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What Are The Macroeconomic Effects of High-Frequency Uncertainty Shocks?*

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Abstract

Following the Great Recession, econometric models that better account for uncertainty have gained increased attention, and an increasing number of works evaluate the effects of uncertainty shocks. In this paper, we evaluate the impact of high-frequency uncertainty shocks on a set of low-frequency macroeconomic variables representative of the U.S. economy. Rather than estimating models at the same common low-frequency, we use recently developed econometric methodology that allows us to avoid aggregating high-frequency data before estimating models. The impulse response analysis uncovers various salient facts. First, in line with the existing literature, high-frequency uncertainty shocks are associated with a broad-based decline in economic activity. Second, we find that credit and labor market variables react the most to uncertainty shocks. Third, we show that the responses of macroeconomic variables to uncertainty shocks are relatively similar across single-frequency and mixed-frequency data models, suggesting that the temporal aggregation bias is not acute in this context. Finally, we find that some macroeconomic variables exhibit an asymmetric response to uncertainty shocks over the different phases of the business cycle.

Keywords: MIDAS model, Mixed-frequency VAR, Uncertainty.

JEL Classification Code: E32, E44, C32.

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1 Introduction

Macroeconomic and financial uncertainty substantially increased during the Great Recession and the subsequent years. In fact, uncertainty is often considered as one of the key drivers of the collapse in global economic activity in 2008-2009 (see, e.g., Stock and Watson (2012)), as well as one of the factors hampering the ensuing economic recovery (see, e.g., IMF (2012)). While it has long been acknowledged that uncertainty has an adverse impact on economic activity (see, e.g., Bernanke (1983)), it is only recently that the interest in measuring uncertainty and its effects on economic activity has burgeoned (see, e.g., the literature review in Bloom (2014)).

Uncertainty measures, as derived from financial markets, are typically available at high-frequency. As a result, it is intuitive to directly consider the impact of uncertainty shocks on the macroeconomic environment using high-frequency data without aggregating the data before estimating the models. Specifically, in this paper, we assess empirically to what extent high-frequency uncertainty shocks differ from low-frequency uncertainty shocks. In fact, there is a trade-off when going to high-frequency data, since the increase in information contained in high-frequency data may be clouded by the noise they contain, which may be detrimental for conducting sound statistical inference. Ultimately, this remains an empirical question that depends on the data at hand. Moreover, if the frequency at which economic agents make their decisions differ from the sampling frequency of the data used in the econometric analysis, a potential aggregation bias may arise resulting in improper statistical inference. For example, Hamilton (2008b) empirically shows that changes in expectations of Federal Fund rates within a given month can have an impact on new home sales of this specific month. Evaluating how relevant is the temporal aggregation bias in the context of uncertainty shocks is one of the main focus of this paper.

Empirically, it is highly relevant in the context of uncertainty shocks to study a possible temporal aggregate bias. For example, while the VIX - a common measure of uncertainty - has generally trended lower after the financial crisis, its daily measure is often characterized by large fluctuations, which are not necessarily reflected in a measure aggregated at a lower frequency. In the middle of October 2014, the VIX sharply increased on the back of worries about U.S. and global growth, but subsequently declined in the following weeks so that the monthly increase in the VIX in October 2014 compared with September 2014 was modest.[1] Hence, if economic agents make their decision at a different frequency or different

[1] See, e.g., "Fear returns to stalk markets", *Financial Times*, October 16, 2014.

intervals than the data sampling interval, this could lead to an erroneous impulse response analysis (see, e.g., the early contribution from Christiano and Eichenbaum (1987) as well as Foroni and Marcellino (2014a) and Foroni and Marcellino (2014b) for recent discussions of this issue in the context of DSGE models and structural VAR models, respectively).

This paper contributes to the existing literature along several dimensions. First, unlike most papers in the literature, we use weekly uncertainty when evaluating its impact on lower frequency macroeconomic variables. In doing so, we use relatively recent estimation tools to deal with the mismatch of data frequency: a MIDAS model and a mixed-frequency VAR model estimated via a stacked-vector system representation (see Ghysels (2013)). Using the latter model is relevant, since it permits us to evaluate whether the effects of the uncertainty shocks vary depending on whether the shock took place at the beginning or at the end of the month. Second, when calculating impulse responses, we look at a set of 12 U.S. monthly macroeconomic variables, which allows us to evaluate the effects of uncertainty shocks on a large set of models rather than concentrating on a specific VAR model as it is commonly done in the literature. In doing so, we control for a number of variables including news shocks that are often considered as important drivers of economic fluctuations (see, e.g., the literature review in Beaudry and Portier (2013)).

Our main findings can be summarized as follows. First, we find that uncertainty shocks as measured by both the VIX and the economic policy uncertainty index from Baker et al. (2013) lead to a broad-based decline in economic activity. Second, impulse responses from MIDAS models typically line up well with those obtained from a standard (single-frequency) VAR model. Third, using the time-stamped mixed-frequency VAR from Ghysels (2013) - that enables us to evaluate the effects of a shock depending on its timing in the month - we find that the short-term dynamics of impulse responses is quite different with shocks occurring at the beginning or in the middle of the month typically having a stronger impact in the short-run compared with shocks taking place in the last week of the month. This is especially true for survey and employment data. However, as expected, responses at longer horizons are very similar regardless of the timing of the shock in the month. Fourth, we find that credit and labor market variables react the most to uncertainty shocks. This result is important because uncertainty is often seen as one of the key drivers explaining the sluggish recovery that many advanced economies have experienced in the aftermath of the Great Recession. Moreover, in the sensitivity analysis, we look at the effects of uncertainty shocks on quarterly investment subcategories. We find that the most irreversible investment projects (investment in structures) tend to react the most to uncertainty shocks.

Finally, we do find evidence for a much stronger response of selected macroeconomic variables in recessions compared with expansions (e.g., for survey data, industrial production and employment data).

The structure of the paper is as follows. Section 2 reviews the literature on measuring uncertainty and its macroeconomic effects. Section 3 presents the mixed-frequency data models we use. Section 4 introduces the data and presents the main results, and we conduct a number of robustness checks in Section 5. Section 6 concludes.

2 Literature review

2.1 Measuring uncertainty

As by definition uncertainty cannot be directly observed, various indices have been proposed in the empirical literature in order to measure it. Uncertainty measures can be classified into various classes. First, uncertainty is often defined in terms of financial uncertainty. For example, the VIX, also sometimes referred to as the *fear index* on financial markets, is typically the most widely used measure when trying to assess the effects of uncertainty shocks (see for example Bloom (2009)). This index is a measure of the implied volatility of the S&P 500 index options and increases along with uncertainty on financial markets. As such, the VIX can be seen as a fairly broad measure of uncertainty in that it captures uncertainty directly related to financial markets, but also to the macroeconomic environment to the extent it is related to financial developments.

Beyond stock market volatility, a growing literature aims at measuring uncertainty based on different sources of information, especially macroeconomic information. Scotti (2013) develops a macroeconomic uncertainty index reflecting the agents' uncertainty about the current state of the economy, defined as a weighted average of squared news surprises. The weights are estimated through a dynamic factor model applied to a set of macroeconomic variables. Jurado et al. (2014) calculate an uncertainty index from the unpredictable component of a large set of macroeconomic and financial variables. Rossi and Sekhposyan (2015) instead suggest to measure uncertainty from the distance between the realized value of a variable and its unconditional forecast error distribution, the latter being obtained either from a parametric model or surveys. The underlying idea of Jurado et al. (2014) and Rossi and Sekhposyan (2015) is that uncertainty is not intrinsically related to fluctuations in economic activity, but rather to the extent that economic activity is predictable.

Moreover, uncertainty can also be measured from the disagreement among forecasters on some macroeconomic variables. This approach consists in evaluating the cross-sectional dispersion of conditional forecasts from a panel of economists. For example, Bachmann et al. (2013) measure U.S. uncertainty based on forecast disagreement from the Philadelphia Federal Reserve Business Outlook Survey and they estimate uncertainty in Germany based on the disagreement among the IFO Business Climate Survey participants.

Alternatively, uncertainty can be estimated from news-based metrics. For example, the daily news index from Baker et al. (2013) is built using the number of articles that contain at least one word from three sets of subjects, related to (i) the economy, (ii) uncertainty and (iii) legislation implemented by the U.S. government. The monthly economy policy uncertainty (EPU) indices developed by Baker et al. (2013) for selected European countries, Canada, China, India, Japan and Russia are also constructed starting from news coverage about policy-related economic uncertainty. Alexopoulos and Cohen (2014) construct general economic uncertainty measures based on a detailed textual analysis of *New York Times*' articles, suggesting to use a broader set of keywords than typically used to provide a more complete picture of uncertainty. Finally, another idea is to directly focus on policy uncertainty as computed by the number of temporary tax measures, the underlying idea being that consumers and companies are affected by such uncertainty in their decisions to consume or invest. Baker et al. (2013) use tax code expiration data as reported by the Congressional Budget Office (CBO) for the U.S.

