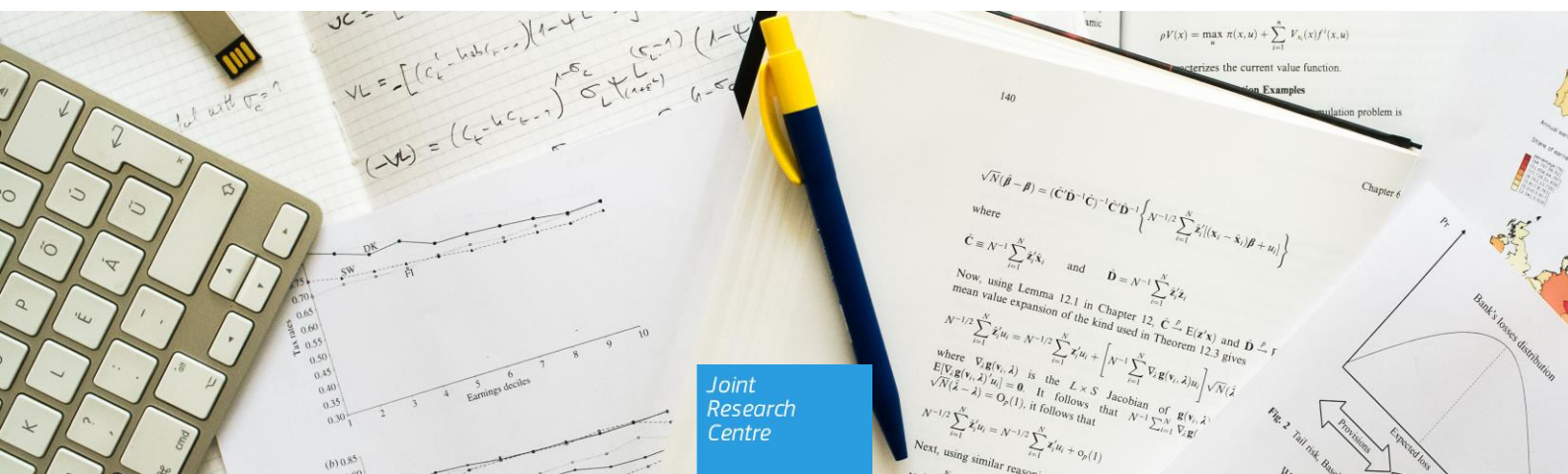# Structural analysis with mixed frequencies: monetary policy, uncertainty and gross capital flows

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2016

Structural analysis with mixed frequencies: monetary policy, uncertainty and gross capital flows

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13th December 2016

Abstract

In this paper we study how monetary policy, economic uncertainty and economic policy uncertainty impact on the dynamics of gross capital inflows in the US. Particular attention is paid to the mixed frequency-nature of the economic time series involved in the analysis. A MIDAS-SVAR model is presented and estimated over the period 1988-2013. While no relation is found when using standard quarterly data, exploiting the variability present in the series within the quarter shows that the effect of a monetary policy shock is greater the longer the time lag between the month of the shock and the end of the quarter. In general, the effects of economic and policy uncertainty on US capital inflows are negative and significant. Finally, the effect of the three shocks is different when distinguishing between financial and bank capital inflows from one side, and FDI from the other.

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1   Introduction

Many observers have stressed the role of gross capital flows in triggering the global financial crisis. Looking at aggregate data, a global financial cycle clearly emerges in capital flows, asset prices and credit growth (Forbes and Warnock, 2012; Milesi-Ferretti and Tille, 2011; Reinhart and Reinhart, 2009). Furthermore, this cycle is generally not aligned with the macroeconomic fundamentals of many of the actors of global financial markets (Claessens, Kose, and Terrones, 2012). Excess credit creation, as well as asset price bubbles, under particular circumstances, can degenerate and act as a trigger for financial crises (Claessens, Kose, and Terrones, 2009; Jordà, Schularick, and Taylor, 2011). Rey (2015), among others, has shown how US monetary policy plays a crucial role in the explanation of the financial cycle, driving the leverage of global banks and credit growth in the international financial system. Focusing on single countries, however, under floating exchange rates domestic monetary policy can set interest rates independently.

Bruno and Shin (2015) focus on one component of US capital inflows, the bank leverage, and investigate how this variable can be affected by US monetary policy. Moreover, based on recent results by Bekaert, Hoerova, and Lo Duca (2013), they consider the strong relation between monetary policy decisions and measured risk as given by the VIX. As regard to the role of risk, following the global financial crisis, a growing literature has addressed the issue of how to measure risk or, more generally, uncertainty, and whether they matter for the business and financial cycles.[1]

Similarly to Bruno and Shin (2015), we examine, employing vector autoregressions (VARs), how US monetary policy and uncertainty influence international markets and affect capital inflows. The very weak results we obtain, however, question a generalization of Bruno and Shin's findings to broad measures of capital inflows, or, perhaps, suggest that the aggregation of high frequency time series, like the interest rates or the VIX, included in the analysis, might hide some important relation.

In fact, as shown by Christiano and Eichenbaum (1987) a specification error, that they term "temporal aggregation bias", affects both parameter estimates and hypothesis testing when economic agents make decisions at fixed intervals of time that are finer than the sampling frequency of the data. Bayar (2014) analyzes the impact of the temporal aggregation when estimating Taylor-type monetary policy rules. Using interest rates averaged at quarterly frequency to match macro indicators, leads to overestimating the interest rate smoothing parameter and hence biases the interpretation of the persistence of monetary policy changes. Foroni and Marcellino (2014) show that the temporal aggregation of dynamic stochastic general equilibrium (DSGE) models from monthly to quarterly frequency significantly distorts the estimated responses to a monetary policy shock.

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[1]See, e.g., Baker, Bloom, and Davis (2016); Bloom (2009, 2014); Carrière-Swallow and Céspedes (2013); Jurado, Ludvigson, and Ng (2015); Rossi and Sekhposyan (2015); Segal, Shaliastovich, and Yaron (2015).

