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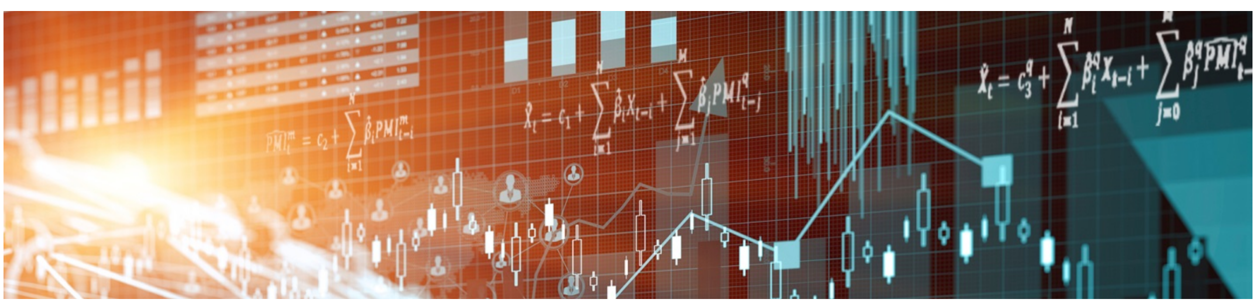

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What Are the Macroeconomic Effects of High-Frequency Uncertainty Shocks

by

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Abstract

This paper evaluates the effects of high-frequency uncertainty shocks on a set of low-frequency macroeconomic variables that are representative of the U.S. economy. Rather than estimating models at the same common low-frequency, we use recently developed econometric models, which allows us to deal with data of different sampling frequencies. We find that credit and labor market variables react the most to uncertainty shocks in that they exhibit a prolonged negative response to such shocks. When examining detailed investment sub-categories, our estimates suggest that the most irreversible investment projects are the most affected by uncertainty shocks. We also find that the responses of macroeconomic variables to uncertainty shocks are relatively similar across single- and mixed-frequency data models, suggesting that the temporal aggregation bias is not acute in this context.

JEL classification: E32, E44, C32

Bank classification: Business fluctuations and cycles; Econometric and statistical methods

Résumé

Dans cette étude, nous évaluons les effets de chocs d’incertitude de haute fréquence sur un ensemble de variables macroéconomiques de basse fréquence représentatives de l’économie américaine. Plutôt que d’estimer les modèles sur des données de même basse fréquence, nous fondons notre analyse sur des modèles économétriques récents qui nous permettent de faire intervenir des données de fréquences d’échantillonnage diverses. Nous constatons que les variables des marchés du crédit et du travail réagissent le plus aux chocs d’incertitude, en ce sens qu’elles présentent une réaction négative persistante à ces chocs. L’analyse de l’investissement ventilé en sous-catégories fait apparaître que les chocs d’incertitude pèsent le plus sur les projets où l’investissement est irréversible. Nous observons en outre des réactions relativement semblables des variables macroéconomiques aux chocs d’incertitude dans les modèles de données à fréquence unique et à fréquence mixte, ce qui donne à penser que le biais d’agrégation temporel n’est pas très important dans ce contexte.

Classification JEL : E32, E44, C32
Classification de la Banque : Cycles et fluctuations économiques; Méthodes économétriques et statistiques

Non-Technical Summary

Economic and financial uncertainty is often considered as a critical factor that contributed to the collapse of economic activity in 2008–2009 and an important element to explain the slow economic recovery that many advanced economies have experienced in the wake of the Great Recession. As a result, the literature on the evaluation of the macroeconomic effects of uncertainty shocks has flourished in recent years.

The key contribution of this paper is to evaluate the effects of uncertainty shocks on the macroeconomic environment using econometric models that can deal with data from different sampling frequencies. In particular, we use a measure of uncertainty at a daily or weekly frequency in our empirical model as opposed to the existing literature, which uses uncertainty measures at a monthly or quarterly frequency to evaluate the macroeconomic effects of uncertainty shocks. The rationale for using a high-frequency uncertainty measure directly in the econometric model is twofold. First, it may be potentially harder to identify uncertainty shocks at a lower frequency given that uncertainty spikes are partly washed out in the process of temporal aggregation. For example, while the VIX – a common measure of uncertainty – has generally trended lower after the Great Recession, its daily measure is often characterized by large fluctuations, which are not necessarily reflected in a measure aggregated at a lower frequency. Second, if economic agents make their decisions at a different frequency or different intervals than the data sampling interval this could lead to an erroneous impulse response analysis. This distortion in parameter estimates and hypothesis testing gives rise to a temporal aggregation bias. Evaluating how relevant is the temporal aggregation bias in the context of uncertainty shocks is one of the main focus of this paper.

Our impulse response analysis uncovers various salient facts. First, we find that credit and labor market variables react the most to uncertainty shocks in that they exhibit a prolonged negative response to such shocks. With respect to detailed investment sub-categories, our estimates suggest that the most irreversible investment projects are those that are affected greatest by uncertainty shocks. Second, we also find 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. This supports the view that temporary high-frequency uncertainty shocks do not have disproportionate consequences for the macroeconomic environment.

1 Introduction

The global economy is frequently hit by uncertainty shocks. For example, in the wake of the financial crisis of 2008–2009, partisan disputes about the U.S. public debt ceiling have triggered bouts of uncertainty, which have proven to be relatively short-lived. Another example of such uncertainty spikes arose in the summer of 2015 when the Chinese economy drew worldwide attention following the sharp decline in its stock market, the devaluation of the renminbi as well as concerns related to economic prospects and the ongoing rebalancing of the Chinese economy. This contributed in large part to a sharp increase in the VIX – a common measure of uncertainty – at a daily frequency that was much less noticeable at a monthly frequency.[1] A question of interest to policy-makers relates to the evaluation of the effects of such high-frequency uncertainty shocks on low-frequency macroeconomic variables, which are typically only available at a monthly or quarterly frequency. In his Jackson Hole speech in late August 2015, Stanley Fischer, Vice Chairman of the U.S. Federal Reserve System, noted that "at this moment, we are following developments in the Chinese economy and their actual and potential effects on other economies even more closely than usual."[2] Some commentators also suggested that those external developments have led the Federal Reserve to delay its first increase in interest rates since the Great Recession.[3] As such, this example suggests that uncertainty shocks that occur at a high frequency have potentially meaningful and disproportionate effects on the macroeconomic environment to the extent that such shocks are significant to the decisions made by economic agents.

Given that uncertainty is often considered as one of the key drivers of the global economy, it is highly relevant to investigate the effects of high-frequency uncertainty shocks on the macroeconomic environment. For example, heightened uncertainty explained part of the collapse in global economic activity in 2008–2009 (see, e.g., Stock and Watson (2012)), and of the sluggish 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 a high frequency. As a result, it is natural to directly consider the impact of uncertainty shocks on the macroeconomic environment using high-frequency data without aggregating the data

[1] In particular, the VIX reached 40.7 on August 24, 2015, which was substantially higher than the August 2015 monthly average of 19.4 and was close to the post–Great Recession high.

[2] See "U.S. Inflation Developments," Stanley Fischer (2015), speech available online at `http://www.federalreserve.gov/newsevents/speech/fischer20150829a.htm`

[3] See, e.g., "Central Banks Warned to Be Firm on Rate Rises," *Financial Times*, December 6, 2015.

before estimating the models. Specifically, in this paper, we assess empirically the extent to which the macroeconomic effects of uncertainty shocks differ when a high-frequency uncertainty measure is used directly in the econometric model rather than aggregating the high-frequency uncertainty variable before the estimation of the econometric model, which is the standard approach. In fact, there is a trade-off when using high-frequency data because 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. From an empirical standpoint, it is highly relevant to study a possible temporal aggregation bias in the context of uncertainty shocks. For example, while the VIX 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, as exemplified in the summer of 2015. As a result, it may potentially be harder to identify uncertainty shocks at a low frequency given that uncertainty spikes are partly washed out in the process of temporal aggregation.

Moreover, if economic agents make their decisions at a different frequency or different intervals than the data-sampling interval, this could lead to an erroneous impulse response analysis (see, e.g., the original contribution of Christiano and Eichenbaum (1987) and Foroni and Marcellino (2014) for a discussion of this issue in the context of dynamic stochastic general equilibrium (DSGE) models as well as Foroni and Marcellino (2015) for an overview of this issue in structural vector autoregression (VAR) models). The distortion in parameter estimates and hypothesis testing resulting from the mismatch between the frequency at which the econometric model is estimated and the frequency at which economic agents make their decisions gives rise to a temporal aggregation bias. Ultimately, the advantage of using high-frequency data remains an empirical question, which depends on the data available. Evaluating the relevance of the temporal aggregation bias in the context of uncertainty shocks is one of the main objectives of this paper.

As a motivation for our analysis, using the same VAR model as in Baker et al. (2015), we find that the responses of employment and industrial production to an uncertainty shock differ in an economically meaningful way depending on the frequency of the estimation (monthly or quarterly). We also perform a small Monte Carlo experiment and find that responses obtained from a single-frequency model are less accurate compared with those obtained from a mixed-data sampling (MIDAS) model, conditional on the data generated from a mixed-frequency data model.