Elaborating from these different uncertainty measures, some authors have proposed composite indices computed as a weighted average of various components. For example, Baker et al. (2013) calculate a monthly measure of U.S. policy uncertainty from four subcomponents: a news-based policy uncertainty index, a federal tax code expirations index, an inflation (CPI) forecast disagreement index and a government purchases forecast disagreement index.

2.2 Macroeconomic effects of uncertainty

While there are many different ways to evaluate uncertainty, qualitatively, there seems to be a strong convergence of results concerning the effects of uncertainty shocks on macroeconomic activity, regardless of the measure used in the empirical analysis. Indeed, there is a broad empirical evidence of a sharp downturn in economic activity in response to uncertainty shocks. A seminal contribution on the effects of uncertainty on economic activity is Bloom (2009) that builds a structural model to evaluate the impact of uncertainty shocks, comparing his results with estimates from a standard VAR model. In his framework, uncertainty shocks are associated with a rapid drop in economic activity followed by sharp rebounds, suggesting that uncertainty shocks amplify the magnitude of business cycles. Leduc and Liu (2013) find that uncertainty shocks produce the same effects than a negative aggregate demand shock based on both VAR and DSGE models. Caggiano et al. (2014) instead provide evidence for a stronger effect of uncertainty shocks in recessions than expansions, suggesting that the effects of uncertainty shocks vary over the state of the business cycle. Additional evidence can be found in the previously quoted papers that put forward various uncertainty measures (see among others Baker et al. (2013), Jurado et al. (2014), and Scotti (2013)). Interestingly, Rossi and Sekhposyan (2015) compare the responses of employment and industrial production to an uncertainty shock using alternatively the uncertainty measure from these three aforementioned papers. They find significantly different quantitative responses depending on the uncertainty measures used, the uncertainty measure from Jurado et al. (2014) generating the most negative responses to an uncertainty shock. The rationale for these different responses is that the uncertainty measure from Scotti (2013) only refers to real economic activity uncertainty, whereas Jurado et al. (2014) measure uncertainty from a larger set of variables including both macroeconomic and financial (bond and stock market indices) variables thereby generating stronger responses from uncertainty shocks. Last, Joets et al. (2015) assess the impact of macroeconomic uncertainty on various raw materials markets and find that some specific markets, such as agricultural or industrial markets, are strongly related to the variability or the level of macroeconomic uncertainty. In addition, they find evidence of non-linearity in this relationship in the sense that its strength depends itself on the degree of uncertainty.

Some recent papers also look at the effect of uncertainty on variables related to monetary policy. For example, Istrefi and Piloiu (2014) consider the effects of policy uncertainty on inflation expectations in the U.S. and the euro area. Using a Bayesian VAR model, they show that the effect of a shock in the EPU index differs depending on the horizon of the inflation expectations: while an uncertainty shock tends to decrease short-term inflation expectations (akin to a negative impact on output), it leads to an increase in long-term expectations. The authors thus point out the monetary policy trade-off between supporting output and anchoring long-run inflation expectations, in response to uncertainty shocks. Also, Aastveit et al. (2013) look at the effects of uncertainty on monetary policy transmission mechanism and conclude that U.S. monetary policy is less effective during periods of high uncertainty. In particular, the response of investment to monetary policy shocks is much weaker when uncertainty is high. An international comparison on the effects of uncertainty shock is provided in Vu (2015) that performs a cross-country analysis on a panel of OECD countries. In particular, he finds evidence for a short-lived negative response of output and interest rates to unexpected stock market volatility shocks not only during financial crises, but also in normal times.

3 Econometric framework for mixed-frequency data

In this section, we present the two types of mixed-frequency data models we use in the empirical application to deal with the frequency mismatch between low-frequency (monthly) macroeconomic variables and high-frequency (weekly) uncertainty variables.

3.1 MIDAS regressions

MIDAS models have been extensively used as a forecasting device in both macroeconomic (see, e.g., Clements and Galvao (2009)) and financial contexts (see, e.g., Ghysels and Valkanov (2012)). However, structural-type studies with MIDAS models are much less common in the literature with the exception of Francis et al. (2012) that study the impact of high-frequency monetary policy shocks on a set of monthly macroeconomic and financial variables. Our basic MIDAS regression reads as follows:

$$X_t = \mu + \beta \sum_{j=1}^{K} b(L;\theta) Unc_t^{w} + \Gamma Z_t + \epsilon_t \tag{1}$$

where μ is a constant term, ϵ_t is the error regression term, $Unc_t^{(w)}$ is a measure of high-frequency (weekly) uncertainty, and Z_t is a set of control variables, including lagged values of X_t. The MIDAS polynomial $b(L;\theta)$ allows us to aggregate the high-frequency uncertainty variable to the frequency of the dependent variable in a parsimonious and data-driven way. It is defined as follows:

$$b(L;\theta) = \frac{exp(\theta_1 j)}{\sum_{j=1}^{K} exp(\theta_1 j)} \tag{2}$$

where K is the number of lags for the high-frequency variable and the hyperparameter θ_1 governs the shape of the weight function. MIDAS impulse responses are calculated using the local projection approach from Jordá (2005), and the model is estimated with non-linear least squares (i.e., minimizing the sum of squared residuals).

3.2 VAR-based impulse responses

As an alternative to the MIDAS approach, we also calculate impulse responses derived from a mixed-frequency VAR model here the data are stacked depending on the timing of the data releases (see Ghysels (2013)). In detail, this type of mixed-frequency VAR is estimated at the low-frequency (monthly) unit and the high-frequency (weekly) variables are reorganized at the monthly frequency depending on the week of the month they refer to. Denote $Unc_t^{(j)}$ the uncertainty measure in week j of month t, and W_t a vector of monthly variables. This mixed-frequency VAR can be written in the same way than a standard single-frequency VAR:

$$Y_t = A_0 + A_1 Y_{t-1} + ... + A_p Y_{t-p} + \epsilon_t \tag{3}$$

where $Y_t = (Unc_t^{(1)'}, ..., Unc_t^{(M)'}, W_t')'$, M is the number of weeks in a month, and p is the number of lags in the VAR model. To calculate impulse responses, we use a standard Cholesky scheme as an identification device, with the ordering of the variables corresponding to the timing of the data releases. This is intuitive, since the uncertainty measure in the second week of the month is always available after the uncertainty measure for the first week of the month. Macroeconomic variables are ordered last in the VAR, since they are not readily available (but instead released with a publication lag). Also, this allows us to conduct a fair comparison with impulses responses obtained from MIDAS models, since MIDAS specifications imply that the control variables are predetermined.[2] The model is estimated with standard least squares method and the lag length is selected with the SIC. Moreover, note also that unlike a MIDAS model where uncertainty acts as a purely exogenous variable, the VAR model endogenously models interactions between the different variables of the system, and thereby permits a richer dynamics than allowed for by MIDAS models.

A few additional comments are required. First, in our empirical analysis (see next section), we estimate the model (3) for each univariate macroeconomic variable that we consider in the analysis in order to disentangle the idiosyncratic effects of high-frequency uncertainty shocks on various types of variables (employment, production, inflation, confidence ...). Second, unlike a mixed-frequency VAR model estimated via the Kalman filter,

[2]Note that this ordering differs from the ordering adopted in a number of papers where slow-moving variables such as macroeconomic variables are ordered first in the VAR, which assumes that they do not react contemporaneously to shocks in fast-moving variables such as financial variables that are placed at the end of the VAR system (see, e.g., Bernanke et al. (2005)). However, we use an ordering that is consistent with the frequency of the data, since temporal aggregation bias is one of the focal points of this paper. In this respect, we follow Ghysels (2013) in that we adopt an ordering of the variables in the VAR that is consistent with the frequency of the data releases.

we obtain M impulses responses from a shock to the high-frequency variable. This implies that the macroeconomic variable will react differently depending on whether the shock to the high-frequency variable takes place in the first or last week of the month. This is not necessarily an undesirable feature from an empirical point of view, since for example, Hamilton (2008a) finds that the impact of a change in Federal funds futures on new home sales varies across the month. In contrast, a mixed-frequency VAR model estimated via the Kalman filter assumes that the low-frequency variable always reacts in the same fashion from a shock to the high-frequency variable regardless on whether the shock took place in the first or last week of the month, since the model is estimated at the high-frequency unit. Third, the estimation of a mixed-frequency VAR via the Kalman filter can prove to be computationally difficult (e.g., when only short time series are available), whereas the mixed-frequency VAR from Ghysels (2013) is estimated with standard estimation tool for VAR models (i.e., least squares). Fourth, we do not impose any restrictions on the lag polynomial in equation (3) so that standard least squares estimation can be implemented. In fact, small-sample simulations in Ghysels et al. (2014) finds that there are only small biases associated with the estimation of an unrestricted model even if the data are generated from a model with restrictions on some of the parameters of the autoregressive matrices. Finally, we also report impulse responses from a standard single-frequency VAR model for comparison purposes.