A partial solution to the temporal aggregation problem is provided by the econometric methodologies developed to analyze variables measured at different frequencies. Since the introduction of mixed data sampled models (MIDAS), however, the analysis has been mainly concerned with univariate time series models, focusing on the potential information contained in high frequency data to better forecast low frequency variables (see, among many others, Clements and Galvao (2008) and Clements and Galvao (2009)). Only recently, authors have started to deal with multivariate models, raising a number of specific and general issues for future research and development. The literature on multivariate models for variables collected at different frequencies falls in two main lines of research.[2] A first approach assumes that there is a high-frequency latent process for which only low-frequency observations are available (the original contribution is Zadrozny (1990). A second approach organizes all variables at different frequencies in a stacked skip-sampled process and jointly investigates their relations more similarly to the traditional literature on VAR processes (see Ghysels (2016)). The former is generally represented in a state-space form and Bayesian or classical approaches are used to match the latent process with the mixture of data observed (see, among many others, Mariano and Murasawa (2003), Giannone, Reichlin, and Small (2008), Arouba, Diebold, and Scotti (2009), Eraker, Chiu, Foerster, Kim, and Seoane (2015), Schorfheide and Song (2015)). The latter, instead, does not consider latent factors and latent shocks, and can be viewed as a multivariate version of the univariate MIDAS regression model (see Andreu, Ghysels, and Kourtellos (2010)).

The contributions of the paper are twofold. First, starting from Ghysels (2016) we propose a mixed frequency VAR model, the MIDAS-VAR, that can be seen as the joint multivariate version of the unrestricted-MIDAS (U-MIDAS) model by Foroni, Marcellino, and Schumacher (2014) and the reverse unrestricted MIDAS (RU-MIDAS) model by Foroni, Guérin, and Marcellino (2015). We also present and discuss the structuralization of the model and provide conditions for the identification of the structural parameters. The relatively simple parametrization allows the standard mix of OLS and maximum likelihood (ML) techniques to provide consistent estimates for the reduced-form and structural-form parameters, respectively. Differently from almost all existing work with mixed frequency models mainly focused on forecasting purposes, we examine the structural effect of variables observed at different frequencies. Although in a completely different way, we move in the direction of Foroni and Marcellino (2014) and Christensen, Posch, and van der Wel (2016) who emphasize the role of mixed frequency variables in DSGE models. Furthermore, we present a formal test procedure to evaluate the benefits of using the MIDAS-VAR (or MIDAS-SVAR) with respect to low frequency traditional VARs or SVARs. Second, we investigate the relationships between US capital inflows, monetary policy and uncertainty using quarterly data of gross capital inflows and monthly frequencies for interest rates and uncertainty indexes. We show the importance of using both frequencies in the analysis; the MIDAS-VAR model allows us to shed light on the weak results obtained by Bruno and Shin

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[2]See Foroni, Ghysels, and Marcellino (2014) for a more detailed list of references.

(2015). We also show that economic uncertainty, measured by the VIX, and economic policy uncertainty, measured by the EPU index of Baker, Bloom, and Davis (2016), capture different aspects of uncertainty, and find that the orthogonal shocks to the two indicators generate different responses in the dynamics of capital inflows.

The rest of the paper is organized as follows: In Section 2 we provide preliminary evidence on the relationships between monetary policy, economic uncertainty and capital inflows, when all variables are selected at quarterly frequency. In Section 3 we introduce the MIDAS-VAR and MIDAS-SVAR models, discuss the identification conditions of the structural parameters and provide some results on the relationships between these models and the traditional VAR and SVAR models. Section 4 is dedicated to the empirical analysis, with a discussion on the identification of the structural shocks and on the estimated Impulse Responses (IRFs) and Forecast Error Variance Decompositions (FEVDs). Section 5 presents further empirical results and performs robustness checks. Section 6 concludes.

2 Preliminary analysis: Why mixed frequency matters

In a recent empirical study Bruno and Shin (2015) investigate the dynamics linking monetary policy and bank leverage. Using a Structural Vector Autoregressive (SVAR) model, they find evidence that a restrictive monetary policy, i.e. an unexpected increase in the Fed Funds rate, has a positive, though moderate, effect on bank leverage, when focusing over the period 1995-2007. In this section we provide a similar analysis in which the US capital inflows are modeled together with the Fed Funds interest rate and a measure of market risk. We also use a SVAR model of quarterly variables of the form

$$A(L) x(t) + C(L) z(t) = \varepsilon(t) \tag{1}$$

where $x(t)$ is the vector of endogenous variables, $z(t)$ is the vector of exogenous ones, $A(L) = A + A_1 L + \ldots + A_p L^p$ and $C(L) = C + C_1 L + \ldots + C_p L^q$ are polynomials in the lag operator L, and ε_t is a vector of orthogonalized residuals. The vector of endogenous variables is $x(t) = \big(i(t), vix(t), k(t)\big)'$ where $k(t)$ represents the US gross capital inflows relative to GDP, $i(t)$ is the Fed Funds rate and $vix(t)$ is the VIX index of implied volatility on US equity options. The sample period is from the first quarter of 1988 through the third of 2013. Finally, we include the growth rate of US industrial production[3] $ip(t)$ and the inflation rate $\pi(t)$ as exogenous variables.[4] These variables have been included to identify the monetary policy shocks in that, as documented in the literature, the Fed Funds rate (through which monetary policy is enacted)

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[3]We have also tried with alternative indicators for the US business cycle: a) the quarterly civilian unemployment rate and b) the output gap. The results are practically identical to those reported in this section.