This paper contributes to the literature along several dimensions. First, unlike most papers in the literature, we use daily or weekly uncertainty when evaluating the macroeconomic impact of uncertainty on lower frequency macroeconomic variables. In doing so, we use recent estimation tools to deal with the mismatch of data frequency: a MIDAS model and a mixed-frequency VAR model estimated using a stacked-vector system representation (see Ghysels (2015)). Using the latter model is relevant because it permits us to evaluate whether the effects of the uncertainty shocks vary depending on when the shock took place: at the beginning or the end of the month. This is potentially important given that the propagation of the shock could well differ depending on whether the shock took place early in or at the end of the month (see, e.g., McCracken et al. (2015) for an illustration of this when investigating the impact of monthly monetary policy shocks on quarterly U.S. GDP, as well as Hamilton (2008), who shows that the timing of the changes in expectations about future federal fund rates within a given month matters for new home sales of this specific month). In addition, when performing our impulse response analysis, we look at a set of twelve U.S. monthly macroeconomic variables, which allows us to evaluate the effects of uncertainty shocks on a large set of variables rather than concentrating our analysis on a specific small-scale 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 (2014)).

Our main findings can be summarized as follows. First, we find that uncertainty shocks as measured by either the VIX or the economic policy uncertainty (EPU) index from Baker et al. (2015) 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, suggesting that there is no evidence in favor of a significant temporal aggregation bias when evaluating the macroeconomic effects of high-frequency uncertainty shocks. This supports the view that, to the extent that uncertainty shocks are not protracted, there are no disproportionate macroeconomic effects attached to short-lived spikes in uncertainty. Third, using the time-stamped mixed-frequency VAR from Ghysels (2015) – which enables us to evaluate the effects of a shock depending on the week it occurred 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 which week in the month the shock took place. 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 disappointing labor market performance and investment weakness 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 – that is, investments that cannot be easily undone – tend to react the most to uncertainty shocks, which lines up well with the model predictions from Bernanke (1983) and Bloom et al. (2007). Finally, we find evidence for a much stronger response of selected macroeconomic variables in recessions compared with expansions (e.g., for survey data, industrial production data 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 motivates the use of data sampled at different frequencies for analysing the effects of uncertainty on the macroeconomic environment by showing that the responses from the Baker et al. (2015) VAR model differ depending on the data-sampling frequency. Section 4 also presents a small Monte Carlo experiment in which we study in a controlled experiment how different the responses are across single-frequency and mixed-frequency models. Section 5 introduces the data and presents the main results, and Section 6 presents the results of a number of robustness checks we conducted. Section 7 concludes.

2 Literature Review

2.1 Measuring uncertainty

Because uncertainty cannot be directly observed, a number of uncertainty measures have been introduced in the literature, and they can be classified into various categories; often it is 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 evaluating the effects of uncertainty shocks. 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 and 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 from a dynamic factor model applied to a set of macroeconomic variables. Jurado et al. (2015) calculate an uncertainty index from the unpredictable component of a large set of macroeconomic and financial variables. Rossi and Sekhposyan (2015) instead suggest measuring 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 (see also Jo and Sekkel (2016) for a related approach). The underlying assumption of Jurado et al. (2015) and Rossi and Sekhposyan (2015) is that uncertainty is not intrinsically related to fluctuations in economic activity but rather to its predictability. Moreover, uncertainty can also be measured from the disagreement among forecasters on selected macroeconomic variables. This approach consists of 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 IFO Business Climate Survey participants.

Alternatively, uncertainty can be estimated from news-based metrics. For example, the daily news index from Baker et al. (2015) is built using the number of articles that contain at least one word from three sets of subjects related to the economy, uncertainty and legislation implemented by the U.S. government. The monthly EPU indices developed by Baker et al. (2015) for selected European countries, Canada, China, India, Japan and Russia are also constructed from news coverage about policy-related economic uncertainty. Alexopoulos and Cohen (2014) construct general economic uncertainty measures based on a detailed textual analysis of articles published in *The New York Times*, suggesting the use of a broader set of keywords than what it is typically used to provide a more complete picture of uncertainty. Finally, another idea is to directly focus on policy uncertainty using 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. (2015) use tax code expiration data as reported by the Congressional Budget Office (CBO) for the United States.

Elaborating from these different uncertainty measures, selected authors have proposed composite indices calculated as a weighted average of various components. For example, Baker et al. (2015) calculate a monthly measure of U.S. policy uncertainty from three components: a news-based policy uncertainty index, a federal tax code expiration index and a forecast disagreement index. The latter index is in turn obtained from the dispersion related to three variables: inflation, as measured by the consumer price index, purchases of goods and services by state and local governments, and purchases of goods and services by the federal government.

2.2 Macroeconomic effects of uncertainty

While there are different ways to measure 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 broad empirical evidence suggesting that a sharp downturn in economic activity takes place in response to uncertainty shocks.

A seminal contribution on the effects of uncertainty on economic activity is Bloom (2009), who 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 (2012) find that uncertainty shocks produce the same effects as a negative aggregate demand shock based on both DSGE and VAR models. Caggiano et al. (2014) provide evidence for a stronger effect of uncertainty shocks in recessions than in expansions, suggesting that the effects of uncertainty shocks vary according to 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. (2015), Jurado et al. (2015), and Scotti (2013)). Interestingly, Rossi and Sekhposyan (2015) compare the responses of employment and industrial production to an uncertainty shock using alternatively the uncertainty measures from these three aforementioned papers. They find relatively different quantitative responses depending on the uncertainty measures used, the uncertainty measure from Jurado et al. (2015) generating the most negative responses to an uncertainty shock. One possible reason for these different responses is that the uncertainty measure from Scotti (2013) only refers to real economic activity uncertainty, whereas Jurado et al. (2015) measure uncertainty from a larger set of variables, including both macroeconomic and financial (bond and stock market indices) variables, thereby generating potentially stronger responses to uncertainty shocks. Moreover, 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 level of macroeconomic uncertainty. In addition, they find evidence in favor of a non-linear relation between macroeconomic uncertainty and the volatility of commodity prices in that the strength of this relation depends on the degree of uncertainty. A related contribution is

Jo (2014), who models uncertainty on the oil market using a quarterly VAR with stochastic volatility. Her impulse response analysis suggests that oil price volatility leads to a significant drop in global real economic activity.

A number of recent papers also look at the effects 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 United States and the euro area. Using a Bayesian VAR model, they show that the effects of a shock in the EPU index differ 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) investigate the effects of uncertainty on the 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) who performs a cross-country analysis on a panel of OECD countries. In particular, he finds evidence in favor of 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: a univariate MIDAS model and a multivariate time-stamped mixed-frequency VAR model. The advantage of using these two models is that we can deal with the frequency mismatch between low-frequency (monthly) macroeconomic variables and high-frequency (weekly) uncertainty variables without aggregating the high-frequency data before estimating the models.

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 environments (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), who 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 t indexes the low-frequency time unit (in our case, months), 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 at the high-frequency unit (in our case, weeks) 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 we estimate MIDAS models with non-linear least squares (i.e., minimizing the sum of squared residuals). Note that the uncertainty measure enters directly in equation (1) and that the MIDAS model we use is univariate so that impulse responses derived from equation (1) are reduced-form impulse responses. Moreover, note that Francis et al. (2012) estimate MIDAS models using the residuals of an autoregressive regression of the daily federal funds as a measure of monetary policy shocks to evaluate the effects of daily monetary policy shocks on the macroeconomic environment. As a result, we also estimated equation (1) using the residuals from an autoregressive regression of weekly uncertainty as a measure of uncertainty shocks so as to use the surprise component of uncertainty. The results were very similar to those obtained when using the uncertainty measure directly, suggesting that there is no clear bias in using the uncertainty measure directly in equation (1) to identify uncertainty shocks. The advantage of using the uncertainty measure directly is that it avoids proceeding in two steps and thereby permits reducing model uncertainty that is detrimental for statistical inference (e.g., to calculate appropriate confidence bands).

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 where the data are stacked depending on the timing of the data releases (see Ghysels (2015)).[4] 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 as a standard single-frequency VAR

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

where $Y_t = (Unc_t^{(1)\prime}, ..., Unc_t^{(M)\prime}, W_t')'$, 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 related to the first week of the month. Macroeconomic variables are ordered last in the VAR because 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 control variables are predetermined. Note that this ordering differs from that adopted in a number of papers where slow-moving variables such as macroeconomic variables are ordered first in the VAR. This assumes that they do not react contemporaneously to shocks in fast-moving variables such as financial variables, which 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 because evaluating the temporal aggregation bias is one of the focal points of this paper. In this respect, we follow Ghysels (2015) and McCracken et al. (2015) in that we adopt an ordering of the variables in the VAR that is consistent with the frequency of the data releases and their publication lags: the high-frequency variables being published with little-to-no delay as opposed to macroeconomic variables. The model is estimated with the 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.

