequency uncertainty shocks is a relevant exercise.

We retain the exact same formulation from the baseline monthly VAR analysis of Baker et al. (2016); that is, we estimate a VAR that includes the following variables: EPU index, S&P 500 index (in log-level), the federal funds rate, employment (in log-level) and industrial production (in log-level). We first estimate a VAR model at the monthly frequency over a sample extending from January 1985 to December 2012 and we include three autoregressive lags, following Baker et al. (2016). The quarterly VAR model is estimated over the same sample period as in Baker et al. (2016); i.e., using data from 1985Q1 to 2012Q4. We include one autoregressive lag in the quarterly VAR model so as to have the exact same information set across the monthly VAR and the quarterly VAR models.

We report responses at a quarterly frequency for both the monthly VAR and the quarterly VAR to ease comparison across models. In the quarterly VAR, monthly data have been aggregated at the quarterly frequency using skip-sampling before estimation; that is, we assume that the monthly data are only observed in the last month of the quarter. For the monthly VAR, responses are aggregated at a quarterly frequency using skip-sampling (we do so to be consistent with the aggregation of the monthly data in the quarterly VAR). Note that one could also aggregate the monthly data at a quarterly frequency, taking a simple arithmetic average of the data over the quarter. However, we do not report results in this case because we are interested in a situation where a data frequency mismatch would naturally arise.

Following Baker et al. (2016), we report responses of industrial production and employment to a 90 points increase in the EPU index. The shock is scaled so as to correspond to an increase in the EPU index from its 2005–2006 to its 2011–2012 average value. Figure A3 shows the cumulative responses for industrial production for the monthly and quarterly VAR along with 90 percent bootstrapped confidence bands based on 2000 replications for the quarterly VAR. Figure A4 is the corresponding figure showing the employment response to the same uncertainty shock. For both employment and industrial production, the response from the monthly VAR is stronger than the response obtained from the quarterly VAR. In fact, the responses from the monthly VAR are outside the coverage area of the quarterly VAR response, suggesting that the difference in responses across monthly and quarterly VAR models is statistically significant. It is also interesting to note that the confidence bands are fairly asymmetric around the least square estimates of the impulse responses. This should just be interpreted as a reflection of the estimation uncertainty in the impulse responses. Moreover, the differences in responses across monthly and quarterly VAR models are also large from an economic point of view in that industrial production is expected to decline by 16.2 percent at a 12-quarter horizon according to the quarterly VAR, whereas the monthly VAR suggests that industrial production declines by 21.5 percent in response to the EPU shock. As for the response of employment, the quarterly VAR estimates that employment contracts by 8 per cent at a 12-quarter horizon following the EPU shock compared with a contraction of 12.8 percent based on estimates from the monthly VAR model.

One economic rationale for estimating different dynamic responses to uncertainty shocks depending on the frequency of the model (monthly or quarterly) is that uncertainty shocks are relatively short-lived in that empirical proxies for uncertainty exhibit little persistence. This suggests that uncertainty shocks are possibly harder to estimate at a lower frequency given that they are partly washed out in the process of temporal aggregation. The responses from the quarterly VAR are indeed somewhat softer compared with responses obtained from a monthly VAR, suggesting that temporal aggregation may potentially play an important role when evaluating the effects of uncertainty shocks on the macroeconomic environment. Overall, this suggests that depending on the frequency of the estimation of the models, the impulse response analysis may differ in an economically meaningful way.

B Monte carlo experiment

We now perform a Monte Carlo experiment to evaluate the finite sample accuracy of the MIDAS responses compared with the responses obtained from a (single-frequency) VAR. This is relevant since we can study the conditions under which impulse response analyses differ depending on the frequency of the data used in the model in a controlled experiment. We use a MIDAS model to generate the data to mimic the conditions of our empirical applications. In doing so, we first assume that the high-frequency variable x_t follows a combination of a Poisson distribution and a normal distribution so as to model the possibility of rare exogenous events as in Ferraro et al. (2015) (i.e., $x_t \sim (\epsilon_t + \eta_t)$ where $\epsilon_t \sim N(0,1)$ and $\eta_t \sim Pois(\lambda)$). The low-frequency variable is then generated as follows

$$y_t = \rho y_{t-1} + \beta \sum_{i=1}^{Q} b(L;\theta) x_{t-\frac{i}{Q}} + u_t,$$

where $x_{t-\frac{i}{Q}}$ is the high-frequency variable, $b(L;\theta)$ is the MIDAS polynomial as outlined in equation (2) of the paper and u_t is the error regression term assumed to follow a normal distribution. We use two sets of parameter values for the data-generating process (DGP): $\{\rho, \beta, \lambda\} = \{0.85, 0.8, 0.2\}$ (this characterizes DGP 1) and $\{\rho, \beta, \lambda\} = \{0.7, 0.5, 0.05\}$ (this characterizes DGP 2). The parameters $\{\rho, \beta, \lambda\}$ represent the persistence of the low-frequency variable, the extent of the relation between the high- and low-frequency variables and the Poisson parameter governing the rate of occurrence of rare events, respectively. The MIDAS parameters θ are held constant across DGPs and set to $\{\theta_1, \theta_2\} = \{0.2, -0.03\}$, which implies hump-shaped weights.

A few additional comments are required. First, the length of the low-frequency time series is set to 200 observations and the length of the high-frequency time series is set to 800 observations. As such, this corresponds to a frequency mismatch of monthly and weekly time series. We also consider a frequency mismatch corresponding to quarterly and weekly time series; that is, we generate low-frequency time series with 200 observations and high-frequency time series with 2600 observations. In all cases, we discard the first 200 observations to account for start-up effects. Second, we generate *M=2000* simulated time series for y_t and x_t for all DGPs. Third, we calculate impulse responses from a MIDAS model and a low-frequency VAR where the high-frequency variable is aggregated using skip-sampling (structural impulse responses are calculated by ordering the high-frequency variable first in the VAR, i.e., assuming that the high-frequency variable is predetermined in our system). Fourth, across all DGPs and for both MIDAS and VAR models, we consider one unit of low-frequency information in the model information set; that is, for the VAR model, we use one autoregressive lag and for the MIDAS model, we include one autoregressive lag and set $K = 4$ for the monthly/weekly frequency mix and $K = 13$ for the quarterly/weekly frequency mix. As such, we abstract from the problem of selecting the appropriate lag length, assuming that it is known. Finally, we report the median estimates of the simulated impulse responses from the bivariate VAR and MIDAS models to a one-standard deviation shock in the high-frequency variable x_t, and we calculate confidence bands taking the 10^{th} and 90^{th} percentile of the 2000 simulated impulse responses.

Figure A5 shows the responses. First, in the case of DGP 1, for both frequency mixes, the MIDAS responses are clearly much closer to the true responses and the short-term dynamics of the VAR response is clearly distant from the short-term dynamics of the true response. In the case of DGP 2, for both frequency mixes, the difference in impulse responses across VAR and MIDAS models are somewhat softened, albeit the MIDAS model is closer to the true response for the near-term dynamics of the low-frequency response. Overall, this small Monte Carlo experiment shows that overlooking the issue of the frequency of the data can potentially lead a researcher to conduct a misleading impulse response analysis.

C Bootstrapping procedure for MIDAS models

In this section, we detail the bootstrapping approach we use to calculate confidence bands for the MIDAS impulse responses. The bootstrapping procedure is derived from section 3.1.3 in Aastveit et al. (2017). It is a block wild bootstrap that is well-suited to account for autocorrelation and heteroskedasticity in the error terms. The block wild bootstrapping procedure we use is described by the following three steps

1. Estimate equation (1) in the paper (i.e., $X_{t+h} = \mu_h + \beta_h B(L^{1/w}; \theta_h) Unc_t^{(w)} + \Gamma_h Z_t + \epsilon_{t+h}$) using the nonlinear least squares method and obtain the set of parameters $\hat{\mu}_h, \hat{\beta}_h, \hat{\theta}_h, \hat{\Gamma}_h$.

2. For $r = 1, ..., R$, simulate $\tilde{X}_{r,t}$ as follows

$$\tilde{X}_{r,(j-1)b_T+l+h} = \hat{\mu}_h + \hat{\beta}_h B(L^{1/w}; \hat{\theta}_h) Unc^{(w)}_{(j-1)b_T+l} + \hat{\Gamma}_h Z_{(j-1)b_T+l} + \epsilon^*_{(j-1)b_T+l+h},$$

   where

$$\epsilon^*_{(j-1)b_T+l+h} = \ddot{\epsilon}_{(j-1)b_T+l+h} \nu_j$$

   We assume that ν_j is a Rademacher variable, that is

$$\nu_j = \begin{cases} 1, & \text{with probability } 1/2 \\ -1, & \text{with probability } 1/2 \end{cases}$$

   Note that b_T denotes non-overlapping blocks of consecutive residuals and assume that $\frac{T-h}{b_T} = k_T$, where k_T is an integer that denotes the number of blocks of size b_T, and $l = 1, ..., b_T$ and $j = 1, ..., k_T$.

3. Re-estimate equation (1) of the paper for each $\tilde{X}_{r,t}$ and each projection horizon h and save the parameter of interest $\hat{\beta}_{h,r}$. Confidence bands are then obtained by concentrating on the percentile of interest of the predictive distribution of the parameters $\hat{\beta}_{h,r}$.

We represent 90 percent confidence bands around the non-linear least squares responses based on $R = 2000$ replications in our bootstrap procedure.[1]

D Additional responses from the mixed-frequency VAR

Figures A6 to A13 show the responses of the 16 macroeconomic variables to an uncertainty shock from the MF-VAR and VAR models. For the MF-VAR models, we report four responses depending on the week of the month the shock hits the economy. 90 percent bootstrapped confidence bands are reported for the MF-VAR model and are based on 2000 replications. The main comments are the following:

- A consistent feature across all variables is that the short-term dynamics of the responses is quite different when the VIX shock takes place in the last week of the month compared with the response to a shock taking place earlier in the month.
- The medium and long-term dynamics of the responses from the VAR and the MF-VAR models line up relatively with each other in that responses from the VAR models typically lie within the confidence bands of the responses from the MF-VAR model.