4 Empirical Analysis

4.1 Data

We consider the responses of the following macroeconomic variables to an uncertainty shock: a coincident indicator from the Conference Board, survey data (ISM Manufacturing and consumer sentiment), inflation (CPI-all items), real personal income, industrial production, employment, unemployment rate, retail sales, and credit variables (i.e., business loans, real estate loans, and consumer loans). These variables represent a broad set of macroeconomic variables that capture different sectors of the U.S. economy. Table 1 provides additional information on the data, and Figure 1 plots the data after appropriate transformation. The set of variables we use is broadly similar to the variables used in the work of Francis et al. (2012), which evaluates the impact of high-frequency monetary policy shocks on a set of macroeconomic variables, using MIDAS models.

In the empirical application, we assume that each month has a fixed number of weeks (four) so as to obtain a balanced dataset. This is a relatively standard way to proceed when combining monthly data with weekly data (see e.g. Hamilton and Wu (2014)). Specifically, the daily data are rearranged at the weekly frequency so that a month can be divided in four weeks as follows. Assume that D_t is the number of traded days in month t, the weekly estimates of volatility are obtained as follows:

- week 1 extends from 1 to $D_t - 15$,
- week 2 extends from $D_t - 14$ to $D_t - 10$,
- week 3 extends from $D_t - 9$ to $D_t - 5$,
- week 4 extends from $D_t - 4$ to D_t.

The weekly estimates of uncertainty are then obtained as the last observation of each week as defined above. Results based on the weekly average of the daily observations led to qualitatively similar results. As a set of control variables Z_t in equation (1), we use the lagged value for the dependent variable as well as a news shock variable ($News_t$) that is defined as the monthly forecast revision in one-year-ahead expected U.S. GDP growth according to the Consensus Economics survey:

$$News_t = Y_t^e - Y_{t-1}^e \tag{4}$$

In this respect, we follow Kilian and Hicks (2013) and Leduc and Sill (2013) in defining a news shock. Specifically, Kilian and Hicks (2013) use the forecasts revisions in the forecasts of real activity from the Economic Intelligence Unit to evaluate the impact of exogenous shocks to real economic activity on the real price of oil. Leduc and Sill (2013) instead use quarterly survey forecasts of the unemployment rate in standard VAR models to study how changes in expectations contribute to fluctuations in macroeconomic aggregates. In our empirical application, we use expectations about future U.S. GDP growth from Consensus Economics that are available every month for current-year growth, and next year growth starting from January 1990. To obtain fixed-horizon expectations, we follow Dovern et al. (2012) so as to obtain one-year-ahead expectations:

$$Y_t^e = \frac{k}{12} x_{t+k|t} + \frac{12-k}{12} x_{t+12+k|t} \tag{5}$$

where Y_t^e is the one-year-ahead expected GDP growth rate, $x_{t+k|t}$ is the current-year forecast for GDP growth, and $x_{t+12+k|t}$ is the next year forecast for GDP growth with horizons $k \in \{1, 2, ..., 12\}$ and $k + 12$ months, respectively. Figure 2 plots the revisions (or news, see equation(4)) to U.S. GDP growth with shaded areas corresponding to the recessions identified by the NBER business cycle dating committee. We do observe a cyclical pattern for the news shock series in that agents tend to revise down their expectations in the midst of recessions, and revise them up shortly after the end of recessions. Note also that in our analysis the news shocks are directly observable. Hence, they differ from the news shocks in Beaudry and Portier (2006) or Barsky and Sims (2011) where the news shocks (or changes in agents' information) are unobservable and thereby have to be recovered from the data by the econometrician. Note also that this news variable differs from the surprise component in Scotti (2013) that she uses to measure uncertainty (defined from the difference between the realization of a given economic activity indicator and the corresponding Bloomberg consensus forecast), since our news measure refers to changes in one-year-ahead forecast of U.S. economic activity, thereby likely reflecting changes in broader economic conditions. Moreover, we find that the news variable in equation (4) does not Granger-cause the uncertainty variable, suggesting that the uncertainty measure (the VIX) and the news variable do not capture the same economic phenomena.

4.2 Baseline Empirical Results

The estimation sample extends from February 1992 to December 2013. Figure 3 reports the impulse responses to a 10 point increase in the VIX (i.e., a roughly one-standard deviation shock) for the MIDAS regression model and a standard monthly VAR model up to 24 months ahead. Confidence bands for impulse responses from MIDAS models are calculated as $\pm$ 1.65 standard errors of the parameter β entering before the weight function in equation (1). The lag length K for the high-frequency variable in equation (1) is set to five.

First, an increase in uncertainty is associated with a modest and temporary decline in the ISM Manufacturing, and consumer sentiment reacts adversely to a positive uncertainty shock, albeit only upon impact. The coincident indicator from the Conference Board also reacts negatively and significantly to an uncertainty shock for about six months. Second, inflation does not react in a significant way to uncertainty shocks. In contrast, both real personal income and industrial production decline following an uncertainty shock, but in a short-lived way since the effect fades away after six months. Third, labor market variables (employment and unemployment rate) exhibit a persistent adverse reaction to an uncertainty shock. The peak effect on the unemployment rate occurs after roughly a year, with a 10 point increase in the VIX associated with a 0.6 per cent increase in the level of the unemployment rate after 12 months. Retail sales also react negatively to uncertainty shock, but the effect quickly vanishes. Fourth, credit variables decline following an uncertainty shock, and exhibit a somewhat different pattern than real economic activity variables (e.g., industrial production) and sentiment indicators, in that the effects on credit variables is more persistent.

Overall, among the set of indicators we consider, we find that labor market and credit variables are the variables that react the most to uncertainty shocks. However, it is well known that employment variables, especially unemployment rate, are strongly persistent, with strong auto-correlation. Thus their own dynamics is partly reflected in the strong persistence of uncertainty shocks (see Leduc and Liu (2013)). In contrast, credit variables show less persistence in their own dynamics. Thus, the significant adverse impacts of uncertainty shocks are even more remarkable. Interestingly, the credit variable that reacts the most to uncertainty shocks is the loans to businesses followed by consumer loans and real estate loans. This result is consistent with the paper by Valencia (2013) who puts forward a theoretical model in which the loan supply contracts when uncertainty increases. He also shows empirical evidence of this result, by using a set of US commercial banks from 1984 to 2010, especially for banks with lower levels of capitalization. The response of business loans to uncertainty can be seen as one of the factors behind the sluggish economic growth in the wake of the Great Recession in the U.S., preventing the usual bounce-back often seen after recessions.

Finally, it is interesting to note that impulse responses obtained from a standard monthly VAR model typically line up very well with MIDAS impulse responses. This would suggest that there is little to gain in using high-frequency data to evaluate the macroeconomic effects of uncertainty shocks. In other words, this would suggest that the temporal aggregation bias is not acute in this context.

5 Sensitivity Analysis

5.1 Alternative measures of uncertainty

An alternative measure of uncertainty that has gained increased attention in academic and policy-making circles is the economic policy uncertainty (EPU) index from Baker et al. (2013). It is available on a daily basis since January 1985, but we report results on the same sample size than the one we used for the VIX and use weekly EPU so as to provide a fair comparison in the impulse response analysis of these two uncertainty measures. Figure 4 presents the results to a one standard deviation increase in the economic policy uncertainty index. As a benchmark, we also report results corresponding to a one standard deviation increase in the VIX in Figure 4.

It is interesting to note that the impulse responses to a shock in the EPU index exhibit a very similar shape than the impulse responses 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 results we obtained previously in that the variables that react the most to uncertainty shocks are labor market and credit variables.[3]

5.2 Does the timing of the uncertainty shock matter?

Another question related to the use of mixed-frequency data is to evaluate whether variables react differently depending on the timing of the shock in the month. For example, given the persistence typically observed in macroeconomic variables, it is rather intuitive to consider that the short-term response of a monthly macroeconomic variable to a shock occurring in the last week of the month should be somewhat smaller than the response to a shock taking place in the first week of the month.

Figures 5 and 6 report the impulse responses obtained when estimating the time-stamped mixed-frequency VAR described by equation (3), which allows us to tackle this question. Bootstrapped 90 per cent confidence intervals are based on 1000 replications. First, we observe that the timing of the uncertainty shocks matters at short-horizons in that uncertainty shocks taking place in the last week of the month tend to have little effect in the short-run (i.e., upon impact and one-month-ahead) compared with shocks occurring earlier in the month. Note also that this discrepancy in the responses to uncertainty shocks is prevailing for employment data, industrial production and the coincident indicator from the Conference Board. However, as expected, at longer horizons, the impulse responses are similar regardless of the timing of the shocks. Second, impulse responses from the mixed-frequency VAR models are typically relatively similar to those obtained from MIDAS models (except when the shock takes place in the last week of the month in which case the short-term dynamics of the impulse responses is different). Admittedly, while the responses of labor market and credit variables exhibit a similar shape, the magnitude of the responses to the uncertainty shock is somewhat mitigated for the unemployment rate, business loans and consumer loans compared with the responses obtained from a

[3]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 very close to those obtained from a MIDAS model. Detailed results are available upon request.

single-frequency VAR model or a MIDAS model. One reason for this could be that the time stamped mixed-frequency VAR is subject to parameter proliferation, which makes inference on the parameters of the model more challenging.