[4] Note that McCracken et al. (2015) provide a Bayesian estimation method for this time-stamped mixed-frequency VAR. In particular, they show that the time-stamped mixed-frequency VAR performs well at forecasting U.S. macroeconomic variables. They also run a structural VAR analysis and find that the response of quarterly U.S. GDP to a monthly monetary policy shock differs depending on the timing of the shock in the quarter in that monetary policy shocks in the second month of the quarter lead to a much stronger negative response of U.S. GDP compared with shocks taking place in the first or third month of the quarter.

A few additional comments are required. First, in our empirical analysis, we estimate the model described by equation (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 (e.g., employment, production, inflation and survey data). Second, unlike a mixed-frequency VAR model estimated using the Kalman filter, we obtain M impulse 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. For example, Hamilton (2008) finds that the impact of a change in federal funds futures on new home sales varies within the month. In contrast, a mixed-frequency VAR model estimated using the Kalman filter assumes that the low-frequency variable always reacts in the same way after a shock to the high-frequency variable regardless of 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 using 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 (2015) is estimated with standard estimation tool for VAR models (i.e., least squares), which makes estimation straightforward. 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) suggest 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 Why Is it Important to Consider Data Sampled at Different Frequencies?

While there is now a substantial literature on macroeconomic forecasting with models using data sampled at different frequencies, the use of models with mixed-frequency data for structural analysis remains rather limited.[5] In this section, we motivate the use of mixed-frequency data models for evaluating the effects of uncertainty shocks on the macroeconomic

[5]The use of high-frequency data to facilitate identification of structural shocks in low-frequency VAR models is relatively well established (see, e.g., Faust et al. (2004) or Gertler and Karadi (2015)). However, this type of high-frequency identification procedure is based on sequential steps, and high-frequency information is only used to estimate the contemporaneous effects of a specific structural shock in that the (low-frequency) VAR slope coefficients are used to trace out the dynamic responses. This stands in

environment based on an empirical example and Monte Carlo experiments. First, we empirically show that the impulse response analysis in Baker et al. (2015) can differ in an economically meaningful way depending on the frequency of the estimation of the VAR (monthly or quarterly). Second, based on Monte Carlo experiments, we find that when data are generated at different sampling frequencies, single-frequency models can lead to a misleading impulse response analysis as opposed to mixed-frequency data models, which correctly estimate the true dynamics of the responses.

4.1 A motivating example using the Baker et al. (2015) baseline VAR

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. (2015) 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. (2015); 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. (2015). The quarterly VAR model is estimated over the same sample period as in Baker et al. (2015), 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.[6]

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

contrast to the models presented in Section 3 where high-frequency information is used to estimate the dynamic effects of uncertainty shocks in a single step.

[6]Note that we do not use the same VAR system from Bloom (2009) given that he uses detrended data obtained using an Hodrick-Prescott filter before estimating his VAR model, which would constitute an additional complication when performing an analysis across different sampling frequencies.

(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. (2015), we report responses of industrial production and employment to a 90 points increase in the EPU index. The shock is calibrated so as to correspond to an increase in the EPU index from its 2005–2006 to its 2011–2012 average value. Figure 1 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 2 is the corresponding figure showing the employment response to an 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 meaningful 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.

4.2 Monte Carlo experiments

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). The low-frequency variable is then generated as follows

$$y_t = \rho y_{t-1} + \beta \sum_{i=1}^{K} b(L;\theta) x_{t-\frac{i}{K}} + u_t, \tag{4}$$

where $x_{t-\frac{i}{K}}$ is the high-frequency variable, $b(L;\theta)$ is the MIDAS polynomial as outlined in equation (2) 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=1000* 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 1000 simulated impulse responses.

Figure 3 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 lead a researcher to conduct a misleading impulse response analysis. In the next section, our empirical exercise investigates to what extent responses obtained from mixed-frequency models differ from responses of single-frequency VAR models in the context of (high-frequency) uncertainty shocks.

5 Empirical Analysis

5.1 Data

We consider the responses of the following U.S. 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, real estate, and consumer loans). These variables represent a broad set of monthly macroeconomic variables that capture different sectors of the U.S. economy. Table 1 provides additional information on the data, and Figure 4 plots the data after appropriate transformation. The set of variables we use is broadly similar to the variables used in Francis et al. (2012), who evaluate the impact of high-frequency monetary policy shocks on a set of U.S. macroeconomic variables using MIDAS models. In our baseline results, we use weekly VIX as a measure of uncertainty.

In the empirical application, we assume that each month has a fixed number of weeks (four) so as to obtain a balanced data set. 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 the high-frequency variable 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 ($News_t$), which is defined as the monthly forecast revision in one-year-ahead expected U.S. GDP growth according to the Consensus Economics survey

$$News_t = Y_t^e - Y_{t-1}^e. \tag{5}$$

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 revisions to 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 data on the expectations about future U.S. GDP growth from Consensus Economics, which 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

$$Y_t^e = \frac{k}{12} x_{t+k|t} + \frac{12-k}{12} x_{t+12+k|t}, \tag{6}$$

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 5 plots the revisions (or news, see equation(5)) to U.S. GDP growth with shaded areas corresponding to the recessions identified by the NBER Business Cycle Dating Committee. We 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 (5) 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.

5.2 Baseline Empirical Results

The estimation sample extends from February 1992 to December 2013. Figure 6 shows 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 the responses are short-lived 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 at a 12-month horizon. Retail sales also react negatively to an uncertainty shock, but this adverse 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. In particular, business loans exhibit a prolonged negative response to uncertainty shocks.

Overall, among the set of indicators we consider, we find that labor market and credit variables are those that react the most to uncertainty shocks. However, it is well known that employment variables, especially the unemployment rate, are persistent with strong autocorrelation. Thus, their own dynamics is partly reflected in the strong persistence of uncertainty shocks (see Leduc and Liu (2012)). 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 business loans variable followed by consumer loans and real estate loans. This result is consistent with the work by Valencia (2013), who develops a theoretical model in which loan supply contracts when uncertainty increases. Empirically, using bank-level data in the United States from 1984 to 2010, he finds that the effects of uncertainty are more pronounced for banks with lower levels of capitalization. As such, 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 United States, preventing the usual bounce-back typically observed 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 suggests that there is little to gain in using high-frequency data to evaluate the macroeconomic effects of uncertainty shocks. In other words, this provides evidence against a significant temporal aggregation bias in this context. However, note that for selected variables, the short-term dynamics of the responses differ substantially across VAR and MIDAS models. For example, in the case of business loans, the VAR response lies outside the confidence bands of the MIDAS model in the first six months of the projection horizon. Moreover, in the case of industrial production, employment and consumer sentiment, the responses on impact of the VAR model are outside the confidence bands of the MIDAS model. One rationale for these results is that, in these cases, the MIDAS weight functions governing the aggregation of the high-frequency variable differ substantially from the uniform (equal) weight function.

6 Sensitivity Analysis

6.1 Alternative measures 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. (2015). It has been available on a daily basis since January 1985, but we report results on the same sample size as the one we used for the VIX and use weekly EPU to provide a fair comparison in the impulse response analysis of these two uncertainty measures. Figure 7 presents the results to a one-standard-deviation increase in the economic policy uncertainty index. As a benchmark, Figure 7 also reports impulse responses results 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 results we obtained previously in that the variables that react the most to uncertainty shocks are labor market and credit variables.[7]

6.2 Does the timing of the uncertainty shock matter?

Another matter 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 8 and 9 report the impulse responses obtained when estimating the time-stamped mixed-frequency VAR described by equation (3), which allows us to investigate whether the timing of uncertainty shocks matters for the dynamics of the impulse responses. 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

[7]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. Detailed results are available upon request.

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; when that is the 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 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.

6.3 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 affect economic activity, but instead have little or no effect 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 than they do during expansions. Introducing time variation in equation (1) could be done through a variety of approaches, for example, using regime-switching parameters or parameter changes evolving through a smooth transition function. However, given the short length of the time series we use, we refrain from doing so owing to the computational difficulties related to estimating such models. Instead, we model non-linearity using a dummy variable corresponding to the NBER business cycle dates of U.S. recessions.[8] 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

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

[8]This approach is similar to Ghysels et al. (2013), who 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.

where $\mathbf{1_t^{NBER}}$ is a dummy variable that corresponds to U.S. recessions identified by the NBER Business Cycle Dating Committee. Figure 10 shows the regime-dependent impulse responses (i.e., conditional on staying in a given 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 (2015)). 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 given regime helps 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 10 shows that, in line with the results presented in Caggiano et al. (2014), one can see evidence in favor of non-linearity for a number of variables in that the impulse responses in recessions 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 to uncertainty shocks 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.

6.4 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 11 presents the results, which are very much similar to those presented in Figure 6. In fact, impulse responses obtained from daily data very well 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

$$X_t^q = \mu + \beta \sum_{j=1}^{K} b(L;\theta) Unc_t^w + \Gamma Z_t + \epsilon_t, \tag{8}$$

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: investment in structures, equipment, and intellectual property products.[9] The 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 12 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 shows 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 not surprising to find that uncertainty shocks affect the most irreversible investments (i.e., 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 in line with our previous results.

[9] 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 total aggregate nonresidential investment, respectively.