E Robustness check: uncertainty shock based on a dummy variable

We now calculate responses when using a different definition for the uncertainty shock. Following Bloom (2009), the uncertainty shocks are chosen as occurrences in which the Hodrick-Prescott de-trended stock-market volatility is more than 1.65 standard deviations above its mean. When using the Hodrick-Prescott filter, we select the following values

[1] In the working paper version of this paper, we calculated confidence bands for the MIDAS impulse responses by taking ± 1.65 Newey-West standard errors of the parameter β_h entering before the weight function in equation (1) of the paper. Generally speaking, the confidence bands had similar width at short horizons, but the bootstrap procedure led to wider confidence bands for distant projection horizons.

for the filter parameter λ: $(252^4 \times 6.25)$ for daily data, $(52^4 \times 6.25)$ for weekly data and $(12^4 \times 6.25)$ for monthly data. Figure A14 shows the resulting dummy variable for these three sampling frequencies. It is interesting to note that the occurrence of shocks differs depending on the frequency of the analysis. In particular, there are more realization of uncertainty shocks at daily and weekly frequencies compared with the monthly frequency.

A question of interest is to investigate to what extent the impulse response analysis differs depending on the frequency chosen to identify the uncertainty shocks. Figure A15 shows the responses when using a monthly VAR with the uncertainty dummy shock variable obtained from the monthly VIX series together with the MIDAS responses using the uncertainty dummy shock variable obtained from the weekly VIX series. These results support our original conclusions in that the responses from the VAR are typically within the confidence bands of the MIDAS responses.

F Alternative measure of uncertainty

An alternative measure of uncertainty that has gained increased attention in academic and policy-making circles is the EPU index from Baker et al. (2016). It has been available on a daily basis since January 1985, but we report results on the same sample size as the one used for the VIX and use weekly EPU to provide a fair comparison in the impulse response analysis of these two uncertainty measures. Figure G presents the results of a one-standard-deviation increase in the economic policy uncertainty index. As a benchmark, Figure G also reports impulse responses to a one-standard-deviation increase in the VIX.

It is interesting to note that the impulse responses to a shock in the EPU index exhibit a very similar shape to those calculated using the VIX as a measure of uncertainty. In fact, in nearly all cases, the impulse responses to a shock in the VIX systematically lie within the confidence bands of the responses to a shock in the EPU index. As such, this confirms the robustness of the results we obtained previously in that the variables that react the most to uncertainty shocks are labor market and credit variables.[2]

[2]For ease of presentation of the results, we do not show impulse responses to an EPU index shock obtained from a monthly VAR model since they are relatively similar to those obtained from a MIDAS model. Moreover, using the time-stamped MF-VAR model with the EPU index as a measure of uncertainty also leads to short-term dynamics of the responses that depend on the timing of the shock in the month.

G Comparison of responses from MIDAS and mixed-frequency VAR models

Figures A17 and A18 show the responses from selected variables (coincident indicator, industrial production, employment and business loans) for both MIDAS and mixed-frequency VAR models. Overall, the responses from MIDAS and MF-VAR models to an uncertainty shock are quite similar. A noticeable exception is that the short-term dynamics of the responses for the MF-VAR model differs depending on the timing of the shock in the month. Moreover, the response from the MIDAS model for the business loan variable suggests a somewhat stronger response for much of the projection horizon compared with the responses obtained from the MF-VAR.

References

Aastveit, K. A., Foroni, C., and Ravazzolo, F. (2017). Density forecasts with midas models. *Journal of Applied Econometrics*, 32(4):783–801.

Baker, S., Bloom, N., and Davis, S. (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, 131(4):1593–1636.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, 77(3):623–685.

Ferraro, D., Rogoff, K., and Rossi, B. (2015). Can Oil Prices Forecast Exchange Rates? An Empirical Analysis of the Relationship Between Commodity Prices and Exchange Rates. *Journal of International Money and Finance*, 54(C):116–141.

Figure A1. Data – Monthly time series

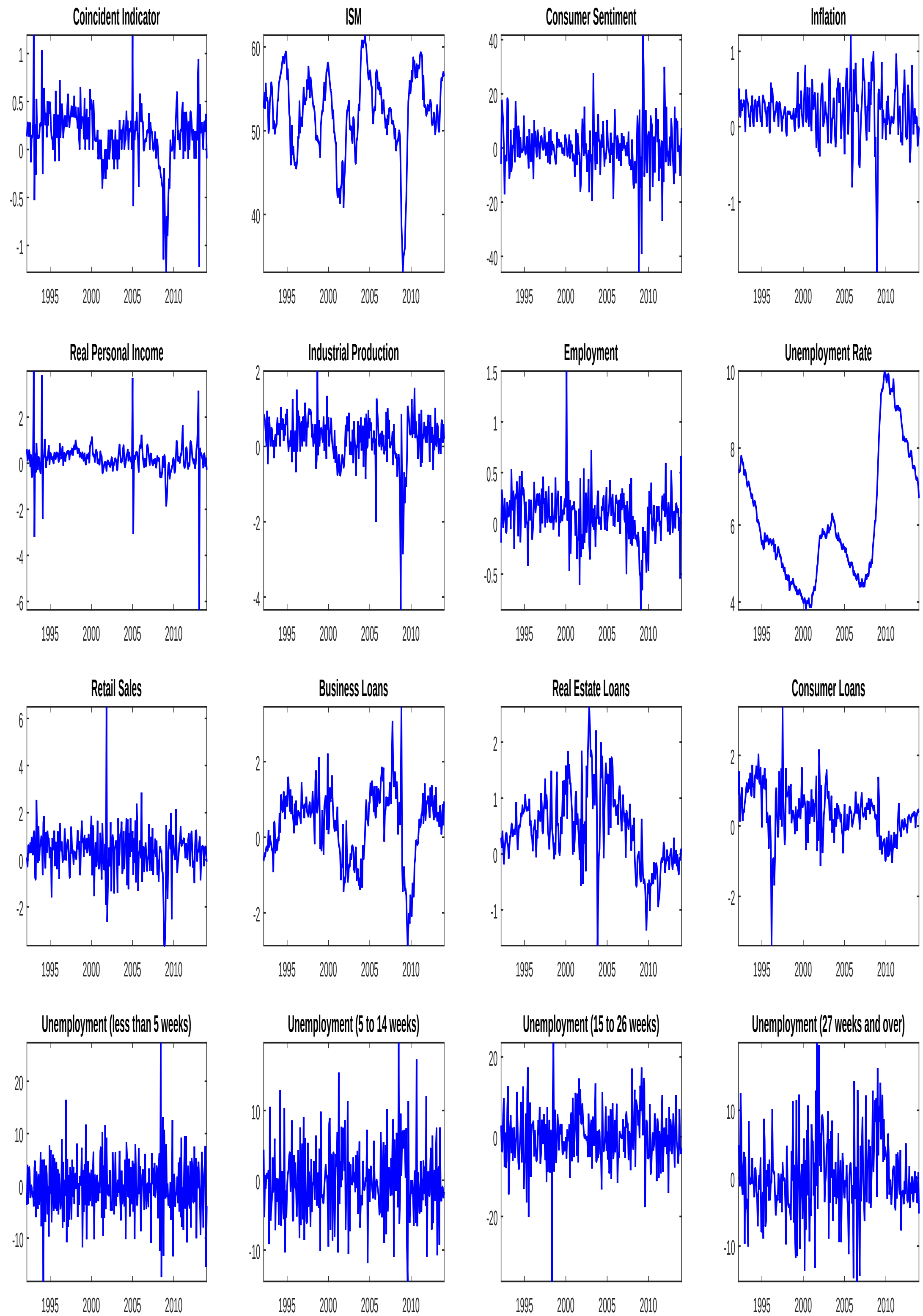
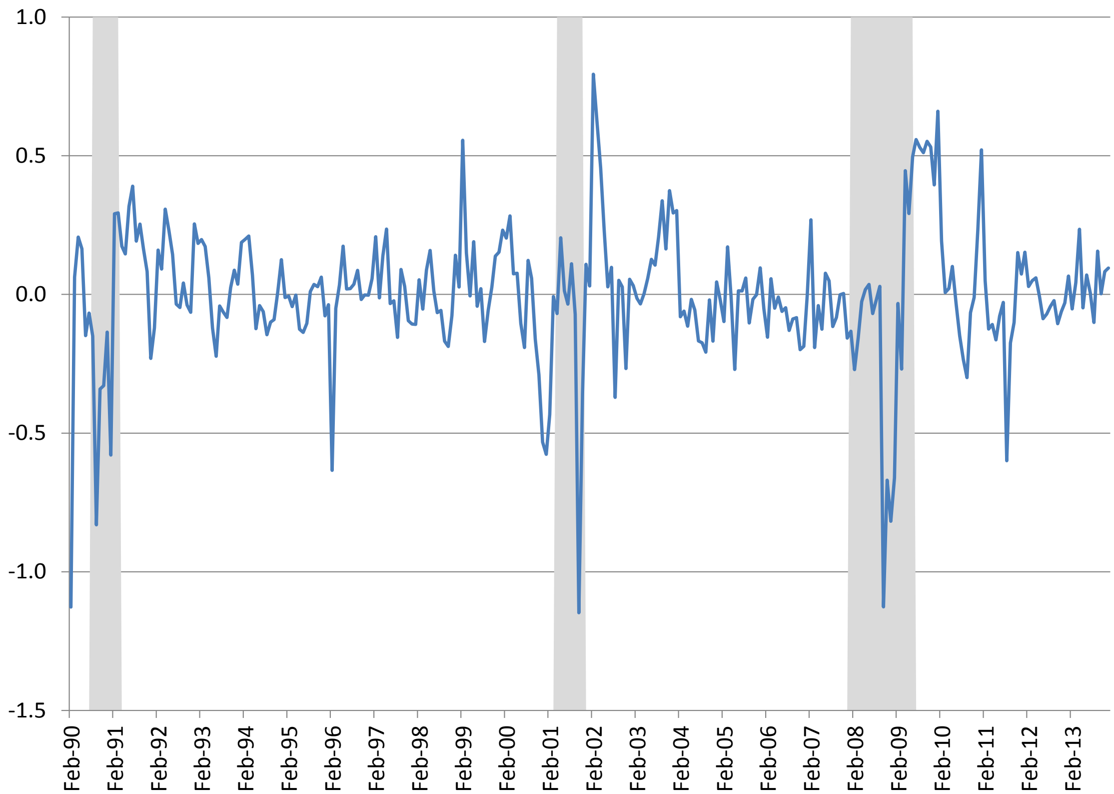
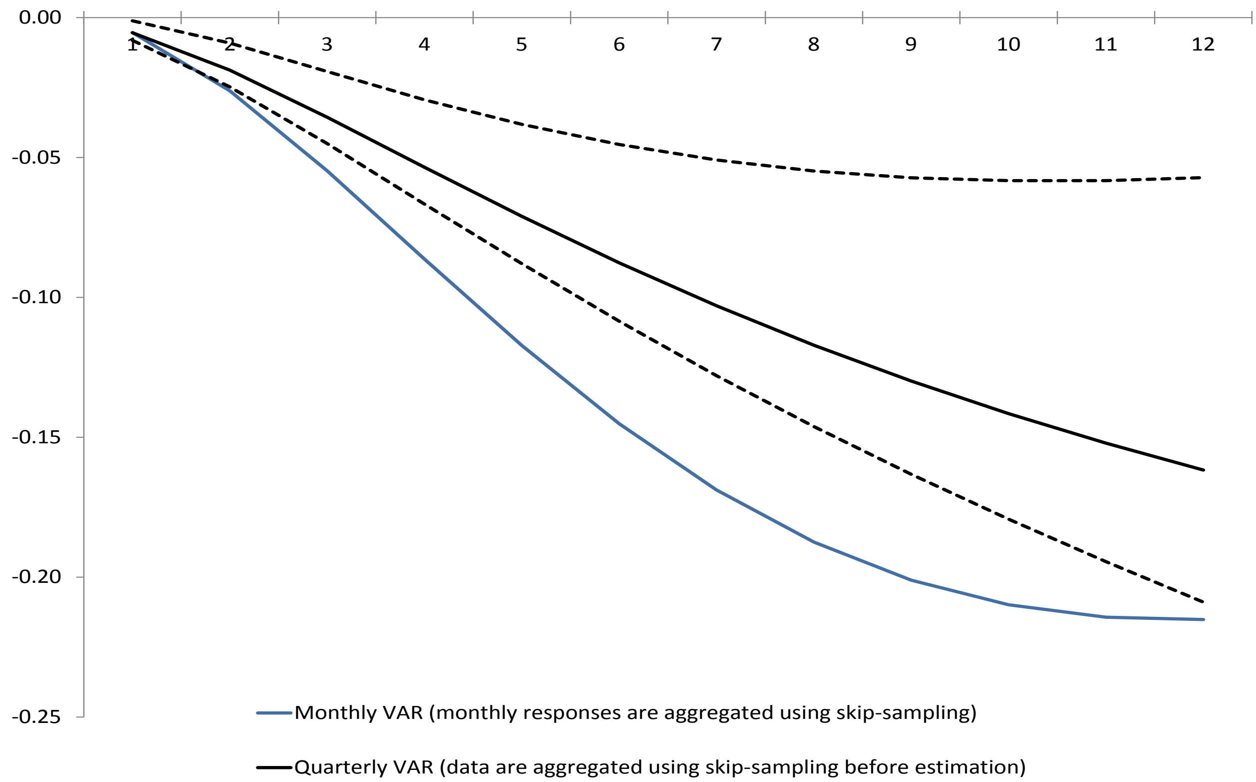