[4]Gross capital inflows are defined as non-residents' purchase minus sales of domestic assets, and series are obtained from International Monetary Fund's International Financial Statistics. All other variables are from the FRED database.

contemporaneously reacts to a real economy indicator and the inflation rate but does not simultaneously affect such variables.[5]

Similarly to Bruno and Shin (2015) we propose a just identified Cholesky structuralization of the SVAR model where the ordering of the variables is (1) Fed Funds rate, (2) VIX index and (3) gross capital inflows. The set of restrictions in the A matrix, together with non-zero coefficients for the two contemporaneous exogenous variables $ip(t)$ and $\pi(t)$ on the first equation allow to identify the first element in $\varepsilon(t)$ as the monetary policy shock $\varepsilon^{mp}(t)$ that potentially affects both the $vix(t)$ and the capital inflows $k(t)$. The second shock, instead, has no simultaneous impact on the short term interest rate while it affects both the $vix(t)$ and the capital inflows, and we label it as the uncertainty shock $\varepsilon^{u}(t)$. The third shock, instead, is a shock hitting the $k(t)$ variable only, and we term it as the capital inflows shock $\varepsilon^{k}(t)$.

Appropriate combination of information criteria (Akaike and Bayesian) and tests on the residuals (Lagrange Multiplier for autocorrelation and Jarque-Bera for multivariate normality) suggest to consider five lags for the reduced form VAR model. Moreover, graphical inspection of the largest eigenvalues and formal Johansen trace-test for cointegration confirm the stationarity of the VAR model in Eq. (1).

In Figure 2 we report the impulse response functions provided by the SVAR model in Eq. (1). In particular, we report the response of capital inflows to a US monetary policy shock and an uncertainty shock. A monetary contraction increases the Fed Funds rate that has a positive impact on capital inflows. As expected, instead, an uncertainty shock negatively affects capital inflows. However, both effects are small, short-lived, and not statistically significant. Furthermore, Table 3 displays the fraction of the capital inflow forecast error explained by the different shocks at horizons between 1 and 20 quarters. Monetary policy and uncertainty shocks explain a practically irrelevant part of US capital inflows in the short-medium run, and a very moderate one in the long run. This first evidence, in short, would suggest a weak influence of US monetary policy and uncertainty on the dynamics of capital inflows.

However, it is worth remembering that, as the capital inflows series is sampled quarterly, as well as all the components of the balance of payments, the whole analysis has been conducted with quarterly data, although VIX and Fed Funds rate, but also industrial production and inflation, are available at higher frequencies. This important feature can be exploited to highlight effects that otherwise would be overlooked. To this end, in the next sections, we develop a SVAR model based on mixed frequencies data. We shall show that the effects of monetary policy on capital inflows are drastically different from those obtained with quarterly data. Furthermore, we will investigate the impact of monthly shocks to stock-market uncertainty and economic policy uncertainty. Again, this is possible in a setup where economic variables are sampled at different frequencies, reflecting market adjustments at different time horizons.

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[5]See, among many others, Christiano, Eichenbaum, and Evans (1999).

3 The MIDAS-SVAR model: Representation and identification

In this section we introduce a multivariate model for investigating the structural relationships between variables observed at different frequencies, as is the case for gross capital inflows, interest rates and uncertainty indicators.

3.1 Representation

Consider two vectors of variables x_L and x_H containing the n_L low-frequency and n_H high-frequency variables, respectively, where x_H are sampled m times more often than x_L. The MIDAS-VAR model, when considering quarterly and monthly series, i.e. $m = 3$, can be written as[6]

$$
\begin{pmatrix} x_H(t,1) \\ x_H(t,2) \\ x_H(t,3) \\ x_L(t) \end{pmatrix} = \sum_{i=1}^{p} \begin{pmatrix} A_{11}^i & A_{12}^i & A_{13}^i & A_1^i \\ A_{21}^i & A_{22}^i & A_{23}^i & A_2^i \\ A_{31}^i & A_{32}^i & A_{33}^i & A_3^i \\ A_{L1}^i & A_{L2}^i & A_{L3}^i & A_L^i \end{pmatrix} \begin{pmatrix} x_H(t-i,1) \\ x_H(t-i,2) \\ x_H(t-i,3) \\ x_L(t-i) \end{pmatrix} + \begin{pmatrix} u_H(t,1) \\ u_H(t,2) \\ u_H(t,3) \\ u_L(t) \end{pmatrix} \tag{2}
$$

$$
\tilde{x}(t) = \sum_{i=1}^{p} A_i \tilde{x}(t-i) + \tilde{u}(t)
$$

where the time index t refers to the low-frequency variables, while for the high-frequency variables the couple (t,j) indicates the month of observation within the quarter t, and where p represents the order of the MIDAS-VAR. The vector of observable variables $\tilde{x}(t)$, sampled at different frequency, will thus be of dimension $\tilde{n} \times 1$, where $\tilde{n} = n_L + m n_H$. This way of writing the model allows us to provide a more compact notation equivalent to the one used for traditional VAR models, i.e.

$$
A(L)\,\tilde{x}(t) = \tilde{u}(t) \tag{3}
$$

where L denotes the low-frequency lag operator, i.e. $Lx_L(t) = x_L(t-1)$ and $Lx_H(t,j) = x_H(t-1,j)$, and $A(L) = I_{\tilde{n}} - \sum_{i=1}^{p} A_i L^i$.

The representation in Eqs. (2)-(3), being a function of the past values of the observable variables, though at different frequencies, can be seen as the reduced form of the model. However, looking, for example, at the (multivariate) equation for the vector of variables $x_H(t,2)$, it is immediately clear that this does not depend on its first natural lag, $x_H(t,1)$. The correct specification of the dynamics of the process does not prevent the error term $u(t,2)$ to be

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[6]Deterministic components, such as constant term, intervention dummies, time trend, are omitted for simplicity but can be managed as in the traditional VAR literature.

correlated with $u(t,1)$. More generally, the covariance matrix of the error terms is defined as

$$
\Sigma_{\tilde{u}} = \begin{pmatrix}
\Sigma_{11} & & & \\
\Sigma_{21} & \Sigma_{22} & & \\
\Sigma_{31} & \Sigma_{32} & \Sigma_{33} & \\
\Sigma_{L1} & \Sigma_{L2} & \Sigma_{L3} & \Sigma_L
\end{pmatrix}
\tag{4}
$$

and none of the blocks is supposed to be zero.