7 Conclusions

This paper evaluates the impact of high-frequency uncertainty 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 uncertainty (VIX) shocks. In contrast, most other real economic activity variables react negatively to uncertainty shocks, but present relatively milder responses compared with employment and credit variables. Moreover, results from the time-stamped mixed-frequency VAR suggest that the timing of the shock is important 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 early in the month. In addition, responses from MIDAS models and standard single-frequency VAR models are relatively similar, suggesting that there is limited insight to gain in using high-frequency data to evaluate the impact of uncertainty shocks. However, based on both MIDAS and time-stamped mixed-frequency VAR models, we find that the short-term dynamics of the responses may vary noticeably across single-frequency and mixed-frequency models.

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 Bloom et al. (2007), 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 in favor of asymmetric responses of macroeconomic variables to uncertainty shocks depending on the state of the business cycle. Overall, our analysis 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 been an important factor to explain the sluggish investment growth and disappointing labor market performance that followed the global financial crisis.

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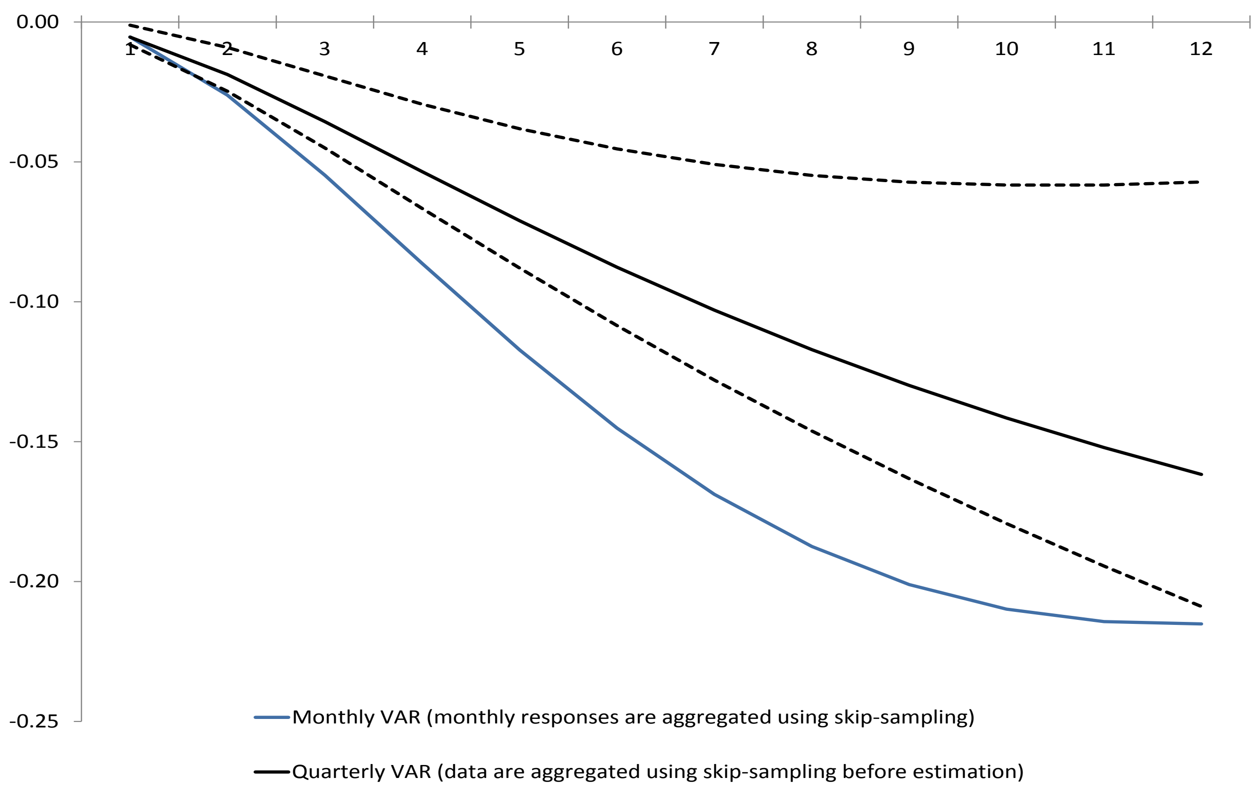
Appendix

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

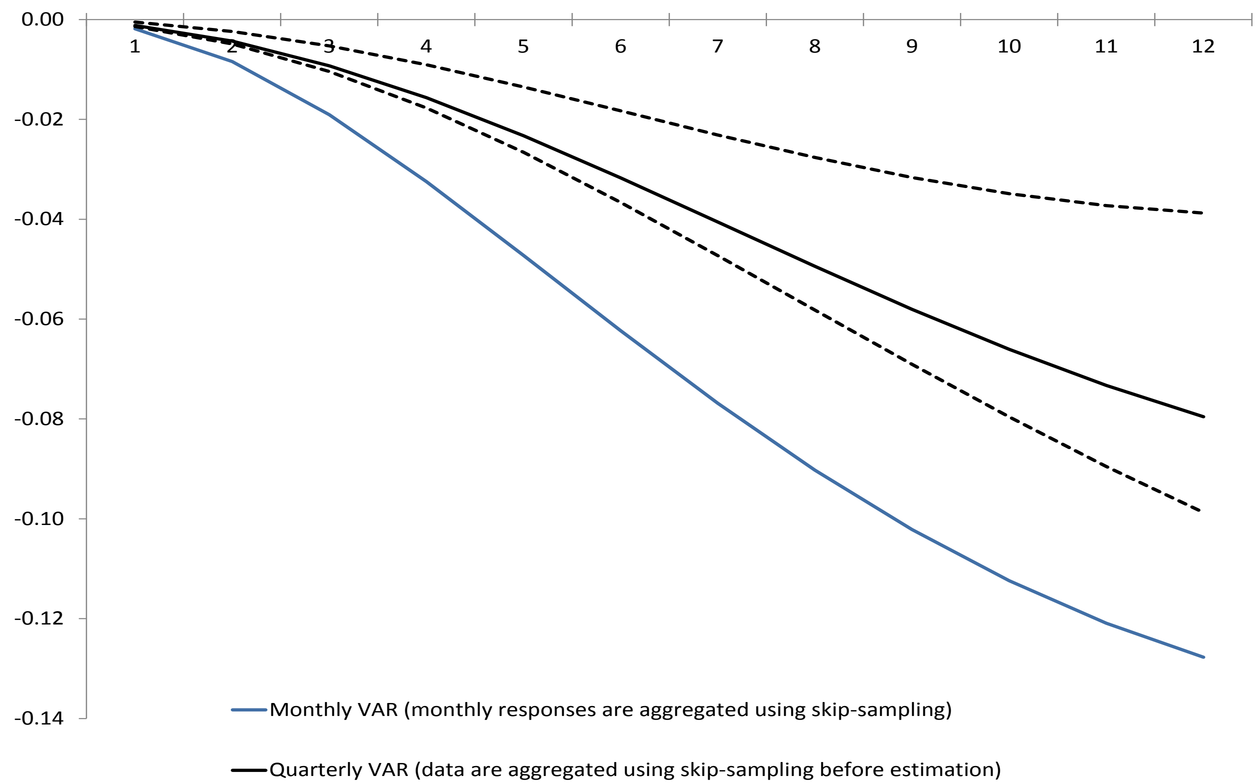
Note: This table shows the dependent variables we use, the data source and the data transformation.

Figure 1: Industrial Production response to an EPU shock



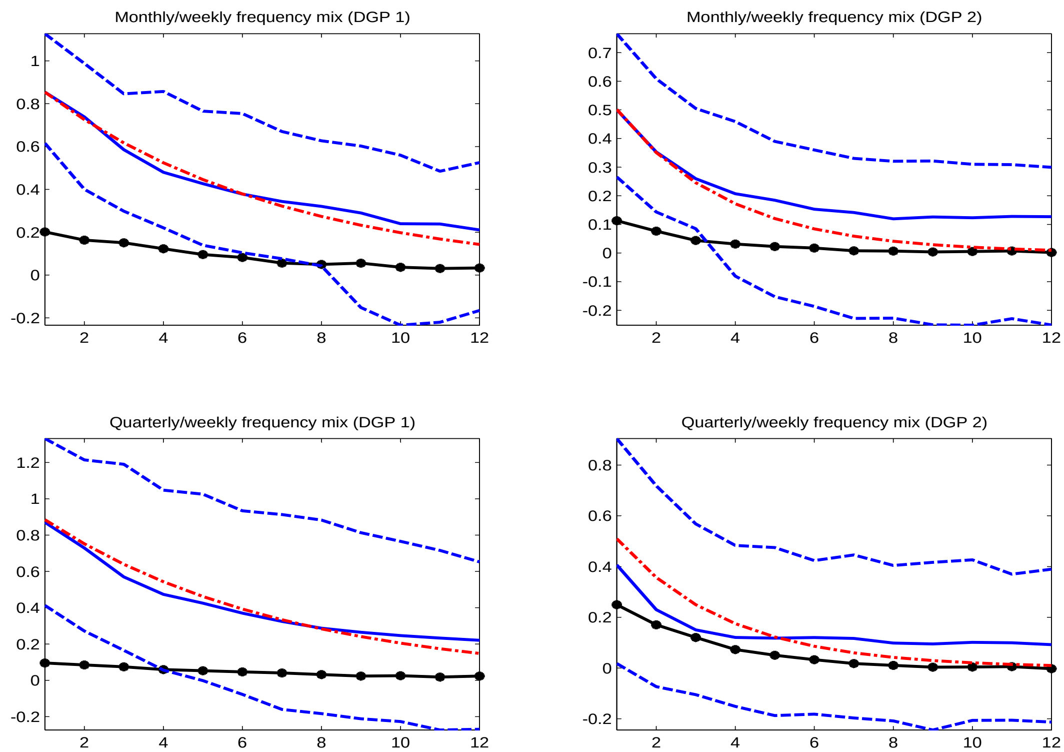
Note: VAR cumulative impulse responses for industrial production to an EPU shock. The EPU shock is calibrated to correspond to a 90-point increase in the EPU index as in Baker et al. (2015). We show responses from a quarterly VAR model where data have been aggregated using skip-sampling and responses 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 2: Employment response to an EPU shock