Figure A2. Data – Forecast Revision variable



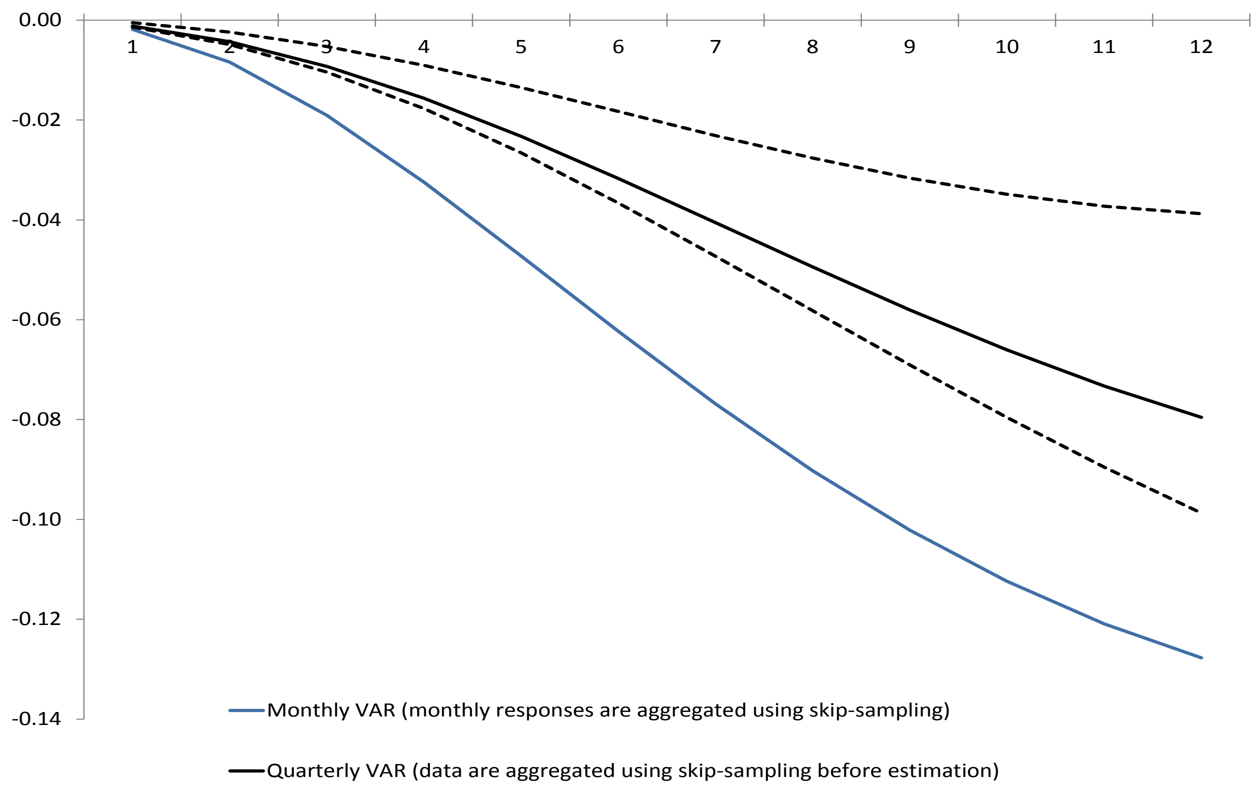
Note: The forecast revision variable, used as a proxy for aggregation economic conditions, is defined as the monthly change in one-year-ahead forecast for U.S. GDP growth obtained from the Consensus Economics survey (see equation (5) in the paper).

Figure A3. Industrial Production response to an EPU shock



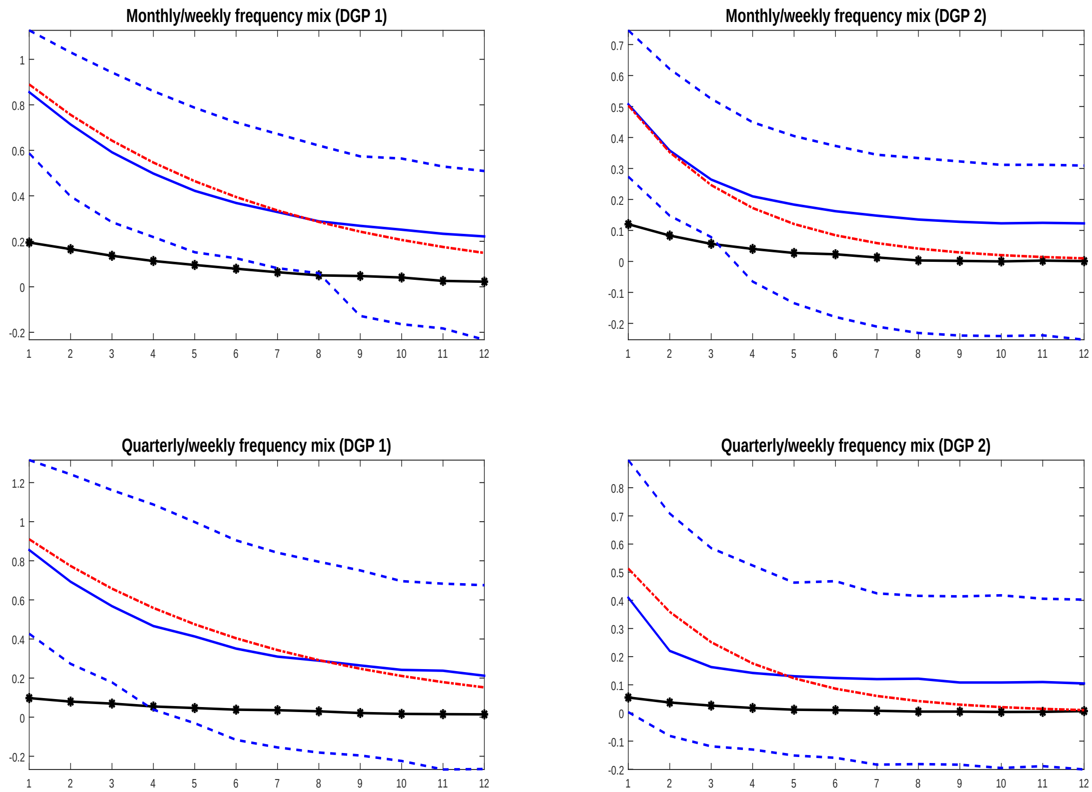
Note: VAR cumulative impulse responses for industrial production to an EPU shock. The EPU shock is scaled to correspond to a 90-point increase in the EPU index as in Baker et al. (2016). We show responses from a quarterly VAR model where data have been aggregated using skip-sampling and responses obtained from a monthly VAR model where monthly impulse responses are also aggregated using skip-sampling. All VAR models are identified using a recursive (Cholesky) decomposition with the following ordering: EPU index, S&P 500 index (in logs), federal reserve funds rate, employment (in logs) and industrial production (in logs). The confidence bands are bootstrapped based on 2000 replications and are reported for the quarterly VAR model.