The covariance matrix $\Sigma_{\tilde{u}}$, thus, contains all contemporaneous relations among the high-frequency variables (Σ_{11}, Σ_{22} and Σ_{33}), among the low-frequency variables (Σ_L), the within-quarter relations between low- and high-frequency variables (Σ_{L1}, Σ_{L2} and Σ_{L3}) and some further dynamic relations among the high-frequency variables (Σ_{21}, Σ_{31} and Σ_{32}).

3.2   Identification of structural relationships: The MIDAS-SVAR model

Ghysels (2016) discusses possible implementations of structural mixed frequency VAR models and, in particular, proposes the distinction between real-time predictions and policy response functions. As we are interested in the latter, i.e. in understanding the structural relationships among the variables, all the relations discussed at the end of the previous section, hidden in the covariance matrix $\Sigma_{\tilde{u}}$, must be explicitly identified.

As common in the literature, we perform policy analysis through impulse response functions (IRFs) describing the dynamic transmission of uncorrelated structural shocks among the variables. Based on the MIDAS-VAR model proposed in Eq. (2), under the assumption of stationarity, the IRFs can be easily obtained through the MIDAS-VMA representation

$$
\begin{aligned}
\tilde{x}(t) &= \left(I_{\tilde{n}} - \sum_{i=1}^{p} A_i L^i \right)^{-1} \tilde{u}(t) \\
&= \sum_{k=0}^{\infty} C_k \tilde{u}(t-k) \equiv F(L)\tilde{u}(t)
\end{aligned}
$$

where $I_{\tilde{n}} = A(L)F(L)$. More specifically, the IRFs generally refer to the $(\tilde{n} \times 1)$ vector of latent uncorrelated structural shocks defined as

$$
A\tilde{u}(t) = B\tilde{\varepsilon}(t) \qquad \text{with} \qquad \tilde{\varepsilon}_t \sim (0, I_{\tilde{n}})
\tag{5}
$$

generating the non-linear relationships $\Sigma_{\tilde{u}} = A^{-1}B\Sigma_{\tilde{\varepsilon}}B'A^{-1\prime}$, connecting the reduced-form moments with the structural parameters A and B, with A and B non-singular $\tilde{n} \times \tilde{n}$ matrices, and the covariance matrix of the structural shocks $\Sigma_{\tilde{\varepsilon}} = I_{\tilde{n}}$ as in Eq. (5).

Remark: MIDAS-SVAR, U-MIDAS and RU-MIDAS. Foroni, Marcellino, and Schumacher (2014) provide formal derivation of single equation Unrestricted MIDAS (U-MIDAS) models where high-frequency variables are exploited to improve the forecast of low-frequency variables. Specifically they obtain an *exact* U-MIDAS representation where the error term enters with a moving average structure (see, e.g., Marcellino (1999) and the references therein). However, given that the parameters of such a structure cannot be exactly determined, they provide an *approximate* version where enough dynamics is included in order to make the residuals white noise. In a similar way, Foroni, Guérin, and Marcellino (2015) derive the *exact* and *approximate* Reverse Unrestricted MIDAS (RU-MIDAS) models where low-frequency variables are incorporated in models for predicting high frequency variables. The stacked presentation of the MIDAS-VAR model adopted in this section allows to handle the set of equations for the low-frequency variables, at the bottom of the model, exactly as the *approximate* U-MIDAS model. Furthermore, as it will be clear in the empirical application described in the next sections, the A matrix in Eq. (5) makes the equations for the high-frequency variables exactly equivalent to the *approximate* RU-MIDAS models. The A matrix, in fact, helps including the dynamics of the high-frequency variables naturally missing in the formulation of the reduced-form specification in Eq. (2).■

The AB-MIDAS-SVAR model, or more simply, the MIDAS-SVAR model described in Eqs. (2) and (5) provides a very general framework for investigating the contemporaneous relations between observable high- and low-frequency variables from one side, and between high- and low-frequency structural shocks from the other, captured by the A and B matrices, respectively. This specification, deeply investigated in Amisano and Giannini (1997) for the traditional SVAR models, is more general than the one proposed in Ghysels (2016) where the only considered source of structural relationships is confined to the A matrix, restricting the B matrix to be simply diagonal. While many empirical applications of SVAR models regarding the transmission of the monetary policy focus on the B matrix (fixing A equal to the identity matrix), Bernanke (1986), Blanchard (1989) and Blanchard and Perotti (2002) provide examples in which both simultaneous relations are possible.

Clearly, the identification of A and B, and, as a consequence, of the latent structural shocks, is subject to restrictions on the parameters. In fact, following the definition of the AB-MIDAS-SVAR model provided in Eq. (5), there are $2\tilde{n}^2$ parameters to be estimated from the $\tilde{n}(\tilde{n}+1)/2$ empirical moments contained in the Σ_u. The following proposition, from Lütkepohl (2006), provides a necessary and sufficient condition for the identification of the two matrices A and B when subjected to the linear restrictions given by

$$S_A vec\, A = s_A \qquad \text{and} \qquad S_B vec\, B = s_B \qquad (6)$$

for some S_A, s_A, S_B and s_B known matrices.