5.3 Is there any evidence of non-linear effects?

The effects of uncertainty on the economy could well be non-linear in that, in specific episodes, uncertainty could severely impact economic activity, but instead have little or no effects in other times. For example, Caggiano et al. (2014) estimate a smoothed transition VAR, and find that the effects of uncertainty shocks are asymmetric over the business cycle in that unemployment and inflation react more to uncertainty shocks during recessions. Introducing time variation in equation (1) could be done through a variety of approaches, for example, via regime-switching parameters or parameter changes evolving through a smooth transition function. However, given the short sample available, we refrain from doing so owing to the computational difficulties related to the estimation of such models. Instead, we model non-linearity using a dummy variable corresponding to the NBER business cycle dates of U.S. recessions.[4] With such specification, we can evaluate whether the impulse responses differ depending on the state of the business cycle. Equation (1) is then modified as follows:

$$X_t = \mu + \beta \sum_{j=1}^{K} b(L;\theta) Unc_t^w + \mathbf{1_t^{NBER}} \beta_{NBER} \sum_{j=1}^{K} b(L;\theta) Unc_t^w + \Gamma Z_t + \epsilon_t \tag{6}$$

where $\mathbf{1_t^{NBER}}$ is a dummy variable that corresponds to U.S. recessions identified by the NBER business cycle dating committee. Figure 7 shows the regime-dependent impulse responses (i.e., conditional on staying in a regime). Note that this is a relatively standard approach for calculating impulse responses in regime switching models, (see e.g., Ehrmann et al. (2003) or Hubrich and Tetlow (2012)). In fact, it is not straightforward to implement the impulse response approach for non-linear models suggested in Koop et al. (1996) in the context of impulse responses obtained from local projections of non-linear MIDAS models. Also, calculating impulse responses conditional on a regime permits to uncover the full dynamics of the responses over the different phases of the business cycle (the unconditional responses being obtained from the linear model in equation (1)).

Figure 7 shows that, in line with the results presented in Caggiano et al. (2014), one can see substantial evidence for non-linearity in that the impulse responses in recessions

[4]This approach is similar to Ghysels et al. (2013) that study time variation in the risk-return trade-off over flight-to-safety episodes based on a dummy variable that corresponds to the 5 per cent left tail distribution of stock returns.

frequently differ from those obtained in expansions. A notable exception to this is in the case of inflation and consumer loans and to a lesser extent retail sales and consumer sentiment in that these variables react in a similar way regardless of the state of the business cycle. In contrast, coincident indicator, ISM, real personal income, industrial production, employment and real estate loans do not show a significant response to uncertainty shocks in expansions, but instead react negatively and significantly to uncertainty shocks in recessions. Finally, the unemployment rate and business loans react adversely to uncertainty shocks in both recessions and expansions regime, albeit much less so in expansions than in recessions.

5.4 Different frequency mixes

As an additional robustness check, we now estimate equation (1) using the VIX at a daily frequency. Specifically, the weight function is now modified so as to include 20 lags for the daily uncertainty measure. In doing so, it is important to keep in mind that there is a potential trade-off in using higher-frequency data in that this additional information may be overshadowed by the noise contained in the daily data.

Figure 8 presents the results. The results are very much similar to those presented in Figure 3. In fact, impulse responses obtained from daily data nearly perfectly mirror impulse responses obtained with weekly data. As a result, the variables that react the most to uncertainty shocks are labor market and credit variables, whereas most other variables only present a relatively short-lived adverse response to uncertainty shocks. Overall, this evidence suggests that there is no gain in using daily data compared with weekly data.

Alternatively, we also consider a different frequency mix, using quarterly and weekly data. Given that we found that credit variables react the most to uncertainty shocks, we now investigate to what extent quarterly investment is affected by weekly uncertainty shocks. As a result, equation (1) is modified as follows:

$$X_t^q = \mu + \beta \sum_{j=1}^{K} b(L;\theta) Unc_t^w + \Gamma Z_t + \epsilon_t \tag{7}$$

where X_t^q is a measure of quarterly investment, Unc_t^w is a weekly measure of uncertainty (VIX), and Z_t is a set of quarterly variables (lagged dependent variable and the news shock). For X_t^q, we first use aggregate nonresidential investment, but also three of its subcategories, that is, investment in structures, equipment, and intellectual property products.[5] The

[5] In 2014, investment in structures, equipment, and intellectual property products each accounted for about 23 per cent, 46 per cent, and 31 per cent of aggregate nonresidential investment, respectively.

investment measure is taken as 100 times the change in its logarithmic level, the MIDAS lag length polynomial K is set to 13 so as to include one quarter of information, and the sample size extends from 1992Q2 to 2013Q4. For ease of comparison with the previous results, impulse responses are calculated with a maximum horizon of eight quarters, and we also report results using a single-frequency (quarterly) VAR model.

Figure 9 presents the results. First, as expected, aggregate nonresidential investment reacts negatively to uncertainty shocks, with a peak impact reached after two quarters, and the response is significantly negative after up to seven quarters. Second, investment in equipment also reacts negatively to uncertainty shocks with a maximum impact after two quarters, whereas investment in intellectual property products do not react significantly to an uncertainty shock. Third, the uncertainty shock leads to a strong decline in investment in structures with a peak impact after four quarters, and a significantly negative response over the entire projection horizon. This suggests that investment in structures reacts the most to uncertainty shocks. One rationale for the strong negative response of investment in structures to uncertainty shocks is that they typically refer to the most irreversible projects in that they cannot be easily undone (as opposed to investments in equipment and intellectual property products). As a result, in the context of investment in structures, waiting for additional information is valuable to correctly evaluate long-term returns in that this likely outpaces the benefits from early investment decisions. Therefore, it is rather intuitive to find that uncertainty shocks affect the most irreversible investments, that is, investment in structures. Finally, impulse responses from the quarterly VAR model are broadly in line with the responses from the MIDAS model, suggesting that the temporal aggregation bias is not severe in this context, which is line with our previous results.

6 Conclusions

This paper evaluates the impact of high-frequency shocks on a set of (low-frequency) macroeconomic variables. In doing so, we use recent econometric methods to deal with the mismatch of data frequency, calculating impulse responses from both MIDAS models and time-stamped mixed-frequency VAR models. Our analysis suggests that labor market and credit variables react the most to uncertainty shocks, showing a persistent and negative response to an increase in the VIX. In contrast, most other real economic activity variables present relatively milder responses to uncertainty shocks. Moreover, results from the time-stamped mixed-frequency VAR suggest that the timing of the shock matters for the short-term dynamics of the impulse responses in that a shock taking place in the last week of the month typically leads to a much softer response in the short-run than a shock occurring in the earlier weeks of the month. In addition, responses from MIDAS models and standard single-frequency VAR models are very much similar, suggesting that there is little insight to gain in using high-frequency data to evaluate the impact of uncertainty shocks. These findings are robust to a range of robustness checks, including the use of a different measure of uncertainty and the use of daily data. We also investigate which quarterly investment categories are the most sensitive to uncertainty shocks. In line with the model predictions from Bernanke (1983), we find that the the most irreversible investment projects (investment in structures) exhibit the strongest responses to uncertainty shocks. Finally, we also find some evidence for asymmetric responses of macroeconomic variables to uncertainty shocks over the state of the business cycle. Overall, this suggests that uncertainty is likely to have played a significant role in the disappointing economy recovery that most advanced economies have experienced in the wake of the Great Recession. In particular, our findings show that uncertainty has likely been an important behind the sluggish investment growth and disappointing labor market performance that followed the global financial crisis.

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Table 1: Data

Data	Source	Transformation
Retail sales	Census Bureau	Log Difference
Payroll employment	Bureau of Labor Statistics	Log Difference
Unemployment rate	Bureau of Labor Statistics	Level
Industrial production	Federal Reserve Board	Log Difference
Real personal income	Bureau of Economic Analysis	Log Difference
CPI - All items	Bureau of Labor Statistics	Log Difference
Coincident indicator	The Conference Board	Log Difference
ISM - Manufacturing	Institute for Supply Management	Level
Consumer Sentiment	The Conference Board	Level
Commercial and Industrial Loans	Federal Reserve Board	Log Difference
Real Estate Loans	Federal Reserve Board	Log Difference
Consumer Loans	Federal Reserve Board	Log Difference

Note: This table shows the dependent variables we use, the data source and data transformation.