Note: VAR cumulative impulse responses for employment to an EPU shock. The EPU shock is calibrated to correspond to a 90-point increase in the EPU index as in Baker et al. (2015). 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 3: 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 1000 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 4: Data – Monthly time series

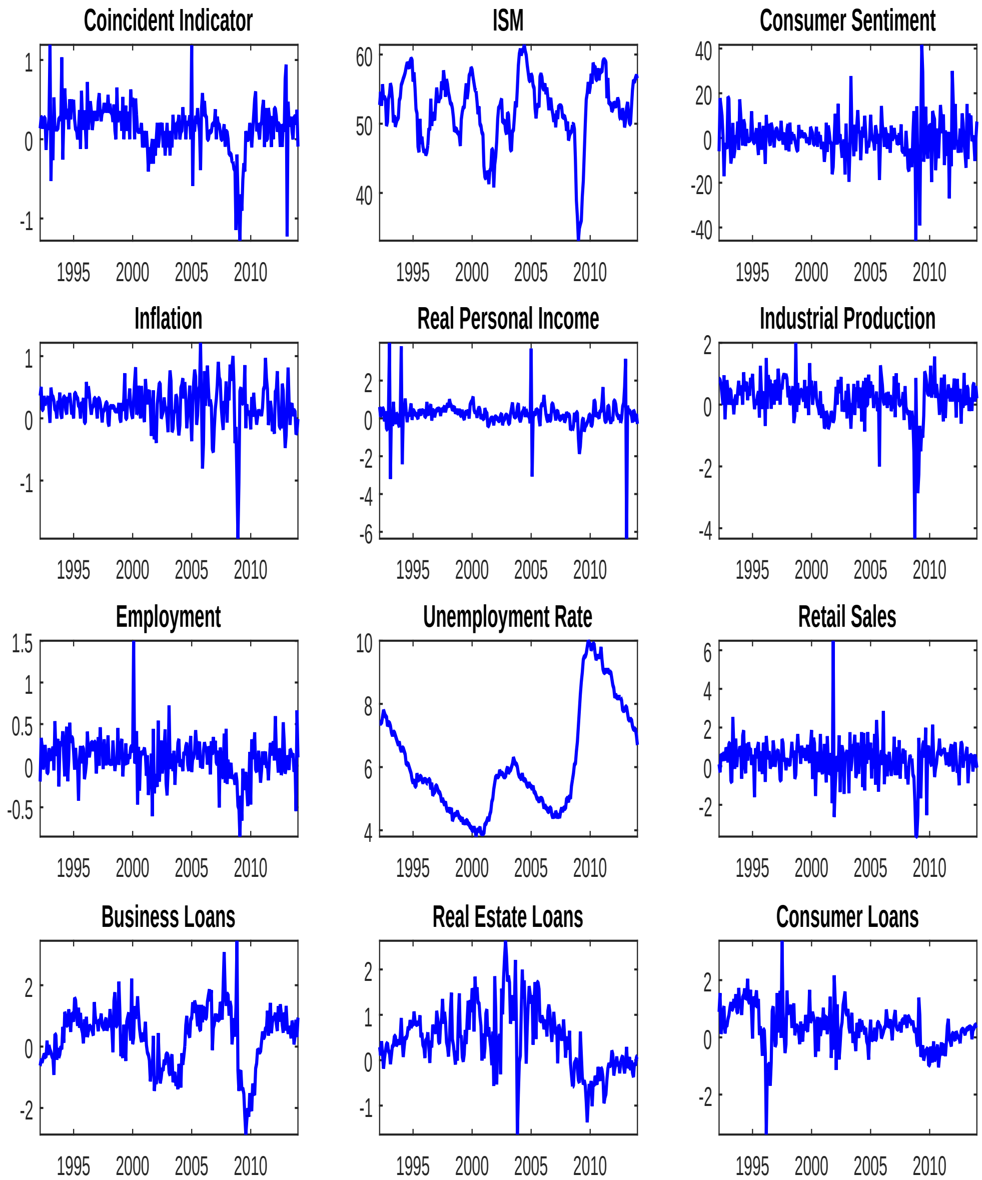
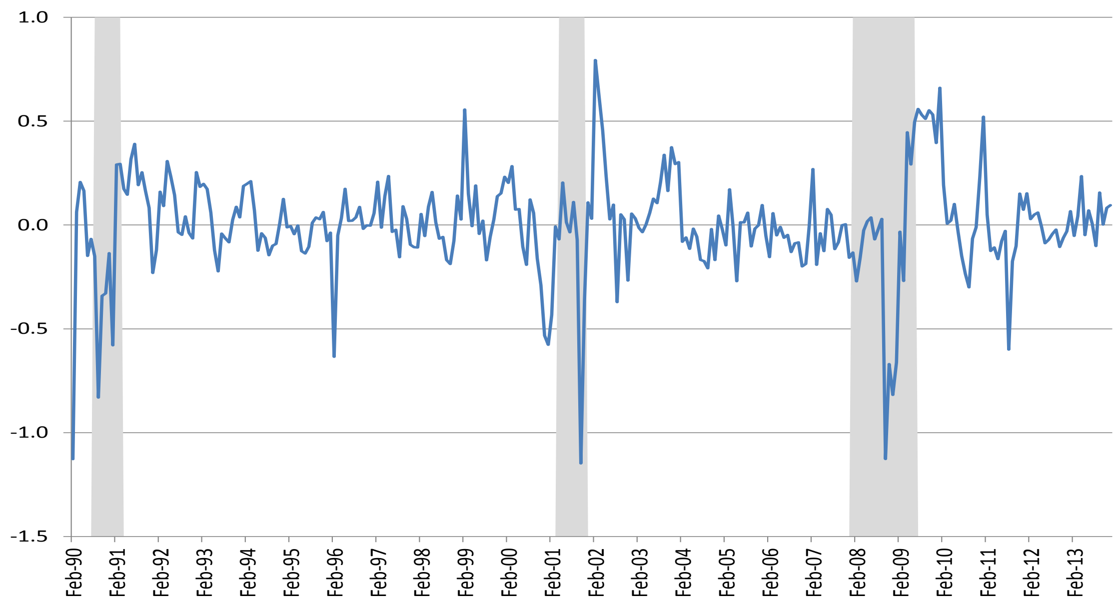
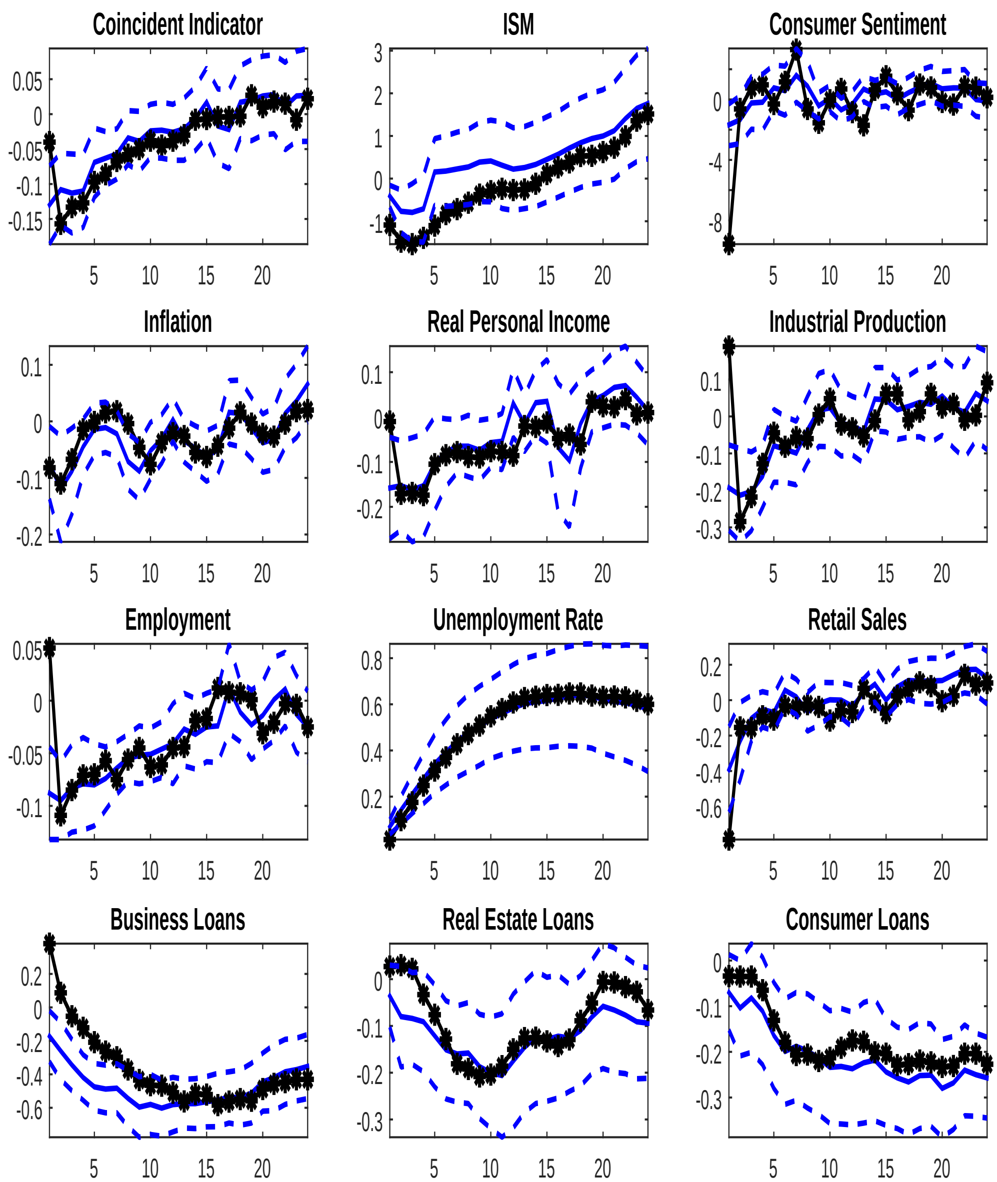