Proposition 1 *(local identification of the AB-model)*

Consider the AB-MIDAS-SVAR model reported in Eqs. (2) and (5), subject to the restrictions in Eq. (6). For a given covariance matrix of the error terms $\Sigma_{\tilde{u}}$, the parameters in A and B are locally identifiable if and only if

$$rank \begin{pmatrix} -2D_{\tilde{n}}^+ \left(\Sigma_{\tilde{u}} \otimes A^{-1} \right) & 2D_{\tilde{n}}^+ \left(A^{-1}B \otimes A^{-1} \right) \\ S_A & 0 \\ 0 & S_B \end{pmatrix} = 2\tilde{n}^2. \tag{7}$$

Proof: The Proposition can be proved by calculating the Jacobian and applying the results in Rothenberg (1971). See Lütkepohl (2006), page 365, for the details. ∎

Ghysels (2016) discusses about the importance of the triangular Cholesky factorization in the mixed frequency VAR framework, where the high-frequency variables have a natural order for intra-t timing of shocks. In its contribution, however, Ghysels mainly focuses on the potential source of information coming from the high-frequency variables in explaining the dynamics of the low-frequency ones. As we will discuss in the next section, instead, the AB-MIDAS-SVAR framework offers a very flexible tool to see how both low- and high-frequency variables might interact each other and provide a better understanding of macroeconomic variables fluctuations.

3.3 Mapping from MIDAS-SVAR to SVAR

Ghysels (2016) discusses the asymptotic properties of misspecified VAR model estimators, where the misspecification arises from a wrong selection of the sampling frequency of the variables. The analysis proceeds by considering a high-frequency VAR model (characterized by latent processes if the actual series are observed at a lower frequency only) and compare it to a low-frequency one obtained by certain aggregation schemes. As expected, the main finding (Proposition 5.1) states that the asymptotic impact of miss-specification is a function of the aggregation scheme. In what follows, we restrict the analysis to the two kinds of VAR models used in the empirical analysis: A low-frequency quarterly VAR model and a monthly-quarterly MIDAS-VAR models. The aim of the section is to provide a testing strategy to verify whether aggregating the data and passing to a low-frequency VAR generates a substantial loss of information that might invalidate the analysis. We first focus on the dynamics of the VAR, while then moving to the structural part of the model.

3.3.1 Matching the dynamics

Let start with the MIDAS-VAR model in which we exploit the different sampling of the variables, monthly and quarterly, with one single quarter-lag for simplicity:

$$
\begin{pmatrix} x_H^1(t,1) \\ x_H^1(t,2) \\ x_H^1(t,3) \\ x_L^2(t) \end{pmatrix} = \begin{pmatrix} A_{11}^1 & A_{12}^1 & A_{13}^1 & A_1^1 \\ A_{21}^1 & A_{22}^1 & A_{23}^1 & A_2^1 \\ A_{31}^1 & A_{32}^1 & A_{33}^1 & A_3^1 \\ A_{L1}^1 & A_{L2}^1 & A_{L3}^1 & A_L^1 \end{pmatrix} \begin{pmatrix} x_H^1(t-1,1) \\ x_H^1(t-1,2) \\ x_H^1(t-1,3) \\ x_L^2(t-1) \end{pmatrix} + \begin{pmatrix} u_H^1(t,1) \\ u_H^1(t,2) \\ u_H^1(t,3) \\ u_L^2(t) \end{pmatrix} \tag{8}
$$

where x_H^1 collects the monthly series while x_L^2 the quarterly ones.

This specification should be compared to a traditional VAR in which both groups of variables are observed at the same quarterly frequency, i.e.

$$
\begin{pmatrix} \bar{x}_L^1(t) \\ \bar{x}_L^2(t) \end{pmatrix} = \begin{pmatrix} \bar{A}_{11}^1 & \bar{A}_{12}^1 \\ \bar{A}_{21}^1 & \bar{A}_{22}^1 \end{pmatrix} \begin{pmatrix} \bar{x}_L^1(t-1) \\ \bar{x}_L^2(t-1) \end{pmatrix} + \begin{pmatrix} \bar{u}_L^1(t) \\ \bar{u}_L^2(t) \end{pmatrix} \tag{9}
$$

where $\bar{x}_L^2 = x_L^2$.

The comparison between the two specifications depends on the form of the time aggregation used for moving from $x_H^1(t,1)$, $x_H^1(t,2)$, $x_H^1(t,3)$ to $\bar{x}_L^1(t)$. The mapping from the MIDAS-VAR to the VAR model reduces to consider a selection matrix G accounting for the function used for aggregating the high frequency variables. Suppose, for example, the quarterly data obtained cumulating monthly data (e.g. GDP):

$$
\bar{x}_L^1(t) = \sum_{i=1}^{3} x_H^1(t,i), \tag{10}
$$

then, define the selection G matrix as follow

$$
G = \begin{pmatrix} I_{n_H} & I_{n_H} & I_{n_H} & 0 \\ 0 & 0 & 0 & I_{n_L} \end{pmatrix} \tag{11}
$$

and pre-multiply both sides of Eq. (8) by **G**. After some algebra, discussed in Appendix A, we obtain that the MIDAS-VAR and the VAR models described in Eq. (8) and Eq. (9), respectively, are equivalent when

$$
\begin{aligned}
H_0^1 &: \left(A_{11}^1 + A_{21}^1 + A_{31}^1\right) = \left(A_{12}^1 + A_{22}^1 + A_{32}^1\right) = \left(A_{13}^1 + A_{23}^1 + A_{33}^1\right) \\
H_0^2 &: A_{L1}^1 = A_{L2}^1 = A_{L3}^1.
\end{aligned} \tag{12}
$$

A natural way for evaluating the benefits of the mixed frequency data *vis a vis* the aggregated ones reduces to implement a Wald- or LR-type test for the joint null hypothesis H_0^1 and H_0^2, against the alternative that at least one of the two is not supported by the data. If the aim

of the analysis is to use the dynamics of the model for forecasting the future values of the endogenous variables, under the null hypothesis in Eq. (12), mixing monthly and quarterly observations does not provide any gain. Under the alternative, the information provided by the mixed frequency is statistically relevant and useful for obtaining more accurate forecasts.