Figure A4. Employment response to an EPU shock



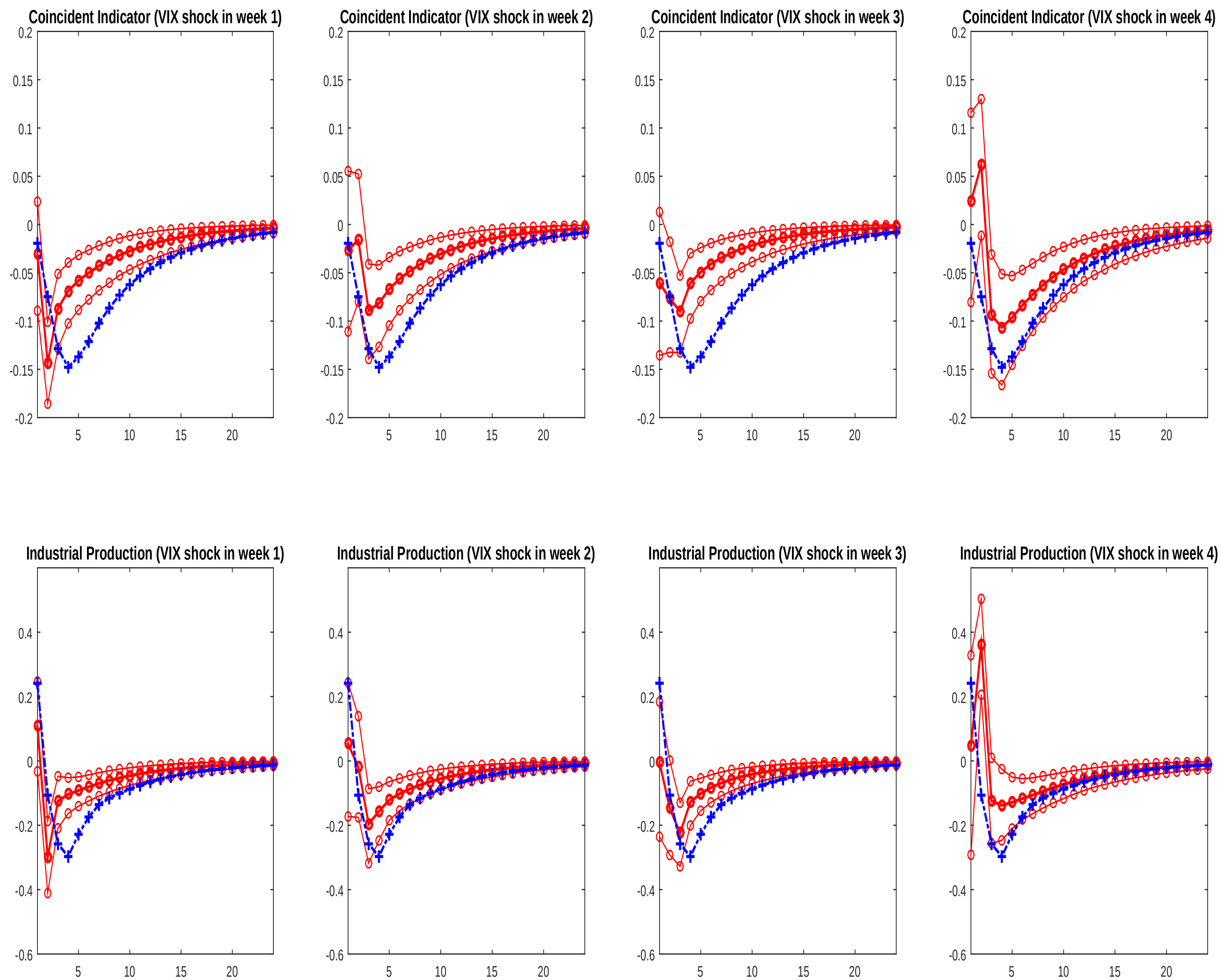
Note: VAR cumulative impulse responses for employment to an EPU shock. The EPU shock is scaled to correspond to a 90-point increase in the EPU index as in Baker et al. (2016). We show responses from a quarterly VAR model where data have been aggregated using skip-sampling and responses obtained from a monthly VAR model where monthly impulse responses are also aggregated using skip-sampling. All VAR models are identified using a recursive (Cholesky) decomposition with the following ordering: EPU index, S&P 500 index (in logs), federal reserve funds rate, employment (in logs) and industrial production (in logs). The confidence bands are bootstrapped based on 2000 replications and are reported for the quarterly VAR model.

Figure A5. Monte Carlo experiment – Response of the low-frequency variable to a shock in the high-frequency variable



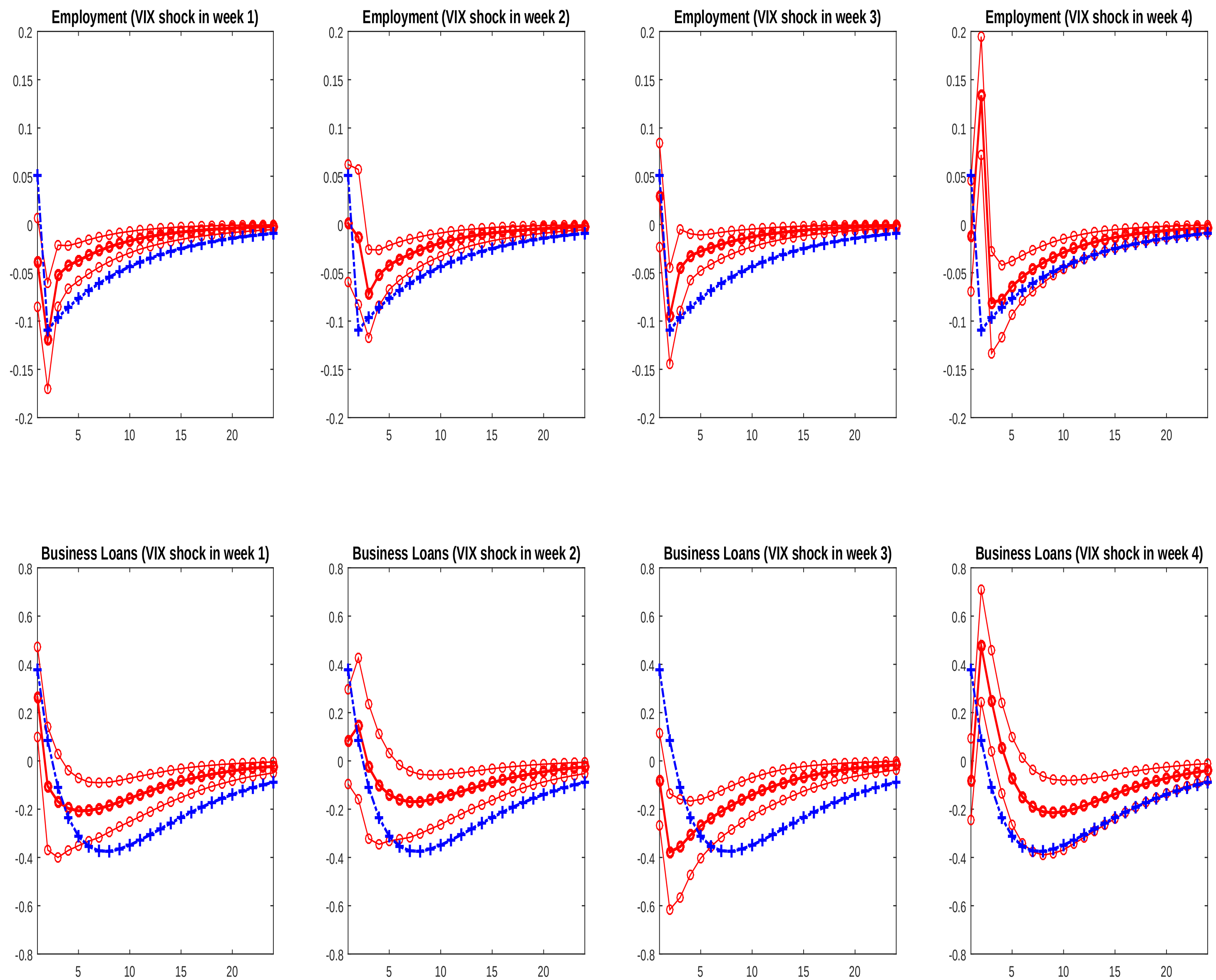
Note: This figure shows the simulated impulse responses of the low frequency variable to a one-standard-deviation increase in the high frequency variable for different frequency mixes and different DGPs. DGP1 uses the following set of parameter values $\{\rho, \beta, \lambda\} = \{0.85, 0.8, 0.2\}$, whereas DGP2 instead uses the following set of parameter values $\{\rho, \beta, \lambda\} = \{0.7, 0.5, 0.05\}$. Each quadrant reports the simulated response obtained from a MIDAS model (solid blue line), a VAR model (circled black line) and the true response implied by the DGP (the dash-dot red line). Responses are calculated as the median of the 2000 simulated responses. Confidence bands for the MIDAS models (dotted blue lines) are obtained from the 10^{th} and 90^{th} percentile of the simulated responses.

Figure A6. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



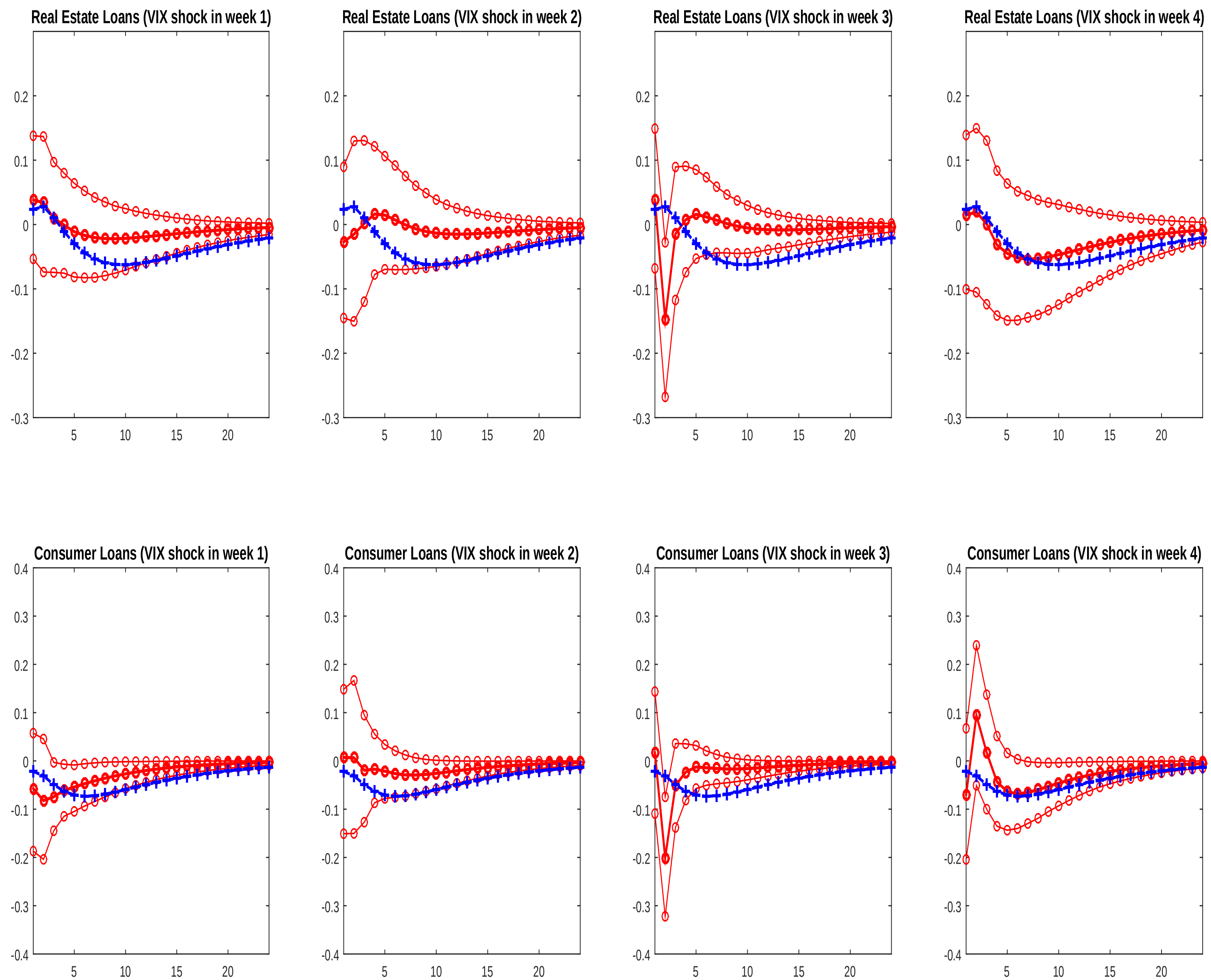
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A7. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