Figure 5: News shock



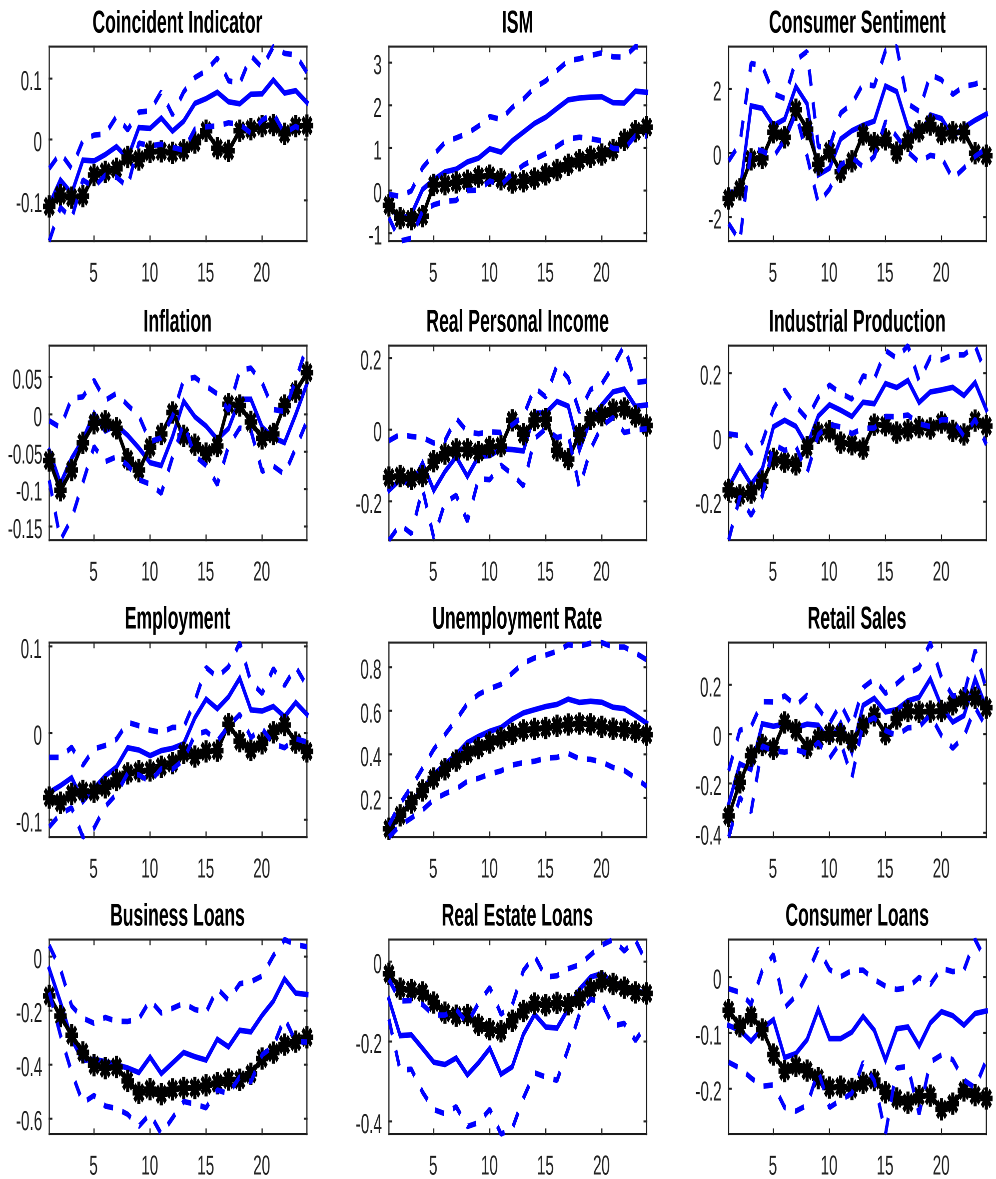
Note: The news shock is defined as the monthly change in one-year-ahead forecast for U.S. GDP growth obtained from the Consensus Economics survey (see equation (5)). Shaded areas are the recession episodes identified by the NBER Business Cycle Dating Committee.

Figure 6: Impulse Responses to an uncertainty shock – MIDAS model



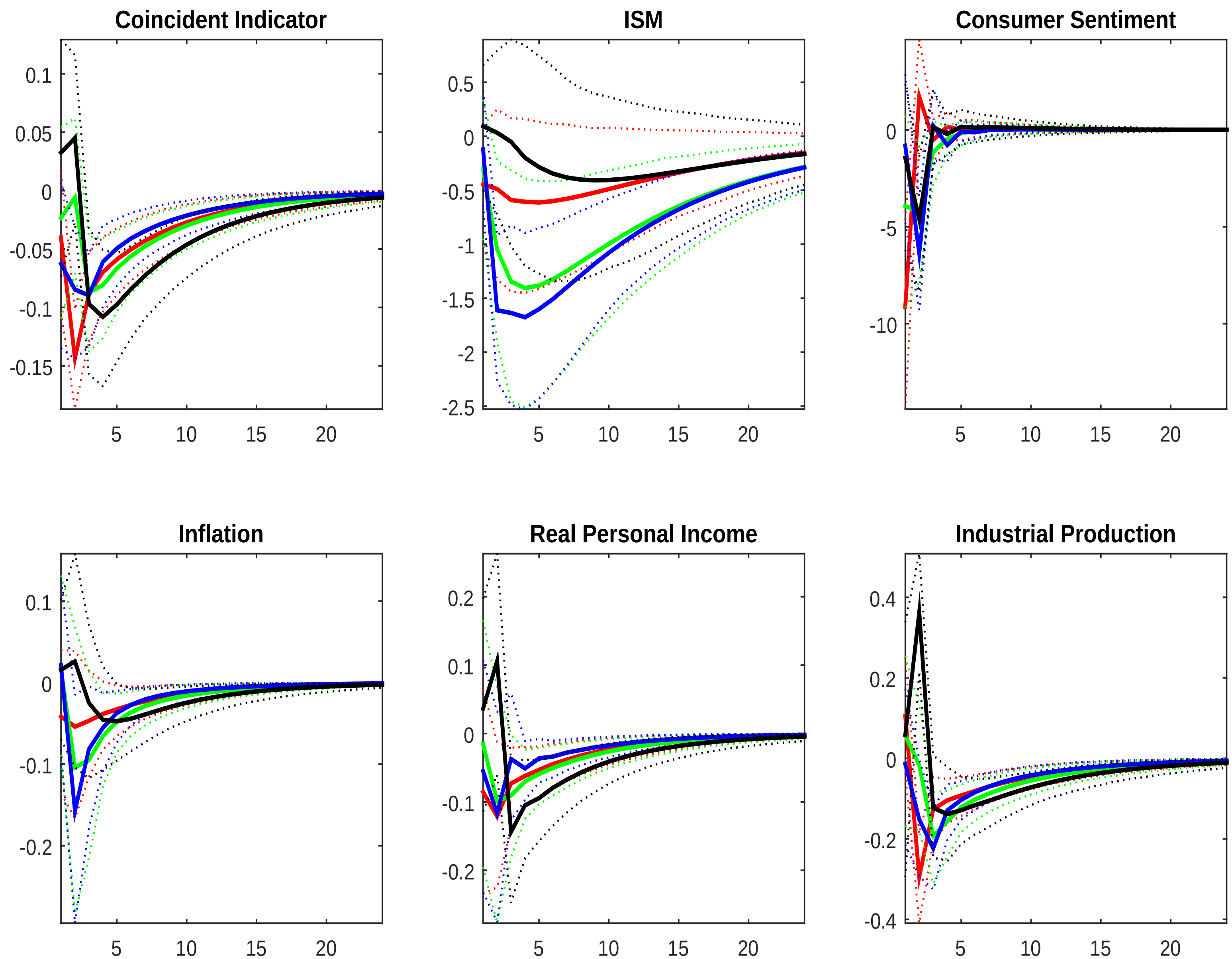
Note: Response to a 10-point increase in the VIX calculated by local projections. Dotted lines represent 90 percent confidence bands for MIDAS impulse responses. The black solid line is the impulse response obtained from a monthly VAR also calculated by local projections.