3.3.2 Matching the structural relationships

The MIDAS-SVAR model considered in Section 3.2, when the frequency of the data is both monthly and quarterly, can be written as

$$
\underbrace{\begin{pmatrix} A_{11} & A_{12} & A_{13} & A_1 \\ A_{21} & A_{22} & A_{23} & A_2 \\ A_{31} & A_{32} & A_{33} & A_3 \\ A_{L1} & A_{L2} & A_{L3} & A_L \end{pmatrix}}_{A} \underbrace{\begin{pmatrix} u_H^1(t,1) \\ u_H^1(t,2) \\ u_H^1(t,3) \\ u_L^2(t) \end{pmatrix}}_{\tilde{u}(t)} = \underbrace{\begin{pmatrix} B_{11} & B_{12} & B_{13} & B_1 \\ B_{21} & B_{22} & B_{23} & B_2 \\ B_{31} & B_{32} & B_{33} & B_3 \\ B_{L1} & B_{L2} & B_{L3} & B_L \end{pmatrix}}_{B} \underbrace{\begin{pmatrix} \varepsilon_H^1(t-1,1) \\ \varepsilon_H^1(t-1,2) \\ \varepsilon_H^1(t-1,3) \\ \varepsilon_L^2(t-1) \end{pmatrix}}_{\tilde{\varepsilon}(t)} \tag{13}
$$

with $\tilde{u}(t)$ and $\tilde{\varepsilon}(t)$ defined as in Section 3.2 and where the elements in A and B must be restricted in order to fulfill the rank condition in Proposition 1.

In the SVAR model with aggregated quarterly data, the specification of the structural relationships are given by

$$
\begin{pmatrix} \bar{A}_{11} & \bar{A}_{12} \\ \bar{A}_{21} & \bar{A}_{22} \end{pmatrix} \begin{pmatrix} \bar{u}_L^1(t) \\ \bar{u}_L^2(t) \end{pmatrix} = \begin{pmatrix} \bar{B}_{11} & \bar{B}_{12} \\ \bar{B}_{21} & \bar{B}_{22} \end{pmatrix} \begin{pmatrix} \bar{\varepsilon}_L^1(t) \\ \bar{\varepsilon}_L^2(t) \end{pmatrix} \tag{14}
$$

where $\left(\bar{u}_L^{1\prime}(t), \bar{u}_L^{2\prime}(t)\right)'$ are the residuals of the quarterly VAR model as in Eq. (9) and $\left(\bar{\varepsilon}_L^{1\prime}(t), \bar{\varepsilon}_L^{2\prime}(t)\right)'$ are the quarterly structural shocks.

If quarterly observations are obtained by averaging monthly realizations, as in Eq. (10), the two specifications in Eq. (13) and (14) can be compared by using the selection matrix G introduced in Eq. (11). Pre-multiplying Eq. (13) by G, allows us to show the relation between the MIDAS-SVAR and the quarterly SVAR models. In particular, if the following relations

$$
\begin{aligned}
H_0^1 &: (A_{11} + A_{21} + A_{31}) = (A_{12} + A_{22} + A_{32}) = (A_{13} + A_{23} + A_{33}) \\
H_0^2 &: A_{L1} = A_{L2} = A_{L3} \\
H_0^3 &: (B_{11} + B_{21} + B_{31}) = (B_{12} + B_{22} + B_{32}) = (B_{13} + B_{23} + B_{33}) \\
H_0^4 &: B_{L1} = B_{L2} = B_{L3}
\end{aligned} \tag{15}
$$

hold, the two specifications are equivalent and using monthly data does not add useful information to identify the structural shocks.

If the aim of the analysis is to identify the structural shocks and to understand their transmission mechanisms, a statistical test can be implemented in order to verify that a (monthly-quarterly) MIDAS-SVAR has to be preferred to a traditional (quarterly) SVAR. The test con-

sists in jointly testing the null hypotheses in Eq.s (12)-(15), that can be implemented through a standard LR- or Wald-type test strategy. As an example, the implementation of a LR-type test reduces to calculate the log-likelihood of the unrestricted model (l^u) and that of the restricted one (l^r) according to both the identifying restrictions and those in Eq.s (12)-(15). The test statistic $LR = -2\left(l^r - l^u\right)$, as well-known, is asymptotically distributed as a χ^2 with the number of degrees of freedom given by the order of the over-identification. If the null hypothesis is not supported by the data, aggregating the data loses substantial information that instead is important in the identification of the structural shocks.

4 Monetary policy, uncertainty and capital flows: Empirical Analysis

In Section 2 we showed evidence of a positive but not significant reaction of capital inflows to a positive shock in the Federal Funds rate, as well as a feeble negative response of capital inflows to an uncertainty shock. In light of the methodology developed in the previous section, we shall present new results emphasizing the role played by the *natural* mixed frequency of the variables in detecting the impact of monetary policy shocks and uncertainty on US capital inflows.

4.1 Measuring monetary policy shocks

The monetary policy reaction function is often thought to have two components: a) a systematic, expected, reaction to key macroeconomic variables (inflation, output gap, etc.) in the spirit of the Taylor (1993) rule; b) an unexpected "monetary policy shock". The operating target for the Fed Funds rate, through which monetary policy is conducted, systematically responds to past changes in macroeconomic variables and to news on output, inflation and possibly unemployment.

The transmission of monetary policy shocks to the real economy is generally investigated through impulse response functions, where the news, i.e. structural shocks, to macroeconomic variables, as well as the monetary policy shocks, are identified jointly in a SVAR framework.[7] In practice, the monetary reaction function is estimated through a regression model in which the Federal Funds rate is regressed on the lagged macroeconomic variables and the contemporaneous news of such variables (once identified), with the residuals representing the monetary policy shocks. The assumption normally used for identification is that the Federal funds rate does not contemporaneously affect macroeconomic variables (e.g. output and inflation). This implies that news to macroeconomic variables are exogenous to the policy rate and monetary policy

---

[7]The literature on the effects of monetary policy shocks to the real economy is huge and mainly differentiates according to the empirical strategy used for the identification of the macroeconomic shocks. See among many others Christiano, Eichenbaum, and Evans (2005) for recursive identification schemes, while Bacchiocchi and Fanelli (2015) and Bacchiocchi, Castelnuovo, and Fanelli (2016) for non-recursive identification schemes and references therein for alternative approaches.

shocks can be derived from a regression of the Federal funds rate on contemporaneous and lagged macroeconomic variables. We exploit this standard identification strategy to estimate monetary policy shocks in what follows.