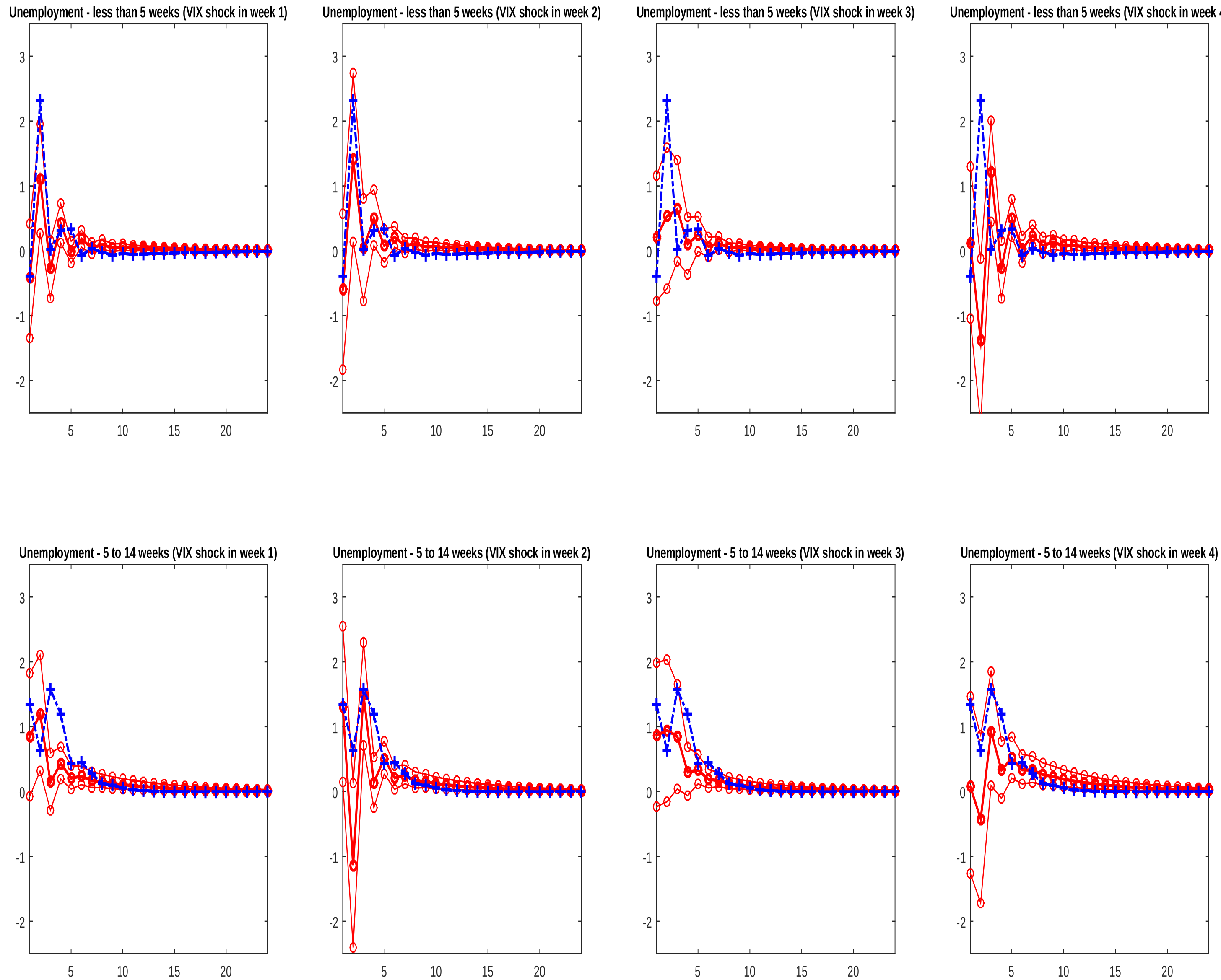
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A8. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



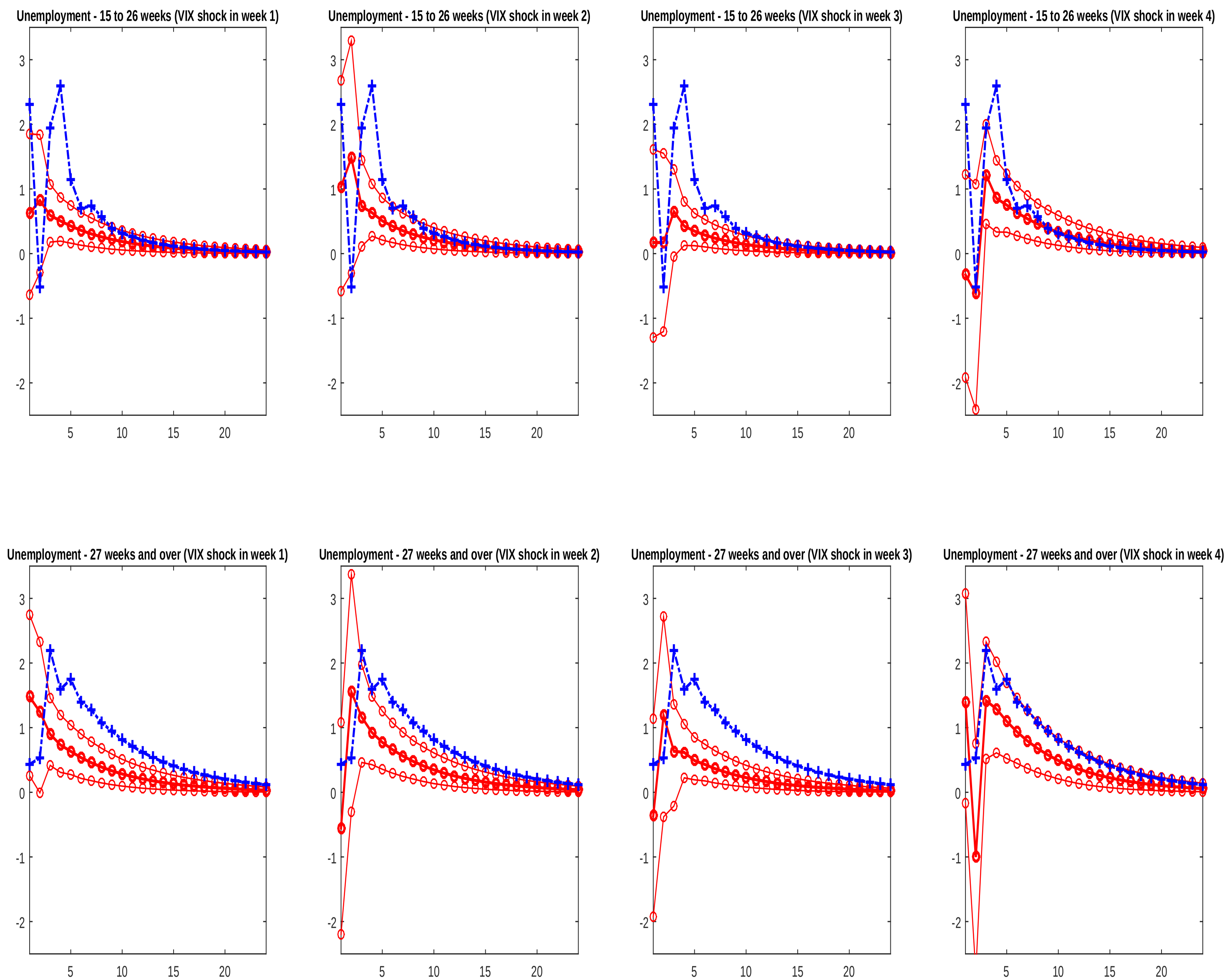
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A9. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