Figure 1: Data - Monthly time series

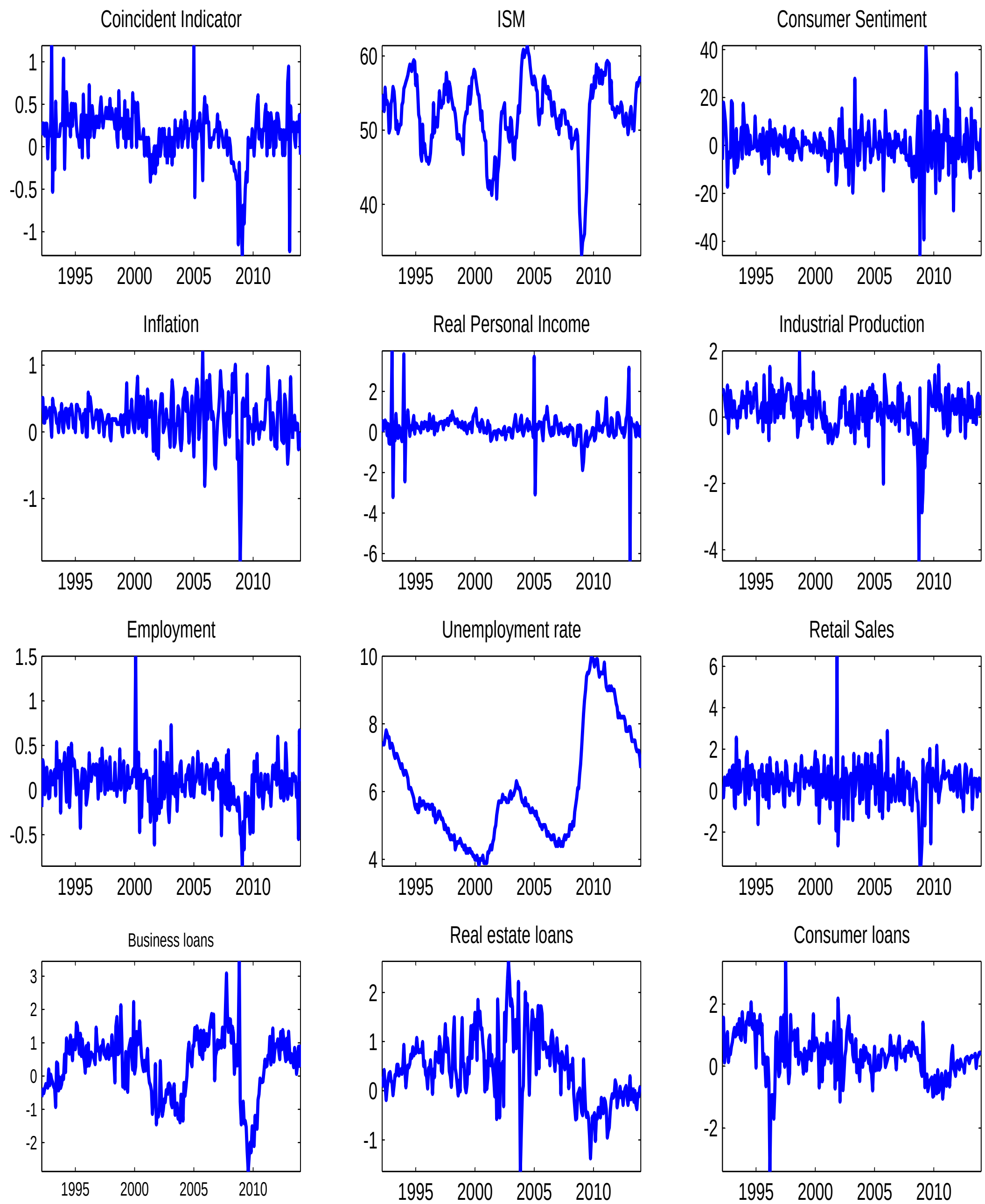
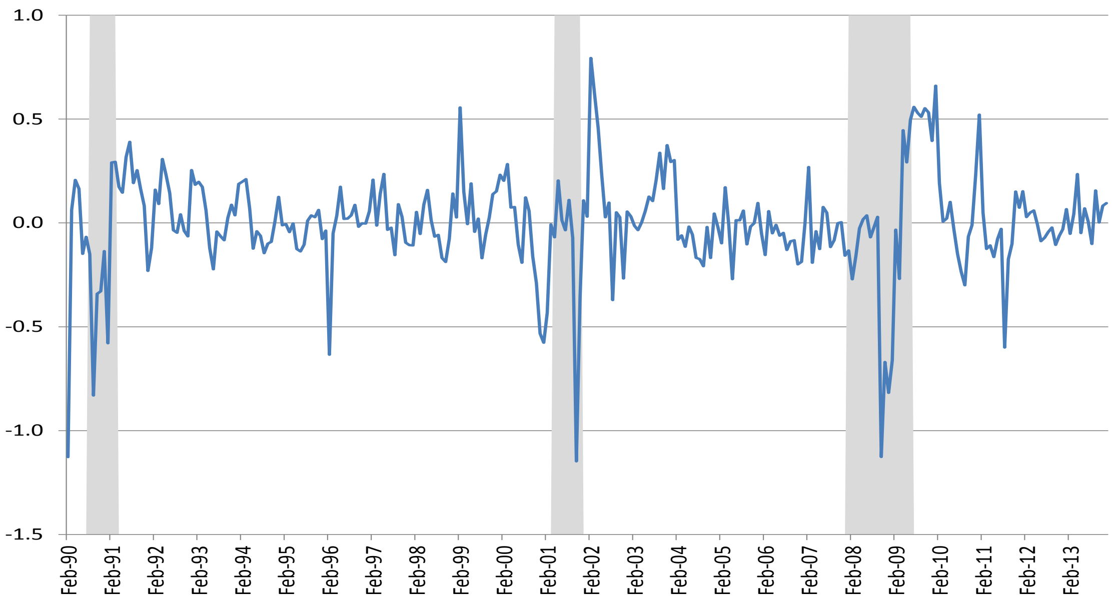
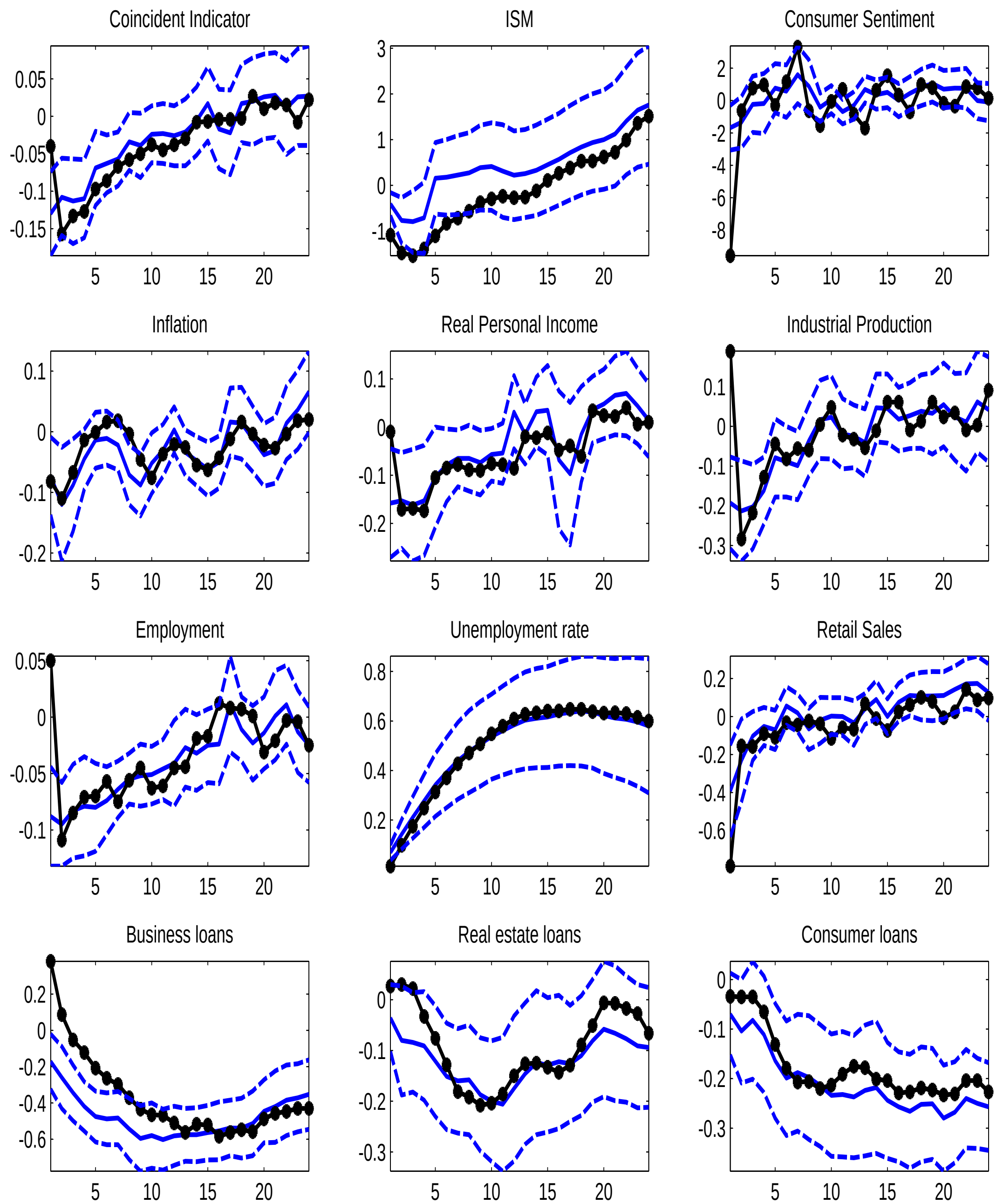