Furthermore, since many macroeconomic variables are available only quarterly, SVAR models used to analyze the transmission of monetary policy shocks to the real economy are often based on this sampling frequency. However, given the preliminary analysis in Section 2, the effect of quarterly-estimated monetary policy shocks on the dynamics of US capital inflows seems negligible. Thus, the natural question is whether the MIDAS-SVAR model presented in Section 3 would allow to find structural relationships observable only at higher frequencies and to mitigate distortions, if any, due to the "temporal aggregation bias" (see e.g. Christiano and Eichenbaum, 1987; Bayar, 2014; Foroni and Marcellino, 2014). The first step is thus to identify the monetary policy shocks at monthly frequency, that becomes possible once including monthly short-term interest rate, monthly inflation and a monthly indicator of the business cycle, i.e. the industrial production, in the MIDAS-SVAR model. The details on the specification of the MIDAS-SVAR model will be provided in Section 4.3.

4.2 Measuring economic and policy uncertainty shocks

After the Great Recession of 2007-09 a large and growing body of literature, both theoretical and empirical, has addressed the issues of how to measure uncertainty and whether it matters for the business and financial cycles.[8] We rely on two empirical proxies to capture different kinds of uncertainty shocks[9]: 1) the Market Volatility index (VIX) of the Chicago Board Options Exchange, and 2) the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016).

The VIX index represents the option-implied expected volatility on the S&P500 index with a horizon of 30 calendar days or, equivalently, 22 trading days. Since the main component of VIX is the risk-neutral expectation of the forward integrated volatility, it is often taken as a proxy of macroeconomic uncertainty.[10] The EPU index of Baker, Bloom, and Davis (2016) measures the frequency of articles in 10 leading US newspapers mentioning the triple of words *economic (or economy)*, *uncertain (or uncertainty)* and one of the following policy-related terms: *congress*, *deficit*, *Federal Reserve*, *legislation*, *regulation*, or *white house*.

As shown by Baker, Bloom, and Davis (2016) the VIX is more correlated with equity market uncertainty (as measured by another news-based index, similar to the EPU) than the EPU index. The two measures have thus a different focus: the VIX is tightly linked with financial

---

[8]See *inter alia*: Carrière-Swallow and Céspedes (2013); Baker, Bloom, and Davis (2016); Bloom (2009); Ferrara and Guerin (2015); Jurado, Ludvigson, and Ng (2015); Rossi and Sekhposyan (2015); Segal, Shaliastovich, and Yaron (2015) and Bloom (2014) for a survey.

[9]We do not refer to uncertainty in the original Knightian sense, rather we follow Bloom (2014) by considering empirical proxies of uncertainty as a mixture of uncertainty and risk.

[10]The use of the VIX index as a forward-looking measure of "broad economic uncertainty" has been proposed by Bloom (2009), who shows that it is highly correlated with a number of alternative proxies of uncertainty.

and macroeconomic uncertainties, while the EPU index captures the uncertainties related to the policy making process.

Figure 1 shows that EPU and VIX are positively correlated, but they often move independently of each other. Notably, we see that during the recovery phase after the 2007-2009 recession, the VIX index has followed a downward trend, while EPU set for a while to a new level, higher than its pre-crisis sample mean.[11] This qualitative evidence supports the fact that the two indexes are proxies of different kinds of uncertainties, with EPU being more related to policy uncertainty while the VIX to macro-financial variability.[12]

In the following analysis we include both the VIX and the EPU in the MIDAS-SVAR to investigate the effect of each type of uncertainty on US capital inflows.

4.3 The MIDAS-VAR reduced-form model

Consider the MIDAS-VAR model

$$A\left(L\right)\tilde{x}\left(t\right) = C\left(L\right)\tilde{z}\left(t\right) + \tilde{u}\left(t\right) \tag{16}$$

with $\tilde{x}\left(t\right) = \left(x_H\left(t,1\right)', \, x_H\left(t,2\right)', \, x_H\left(t,3\right)', \, x_L\left(t\right)'\right)'$, and more precisely

$$
\begin{aligned}
x_H\left(t,j\right) &= \begin{pmatrix} i\left(t,j\right) \\ vix\left(t,j\right) \\ epu\left(t,j\right) \end{pmatrix} \qquad j = 1,..,3 \\
x_L\left(t\right) &= k\left(t\right)
\end{aligned}
\tag{17}
$$

where $i\left(t,j\right)$, $vix\left(t,j\right)$ and $epu\left(t,j\right)$ are the Fed Funds rate, the economic uncertainty indicator measured through the VIX and the policy uncertainty measured by the EPU, all observed at the j-th month of quarter t, while $k\left(t\right)$ measures the gross capital inflows-GDP ratio for the quarter t. Similarly to the VAR model presented in Eq. (1) for analyzing the transmission of shocks in a standard VAR with quarterly variables, we also include a set of exogenous variables $\tilde{z}_t$. Specifically, we include the inflation rate $\pi\left(t,j\right)$ and the industrial production index $ip\left(t,j\right)$, with $j = 1,..,3$, observed at monthly frequency.[13] The inclusion of these variables allows us to identify the monetary policy shock, as discussed in Section 2 for the quarterly VAR, or more

---

[11] The higher post-Great Recession level of EPU can be attributed to events such as the debt-ceiling issue in 2011 and the "Fiscal Cliff" in 2012.