Figure 7: Impulse responses to an uncertainty (EPU) shock – MIDAS model



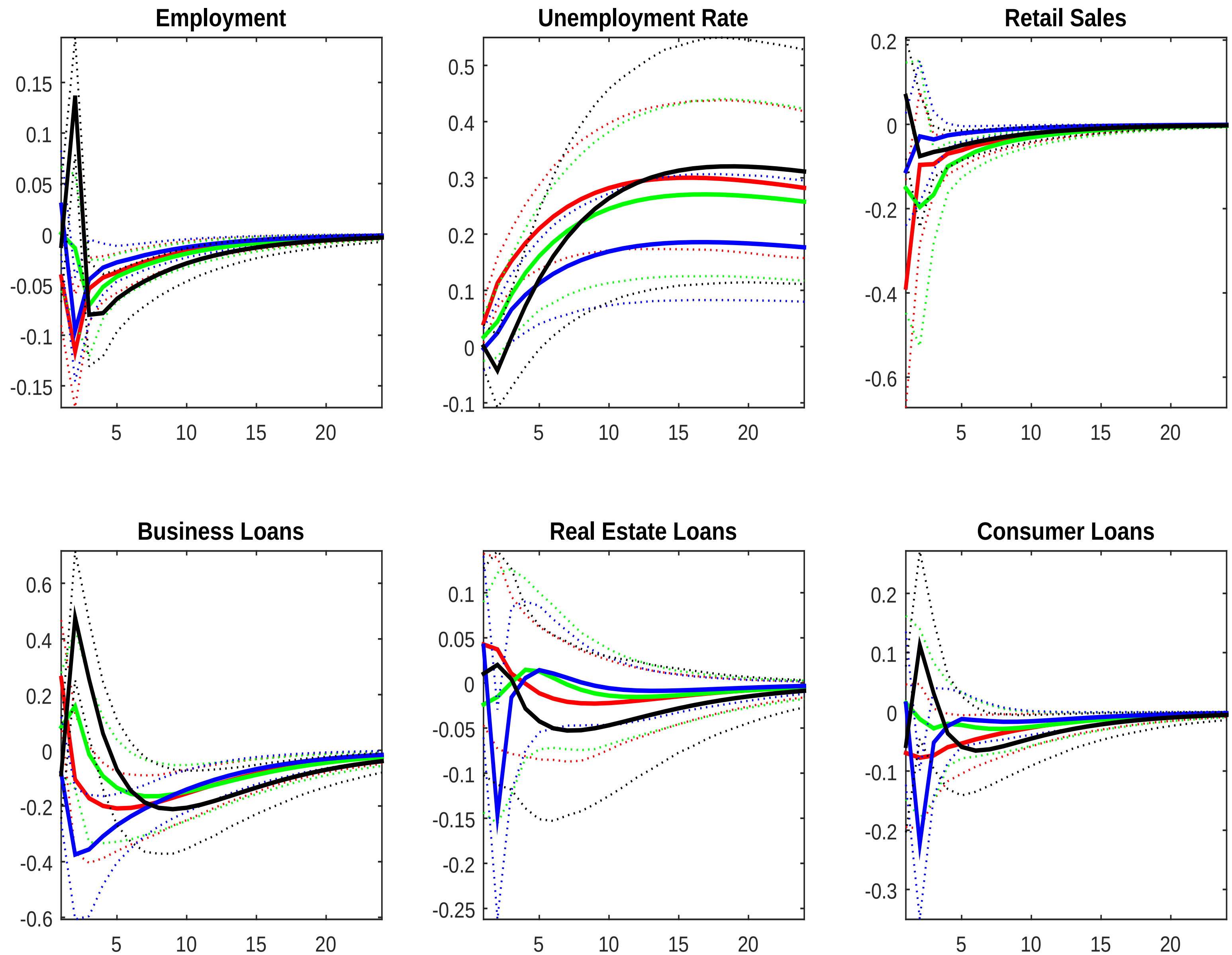
Note: Response to a one-standard-deviation increase in the economic policy uncertainty index calculated by local projections. Dotted lines represent 90 percent confidence bands for MIDAS impulse responses. The black solid line is the MIDAS impulse response to a one standard deviation increase in the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

Figure 8: Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



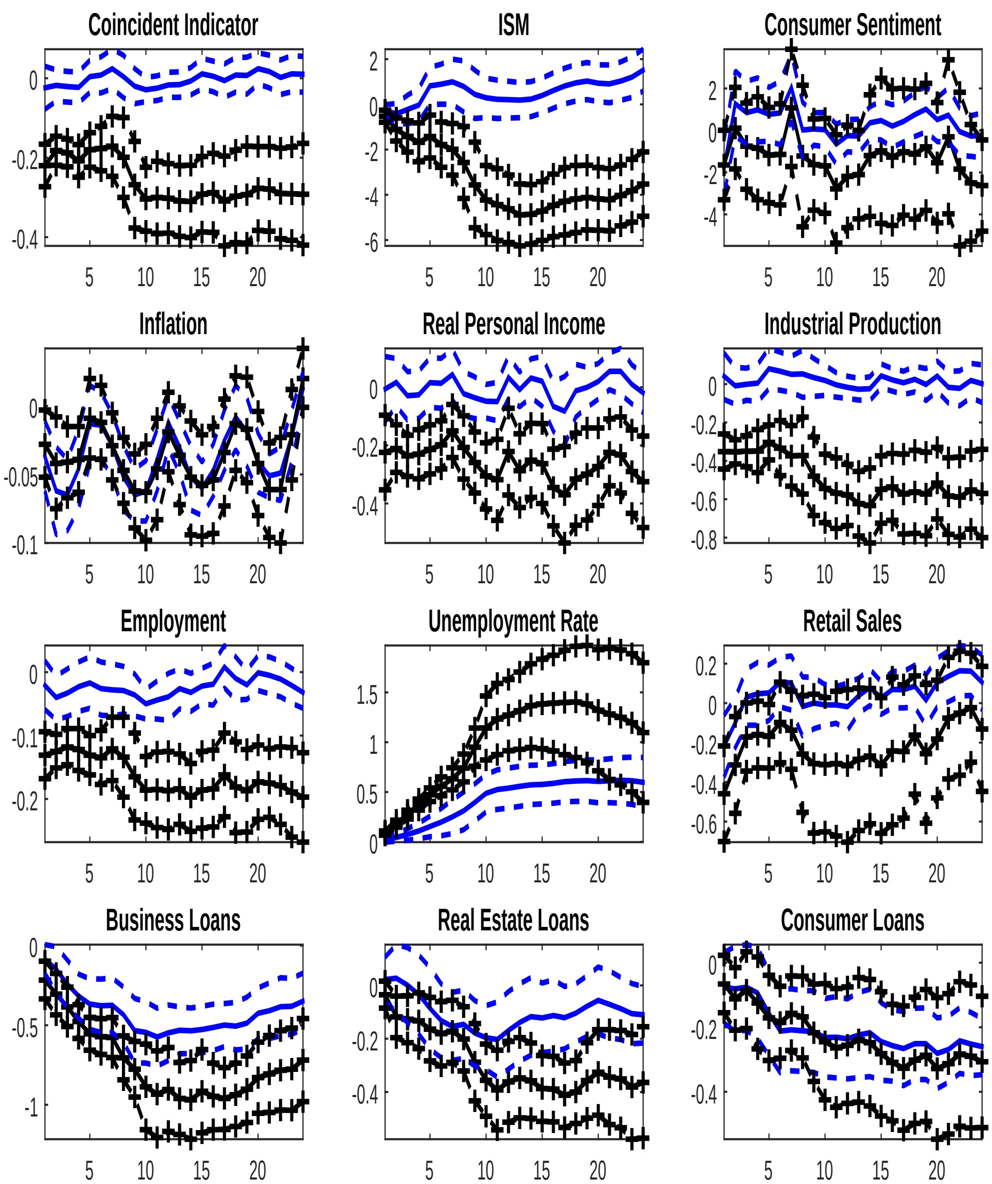
Note: Response to a 10-point increase in the VIX in the first (red line), second (green line), third (blue line) or fourth week (black line) of a month. Dotted lines represent 90 percent bootstrapped confidence bands based on 1000 replications. We use a recursive (Cholesky) identification scheme with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