Figure 2: NEWS SHOCK



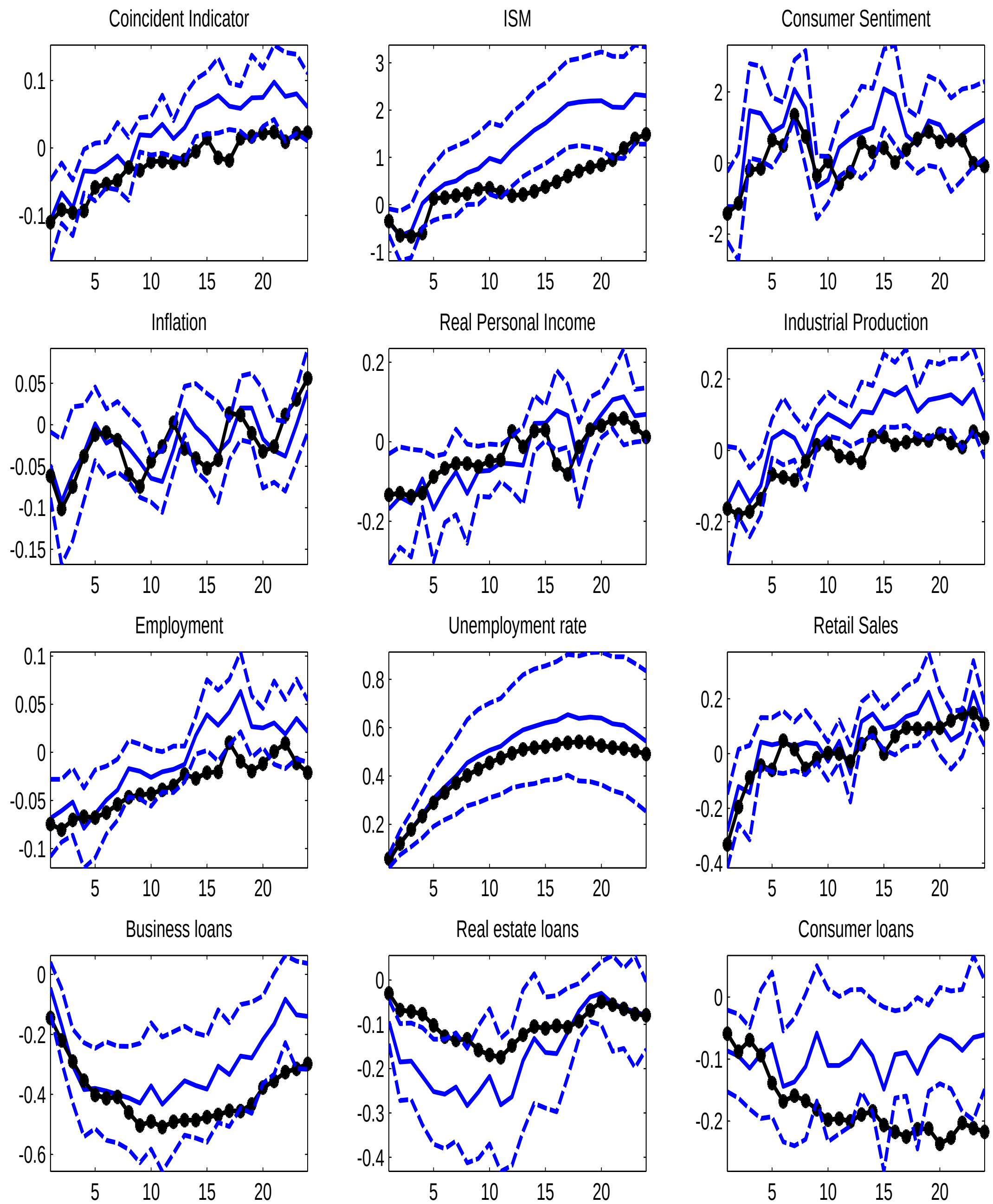
Note: The news shock is defined as the monthly change in one-year-ahead forecast for U.S. GDP growth obtained from the Consensus Economics survey (see equation (2)). Shaded areas are the recession episodes identified by the NBER business cycle dating committee.

Figure 3: Impulse Responses to an uncertainty shock - MIDAS model



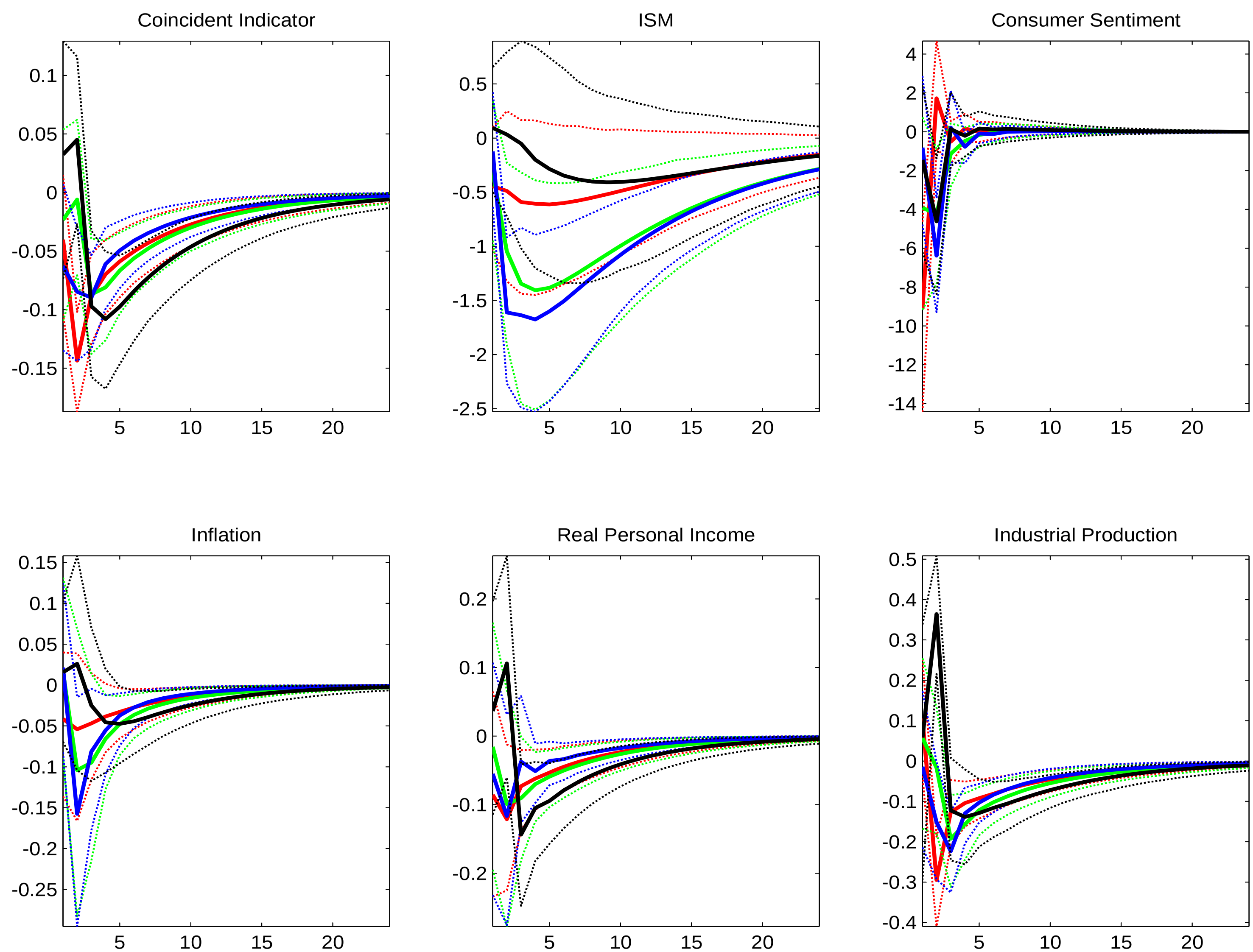
Note: Response to a 10 point increase in the VIX calculated by local projections. 90 per cent confidence bands for MIDAS impulse responses are the dotted lines. The black solid line is the impulse response obtained from a monthly VAR also calculated by local projections.