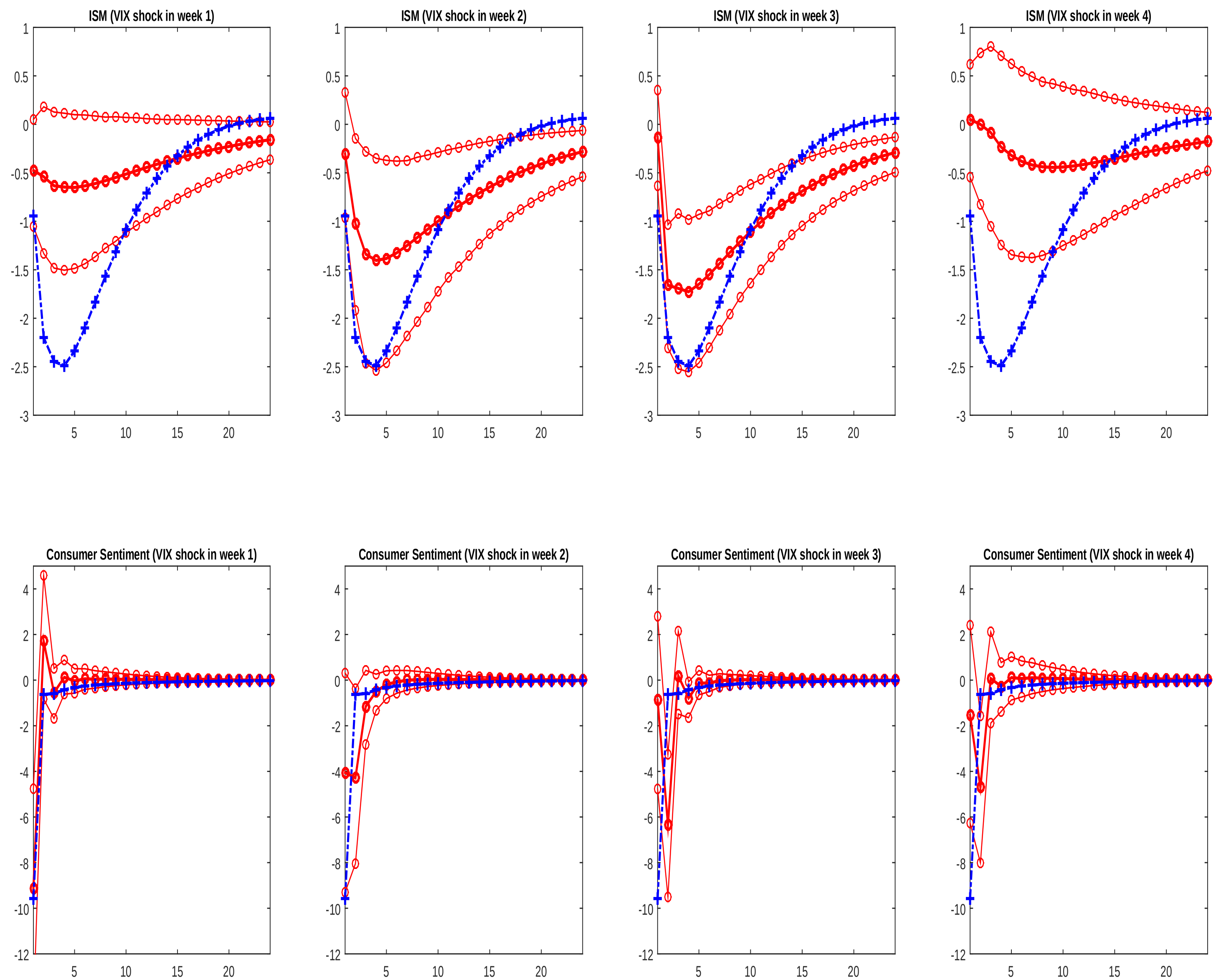
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A10. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



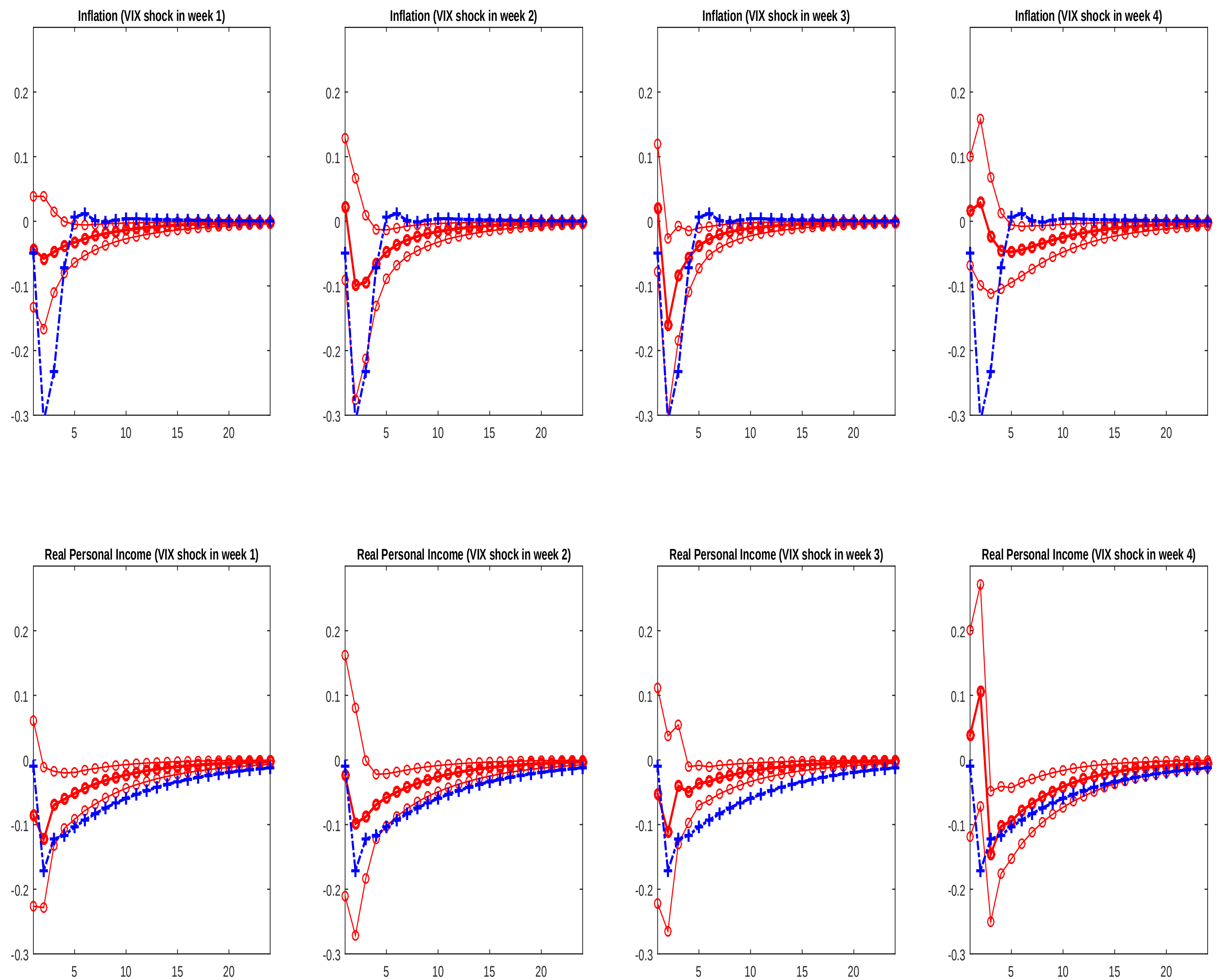
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A11. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



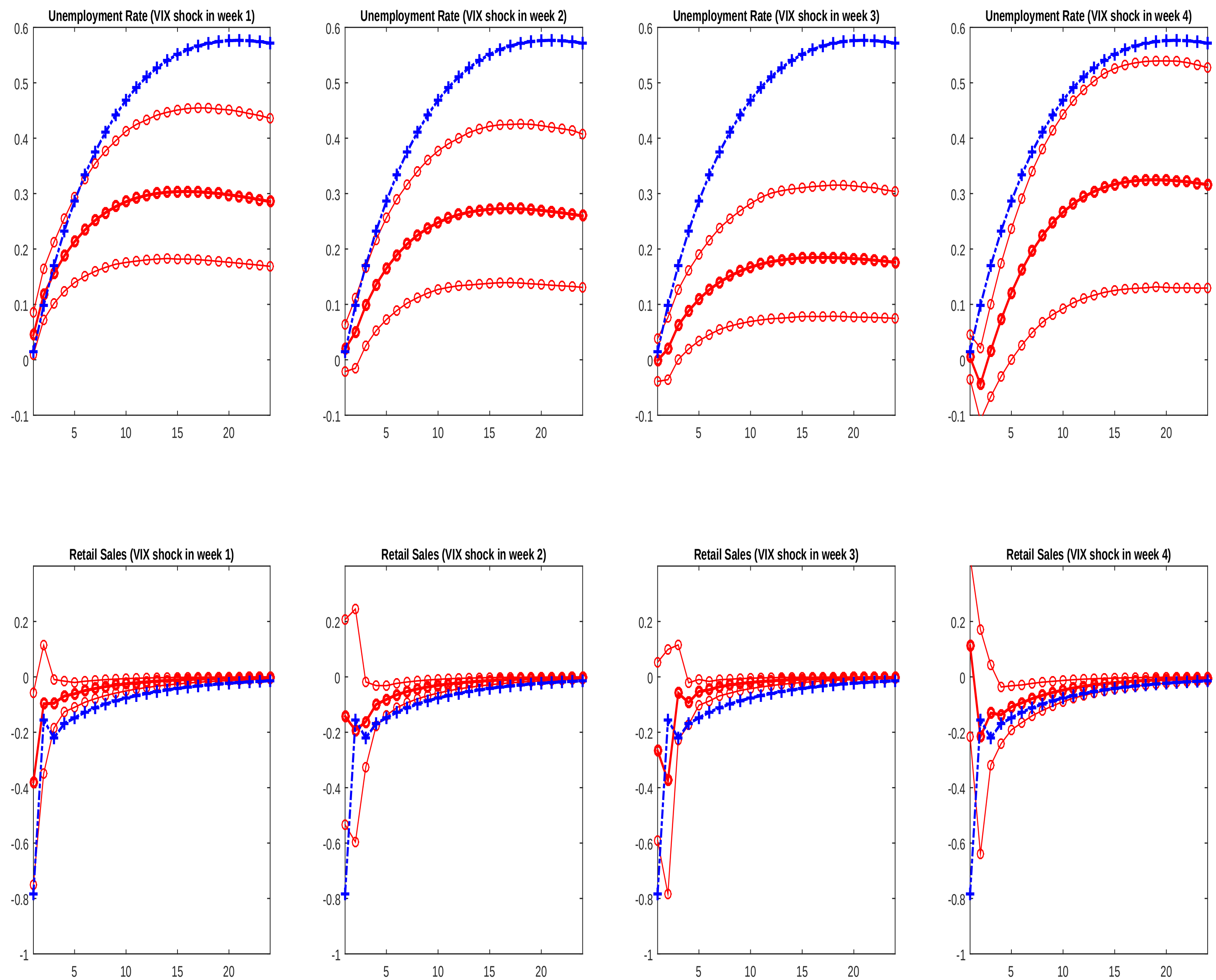
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A12. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