Figure 9: Impulse Responses to an uncertainty shock – Time-stamped MF-VAR



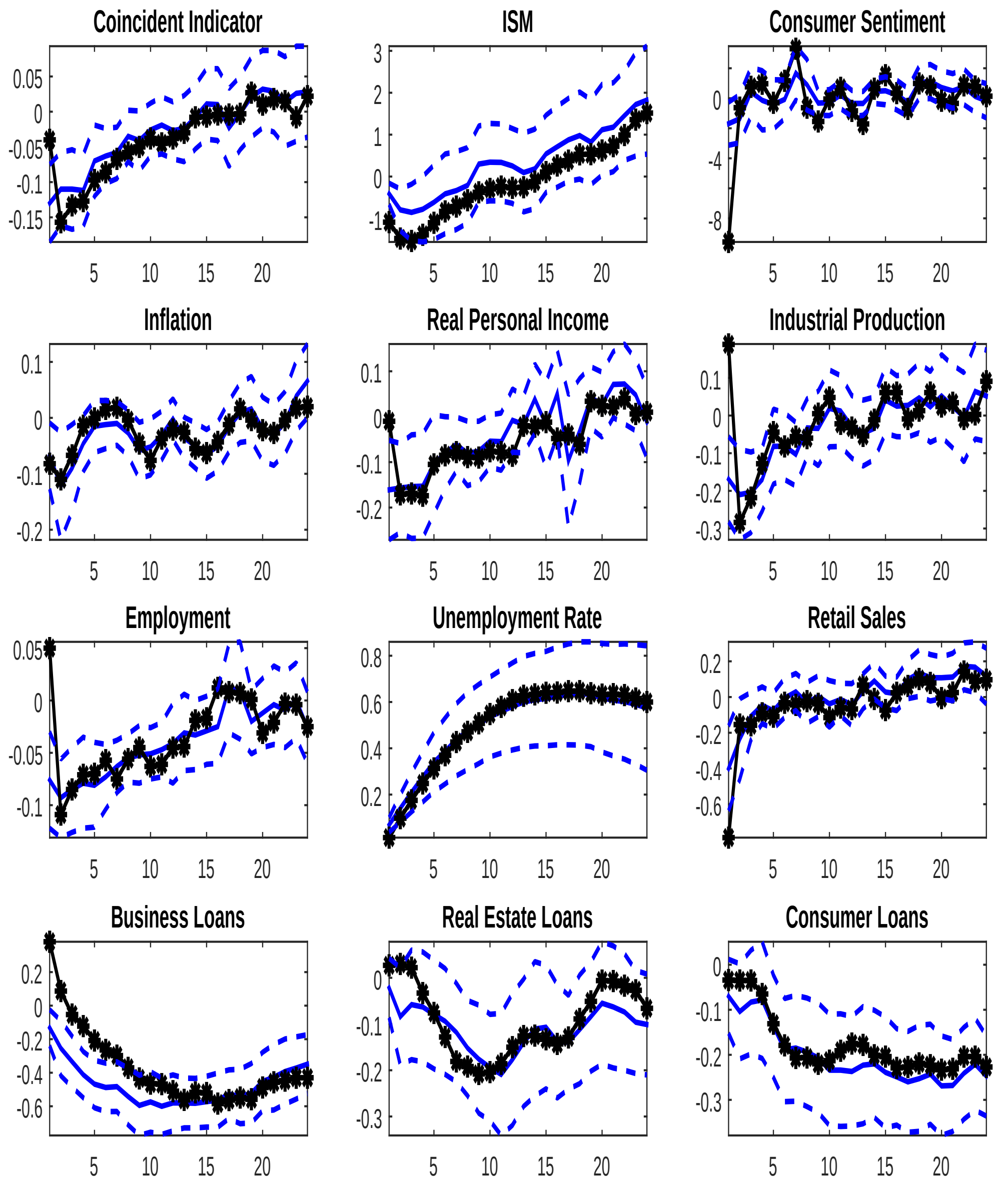
Note: Response to a 10-point increase in the VIX in the first (red line), second (green line), third (blue line) or fourth week (black line) of a month. Dotted lines represent 90 percent bootstrapped confidence bands based on 1000 replications. We use a recursive (Cholesky) identification scheme with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

Figure 10: Regime-dependent impulse responses to an uncertainty shock – MIDAS model



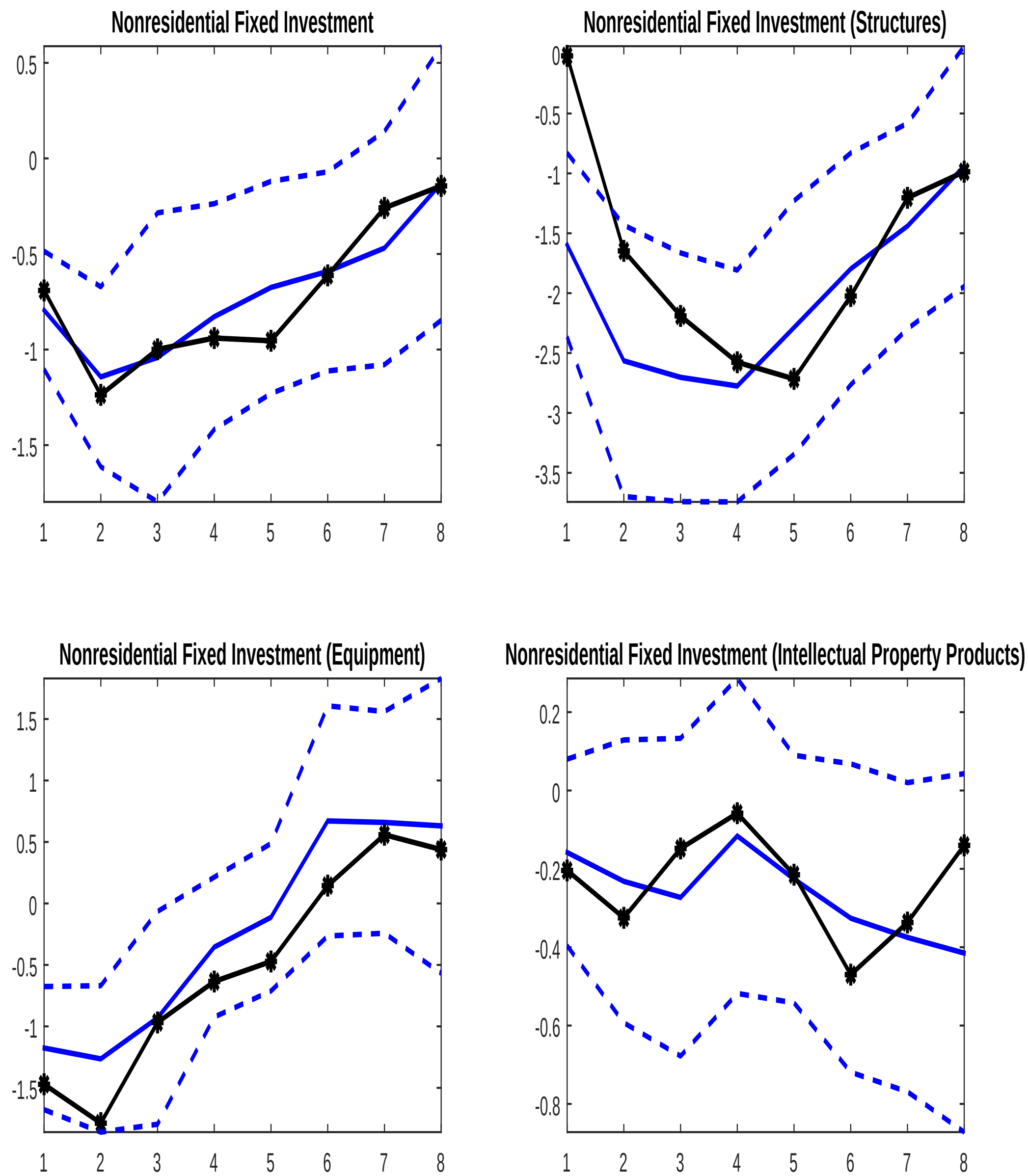
Note: Regime-dependent impulse responses to a 10-point increase in the VIX calculated by local projections. The regimes correspond to U.S. expansions and recessions and are identified exogenously following the NBER Business Cycle Dating Committee (see equation 7). Dotted lines represent 90 percent confidence bands for MIDAS impulse responses. Black circled lines show the responses in recessions, whereas blue solid lines represent responses in expansions.

Figure 11: Impulse Responses to an uncertainty shock (daily data) – MIDAS model



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

Figure 12: 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. Dotted lines represent 90 percent confidence bands for MIDAS impulse responses. The black solid line is the impulse response obtained from a monthly VAR also calculated by local projections.