Figure 4: Impulse responses to an uncertainty (EPU) shock - MIDAS model



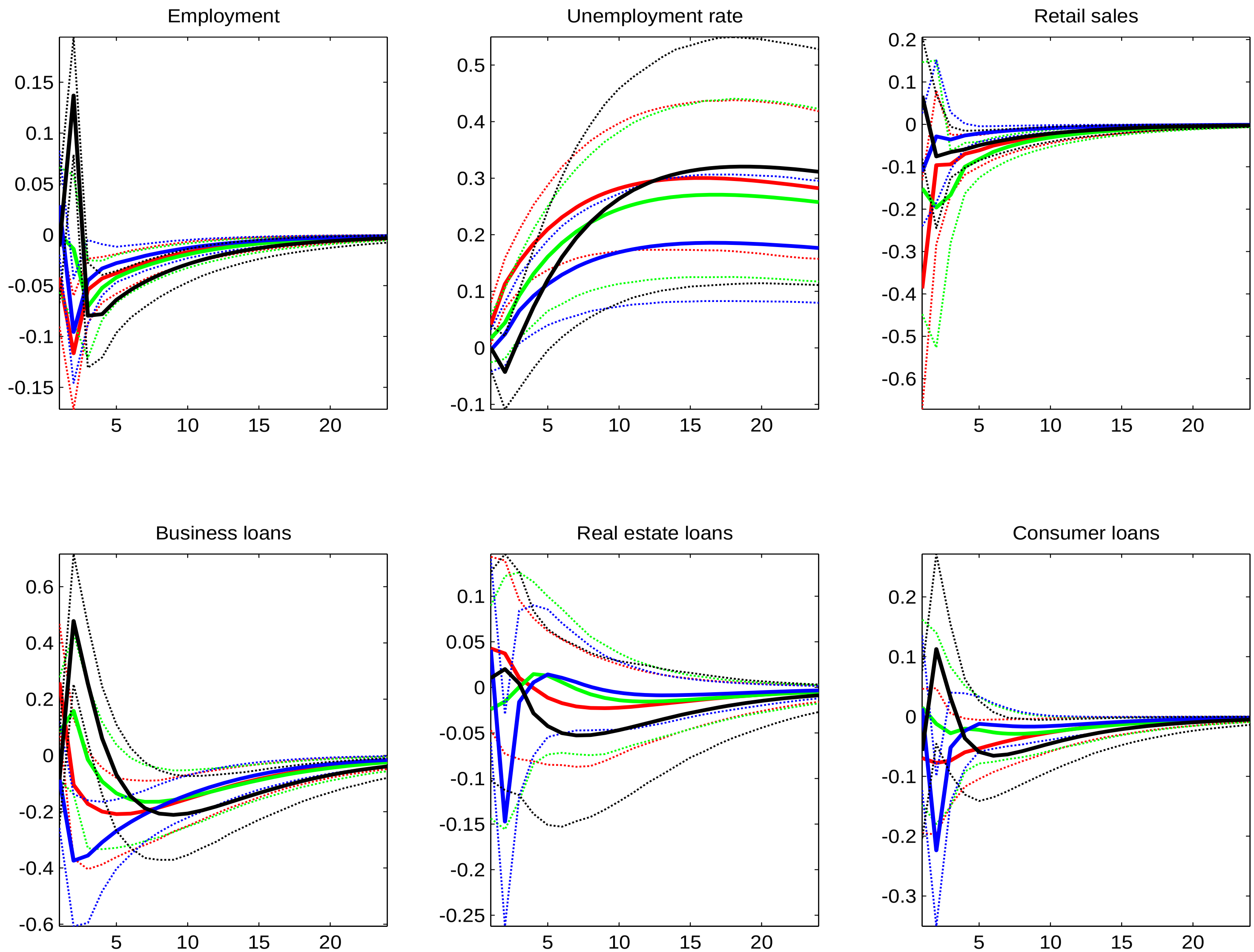
Note: Response to a one standard deviation increase in the economic policy uncertainty index calculated by local projections. 90 per cent confidence bands for MIDAS impulse responses are the dotted lines. The black solid line is the MIDAS impulse response to a one standard deviation increase in the VIX.

Figure 5: Impulse Responses to an uncertainty shock - Time-stamped MF-VAR



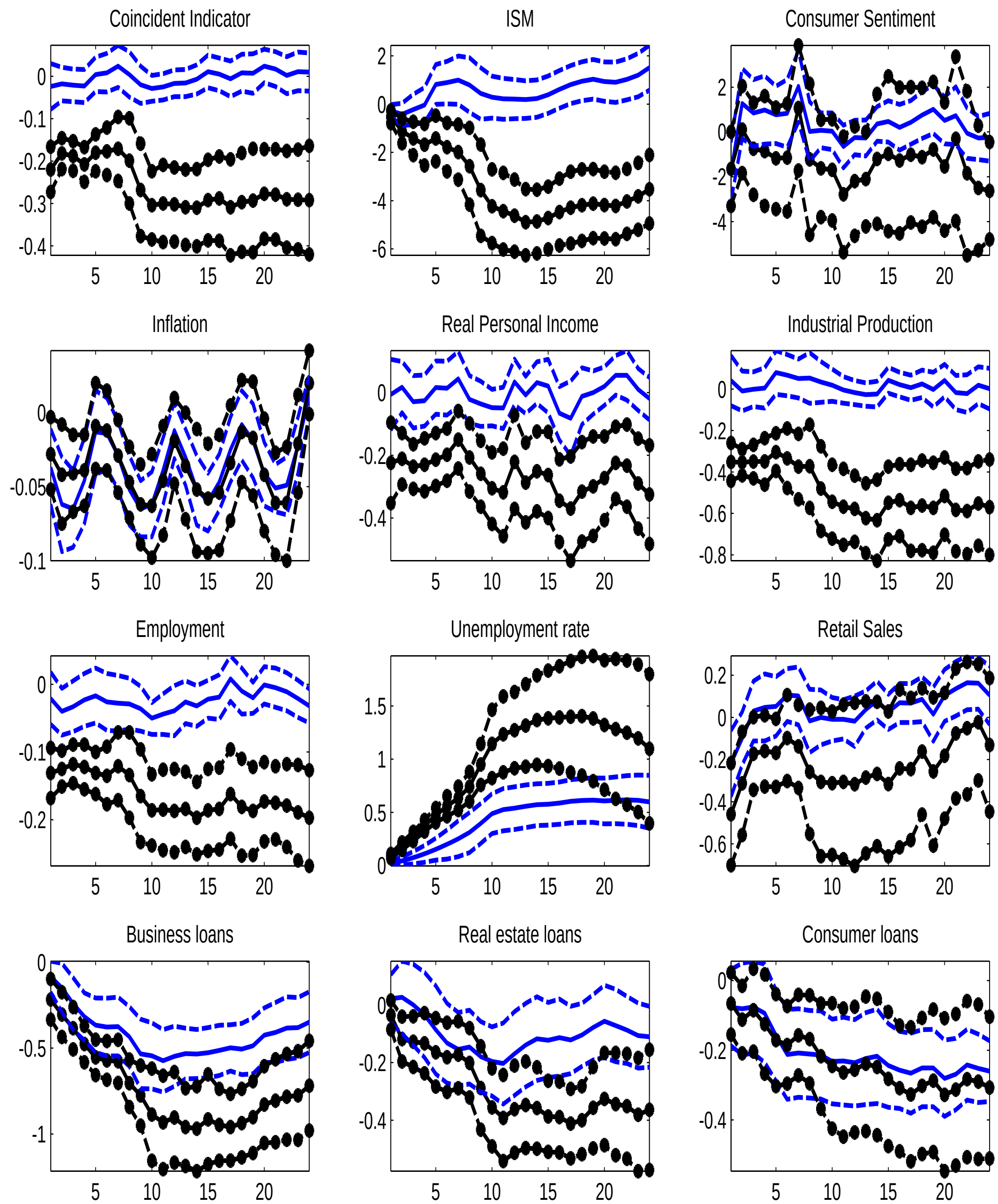
Note: Response to a 10 point increase in the VIX in the first (red line), second (green line), third (blue line) or fourth week (black line) of a month. Dotted lines represent 90 per cent bootstrapped confidence bands based on 1000 replications. We use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system.