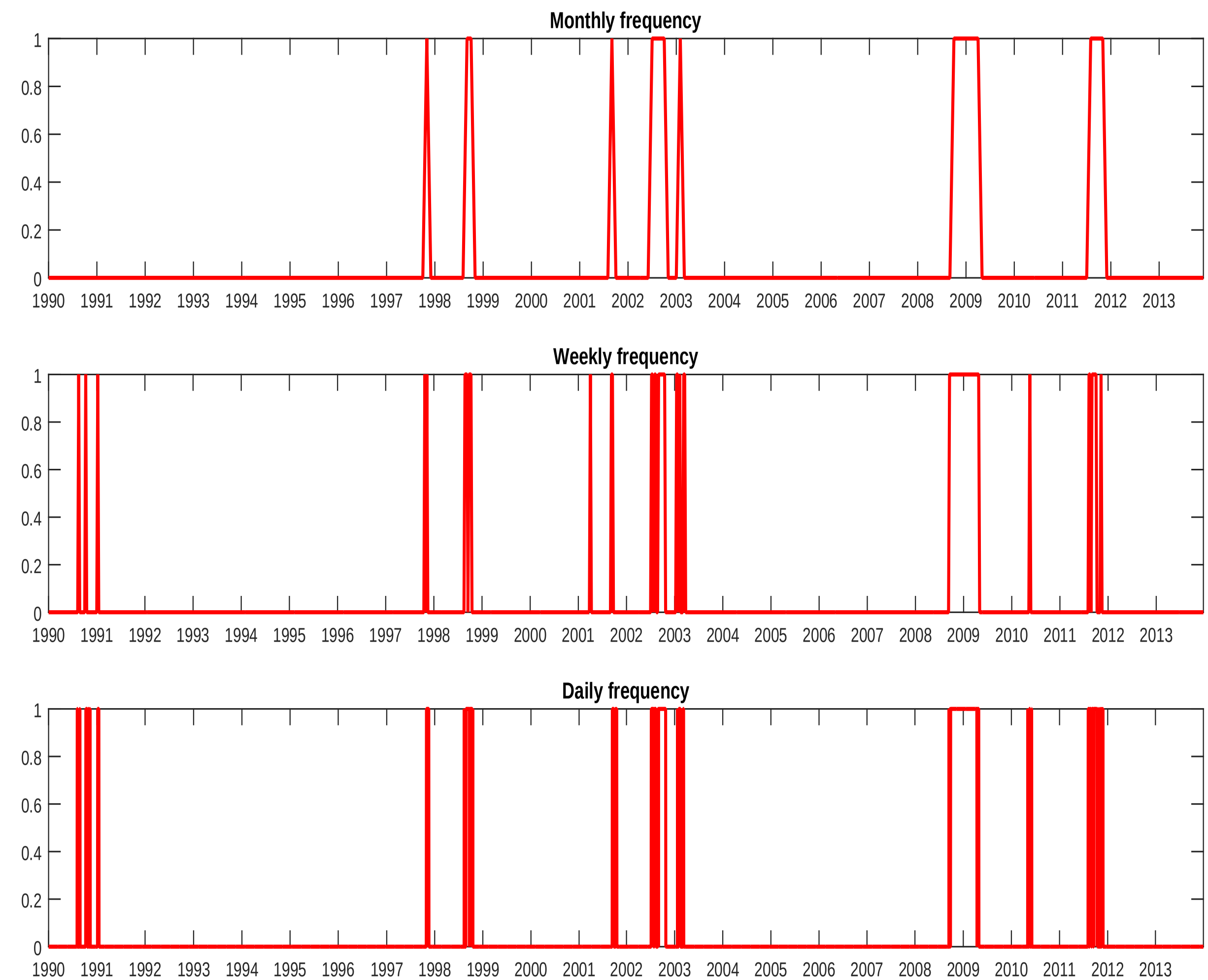
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A13. Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



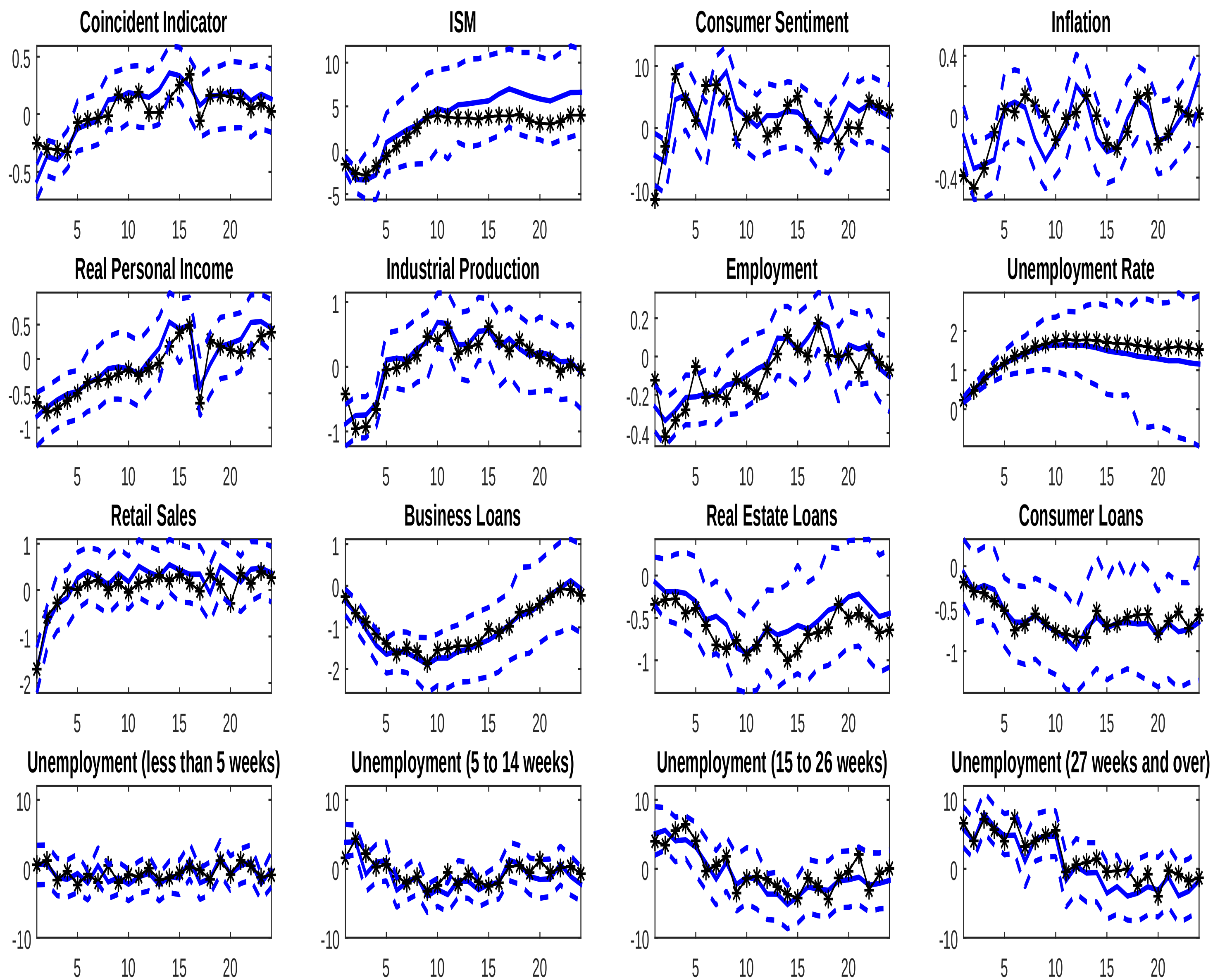
Note: Response to a 10-point increase in the VIX from the time-stamped MF-VAR model (lines with circle symbol) and VAR model (line with plus sign symbol). We show responses to a VIX shock taking place in the first, second, third or fourth week of the month for the MF-VAR. Responses from the VAR model are identical regardless of the timing of the shock in the month. For the MF-VAR and VAR models, we use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system. 90 per cent bootstrapped confidence bands are reported for the MF-VAR model.

Figure A14. Uncertainty shocks as in Bloom (2009) across different sampling frequencies



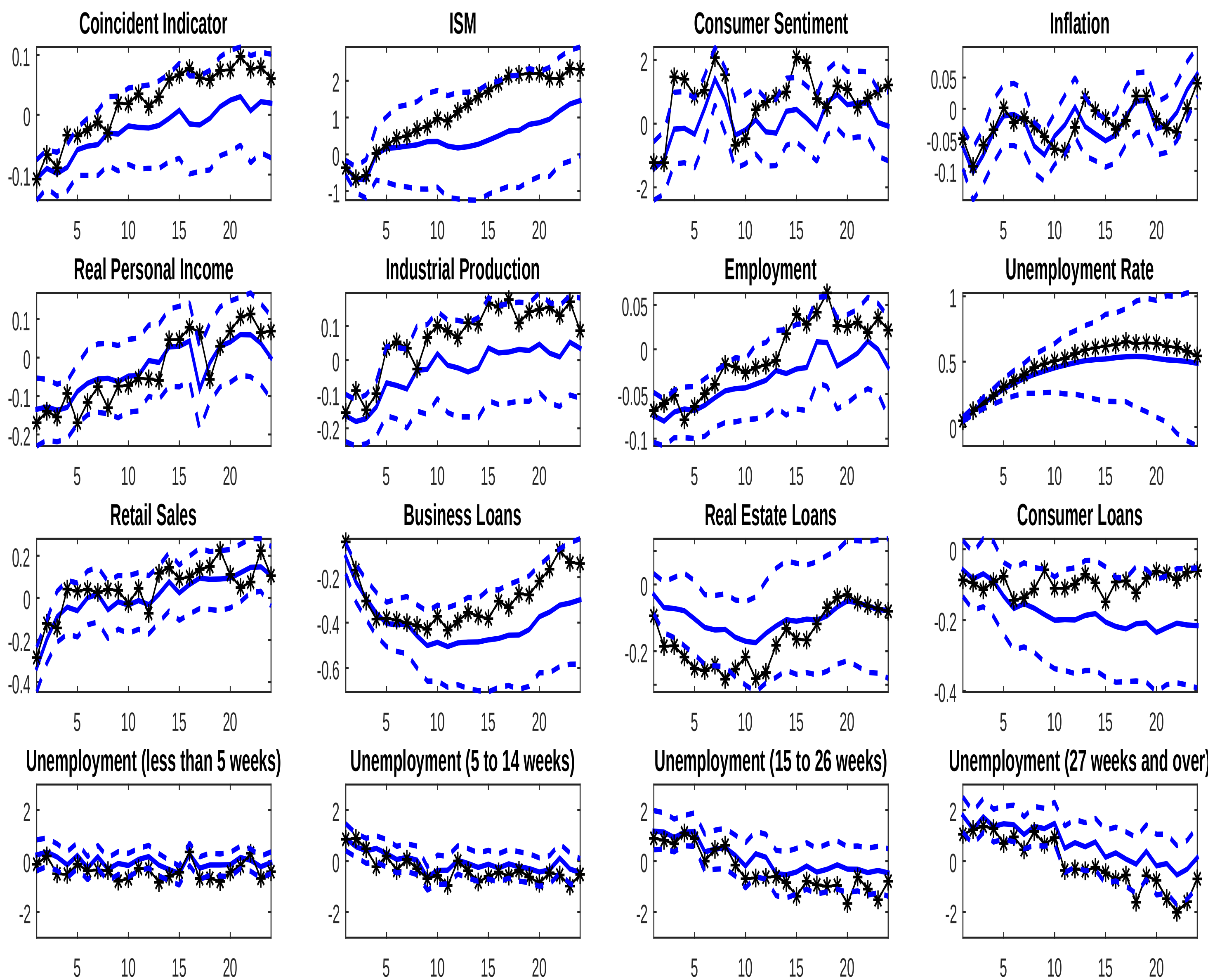
Note: This figure shows the occurrence of uncertainty shocks for three different sampling frequencies (daily, weekly and monthly). The uncertainty shocks are chosen as occurrences in which the Hodrick-Prescott de-trended stock-market volatility is more than 1.65 standard deviations above its mean (we set the filter parameter λ to $(252^4 * 6.25)$, $(52^4 * 6.25)$ and $(12^4 * 6.25)$ for daily, weekly and monthly frequencies, respectively).

Figure A15. Impulse response to an uncertainty shock (alternative shock measure)



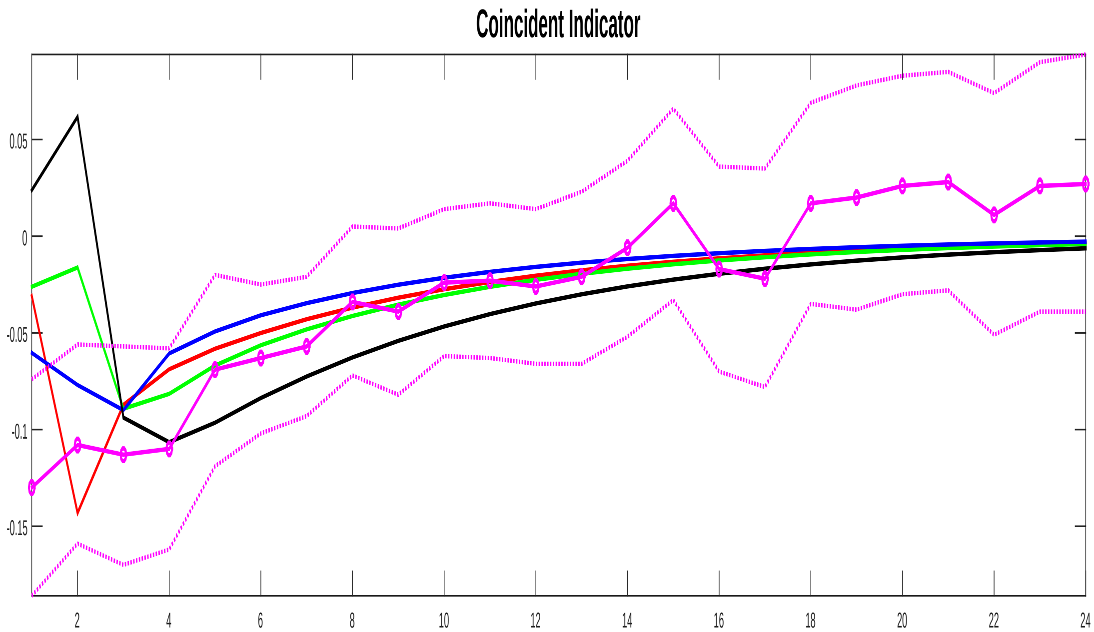
Note: Response to an uncertainty shock calculated by local projections. The uncertainty shocks are chosen as occurrences in which the Hodrick-Prescott de-trended stock-market volatility is more than 1.65 standard deviations above its mean (shocks for these three sampling frequencies are plotted in Figure A14). Dotted lines represent 90 percent bootstrapped confidence bands for MIDAS impulse responses. The black solid line with asterisks is the impulse response obtained from a monthly VAR.

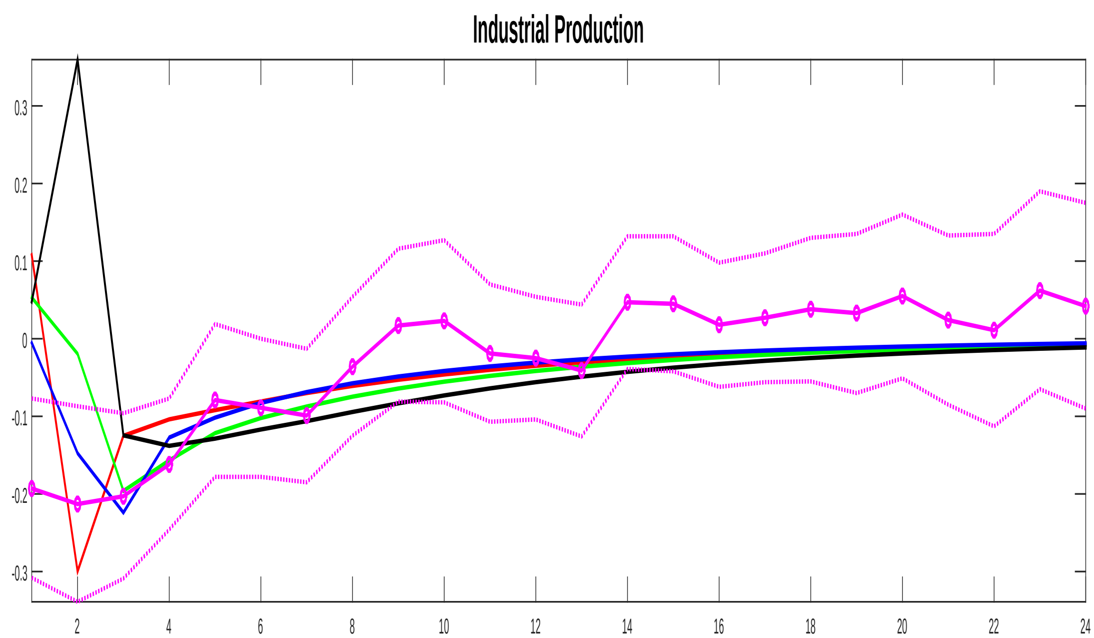
Figure A16. Impulse responses to an uncertainty (EPU) shock – MIDAS model



Note: The black solid line with asterisks is the MIDAS impulse response to a one-standard-deviation increase in the EPU calculated by local projections. The blue solid line is the MIDAS impulse response to a one-standard-deviation increase in the VIX reported with the blue dotted lines corresponding to bootstrapped 90 percent confidence bands.

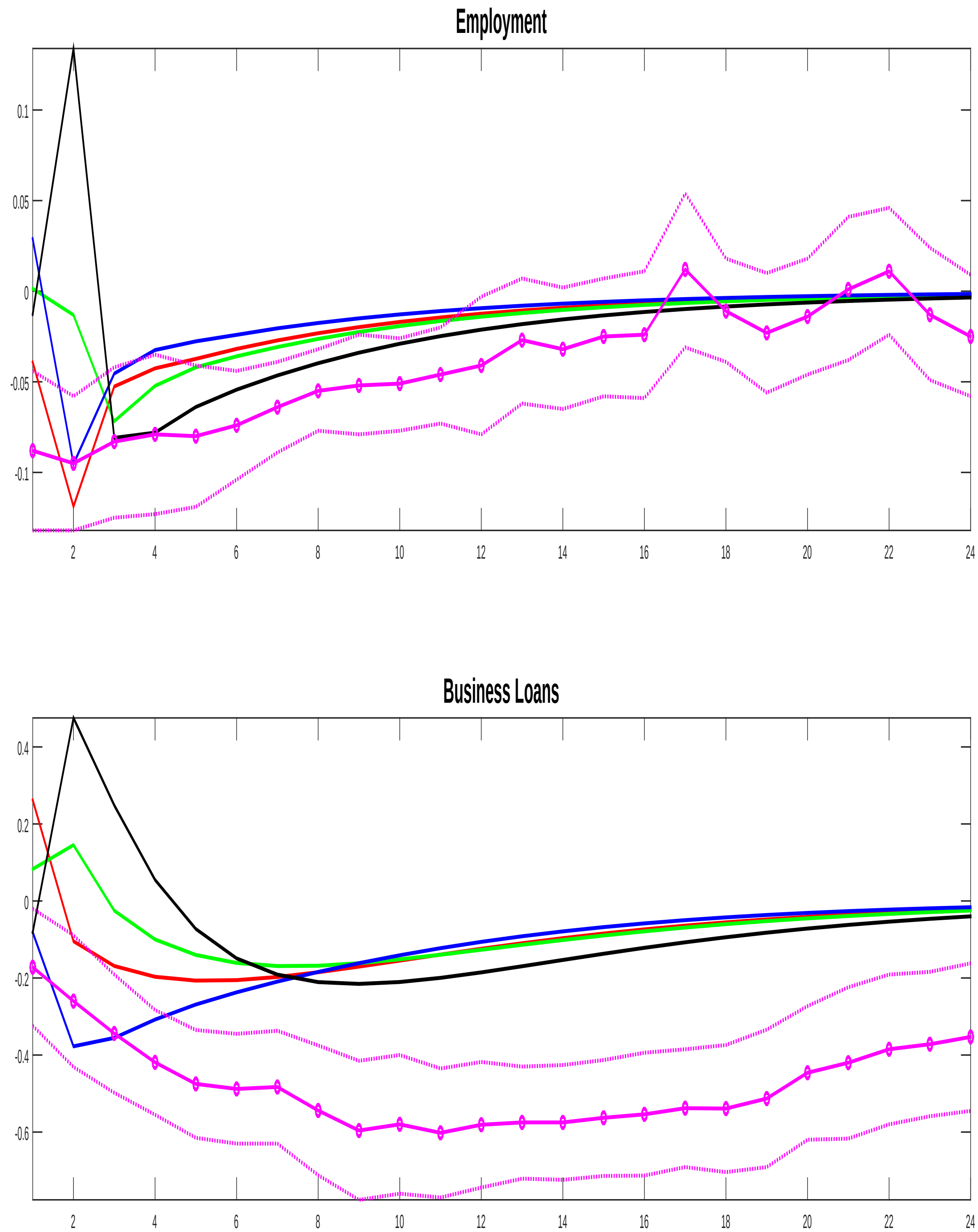
Figure A17. Comparing responses between MIDAS and MF-VAR models





Note: Response to a 10-point increase in the VIX in the first (red line), second (green line), third (blue line) or fourth week (black line) of the month. The magenta line with circle symbol shows the responses from a MIDAS model with the associated 90 percent confidence bands.

Figure A18. Comparing responses between MIDAS and MF-VAR models



Note: Response to a 10-point increase in the VIX in the first (red line), second (green line), third (blue line) or fourth week (black line) of the month. The magenta line with circle symbol shows the responses from a MIDAS model with the associated 90 percent confidence bands.