Figure 6: Impulse Responses to an uncertainty shock - Time-stamped MF-VAR



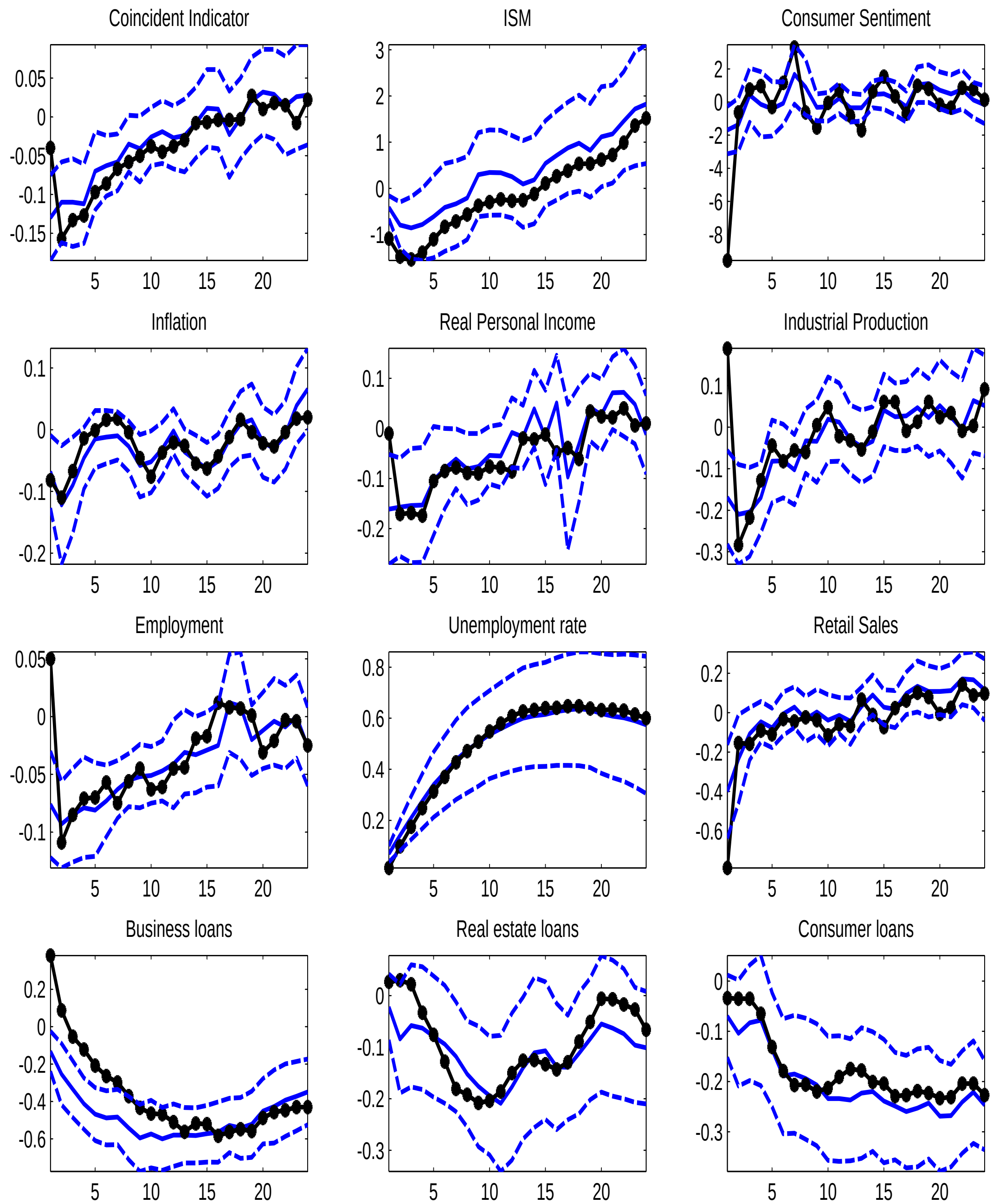
Note: Response to a 10 point increase in the VIX in the first (red line), second (green line), third (blue line) or fourth week (black line) of a month. Dotted lines represent 90 per cent bootstrapped confidence bands based on 1000 replications. We use a recursive (Cholesky) identification scheme with the macroeconomic variable ordered last in the system.

Figure 7: Regime-dependent impulse responses to an uncertainty shock - MIDAS model



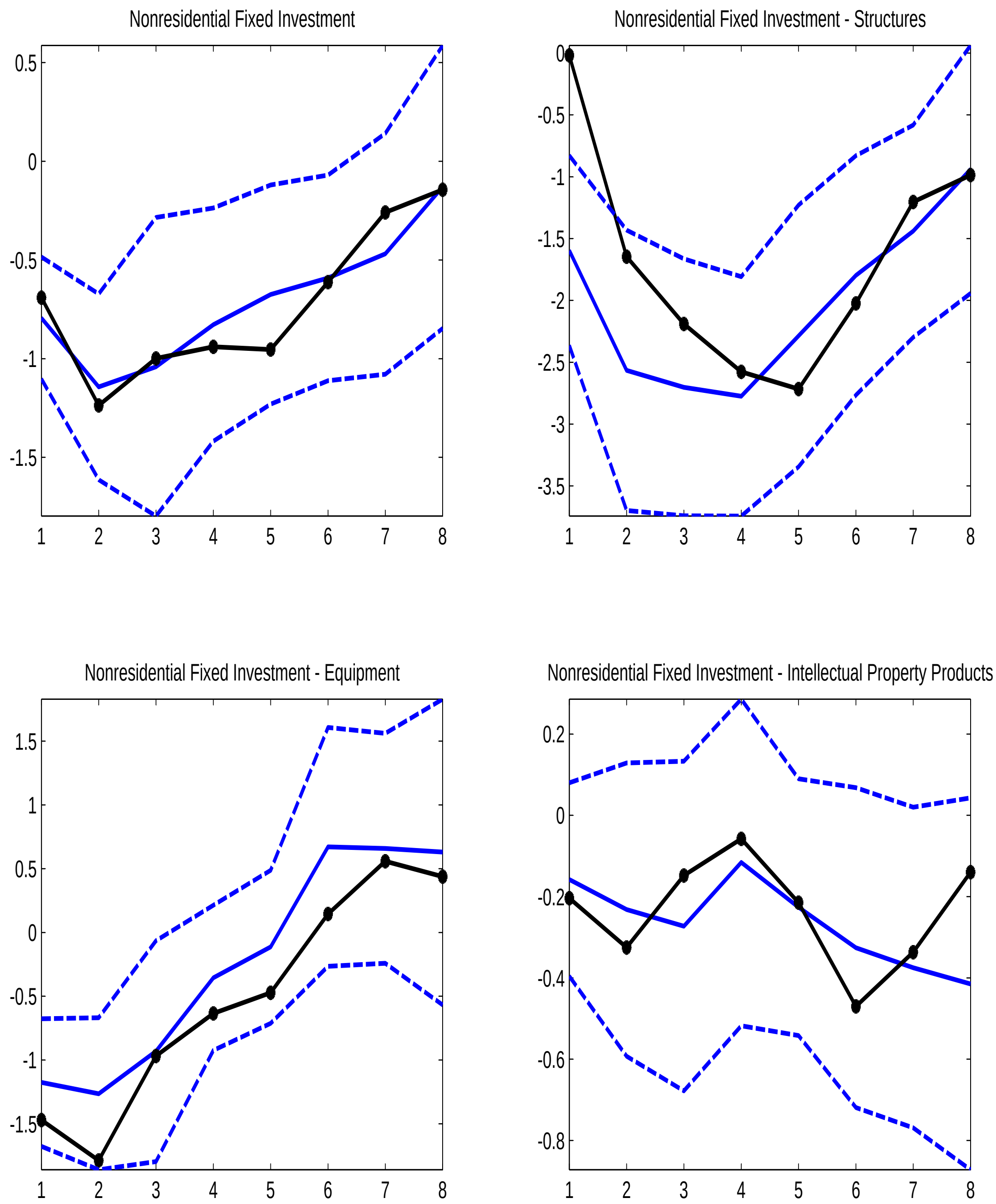
Note: Regime-dependent impulse responses to a 10 point increase in the VIX calculated by local projections. The regimes correspond to U.S. expansions and recessions, and are identified exogenously following the NBER business cycle dating committee (see equation 6). 90 per cent confidence bands for MIDAS impulse responses are the dotted lines.

Figure 8: Impulse Responses to an uncertainty shock (daily data) - MIDAS model



Note: Response to a 10 point increase in the VIX calculated by local projections. 90 per cent confidence bands for MIDAS impulse responses are the dotted lines. The black solid line is the impulse response obtained from a monthly VAR also calculated by local projections.

Figure 9: Impulse Responses to an uncertainty shock (Quarterly/weekly frequency mix) - MIDAS model



Note: Response to a 10 point increase in the VIX calculated by local projections. 90 per cent confidence bands for MIDAS impulse responses are the dotted lines. The black solid line is the impulse response obtained from a monthly VAR also calculated by local projections.