[12] Figure 1 also displays shaded areas associated with NBER recessions: we see that both uncertainty measures tend to increase before economic downturns and thus might be leading indicators of the economic cycle. Both indexes are counter-cyclical: they are negatively correlated with the growth rate of U.S. industrial production (IP) at all leads and lags from one month to a year. Moreover, the largest sample correlations are associated with the one-quarter lagged values of the indexes, thus suggesting that both uncertainty proxies might lead the cycle. See Table 1 in the Appendix.

[13] In the main specification the two exogenous variables enter without lags within the same quarter t, i.e. without considering lags $t-1$, $t-2$,.... Including some lags for t, however, does not alter at all the empirical results presented in this section.

specifically for the MIDAS-SVAR in Section 4.1.

The reduced-form MIDAS-VAR model can be thus modeled as in Eq. (2) where $\Sigma_{\tilde{u}}$ is the covariance matrix of the residuals, as in Eq. (4). The time index remains the quarter t and the reduced form can be treated as a traditional VAR model in which the high frequency variables enter at all monthly frequencies. This, as we see below, helps in identifying the different structural shocks hitting the dependent variables in each month within the quarter.

The optimal number of lags (in quarters) can be obtained through the standard approach. The Akaike and Bayesian information criteria, joint with the standard Lagrange Multiplier tests for the autocorrelation and the multivariate normality of the residuals suggest to include simply two lags. Interestingly, using the same set of variables (but ignoring the mixed frequency structure of the model) and the same approach for detecting the optimal number of lags suggested for the quarterly VAR in Section 2, yields a much richer dynamic structure, i.e. five lags.

4.4 The MIDAS-SVAR and the transmission of monetary policy and uncertainty shocks to capital flows

The AB-MIDAS-SVAR model provides a very general framework for investigating the transmission of policy and non-policy shocks when mixed frequency data are involved in the analysis. As discussed in Section 3.1, the covariance matrix of the residuals $\Sigma_{\tilde{u}}$ hides all contemporaneous relations among the high- and low-frequency variables, the within quarter relations between low- and high-frequency variables and the within quarter dynamics between $x_H(t, i)$ and $x_H(t, j)$, with $i > j$. These relations will be made explicit through the A matrix. The other contemporaneous relations, instead, are specified in the B matrix that shows the simultaneous effect of the structural shocks among the variables, and within the quarter. Definitely, the exactly identified structural form becomes

$$
\begin{pmatrix}
1 & & & & & & & & & \\
& 1 & & & & & & & & \\
& & 1 & & & & & & & \\
* & * & * & 1 & & & & & & \\
* & * & * & & 1 & & & & & \\
* & * & * & & & 1 & & & & \\
* & * & * & * & * & * & 1 & & & \\
* & * & * & * & * & * & & 1 & & \\
* & * & * & * & * & * & & & 1 & \\
& & & & & & & & & 1
\end{pmatrix}
\begin{pmatrix}
u^i(t,1) \\
u^{vix}(t,1) \\
u^{epu}(t,1) \\
u^i(t,2) \\
u^{vix}(t,2) \\
u^{epu}(t,2) \\
u^i(t,3) \\
u^{vix}(t,3) \\
u^{epu}(t,3) \\
u^k(t)
\end{pmatrix}
=
\begin{pmatrix}
* & & & & & & & & & \\
* & * & & & & & & & & \\
* & * & * & & & & & & & \\
& & & * & & & & & & \\
& & & * & * & & & & & \\
& & & * & * & * & & & & \\
& & & & & & * & & & \\
& & & & & & * & * & & \\
& & & & & & * & * & * & \\
* & * & * & * & * & * & * & * & * & *
\end{pmatrix}
\begin{pmatrix}
\varepsilon^{mp}(t,1) \\
\varepsilon^{eu}(t,1) \\
\varepsilon^{pu}(t,1) \\
\varepsilon^{mp}(t,2) \\
\varepsilon^{eu}(t,2) \\
\varepsilon^{pu}(t,2) \\
\varepsilon^{mp}(t,3) \\
\varepsilon^{eu}(t,3) \\
\varepsilon^{pu}(t,3) \\
\varepsilon^k(t)
\end{pmatrix}
\tag{18}
$$

where asterisks ($*$) denote unrestricted coefficients and empty entries correspond to zeros. The previous relation in Eq. (18), using the estimated residuals from the MIDAS-VAR in Eq. (16), allows us to identify the structural shocks $\varepsilon^{mp}(t, j)$, $\varepsilon^{eu}(t, j)$, $\varepsilon^{pu}(t, j)$ and $\varepsilon^k(t)$ that represent the monetary policy shock, the economic uncertainty shock, the economic policy uncertainty

shock and the capital flows shock, respectively. Interestingly, and this represents the value added of our methodology, the mixed frequency nature of the variables allows to identify the high frequency structural shocks hitting the low frequency variables m times ($m = 3$ in our empirical analysis) within the same quarter t.

The "relatively reduced" dimensionality of the model makes the ML estimator, generally used in the traditional SVAR literature, easily implementable and allows hypothesis testing on the restrictions in the A and B matrices in Eq. (18), as well as those on the dynamics of the model, to behave as standard LR tests.[14]

In Section 3.3 we proposed a test for investigating whether the MIDAS-SVAR model is effectively more powerful than a traditional SVAR model, both for the dynamics part and the structural part of the model. The test strongly suggests that the MIDAS-SVAR model performs better than the traditional SVAR using low-frequency variables only. The details concerning the test implementation are provided in Appendix B.

4.5   Estimation Results

Figure 3 graphs the IRFs of capital inflows, $k(t)$, to a monetary policy shock, an economic uncertainty shock, a policy uncertainty shock and a capital flow shock. As previously discussed, the monetary policy shock and both uncertainty shocks are expected to affect the low frequency variable $k(t)$ in all three months within the quarter. Such effects are displayed on the left column of Figure 3 for the monetary policy shock, on the middle column for the economic uncertainty shock and on the right column for the policy uncertainty one. The last graph, at the bottom, reports the response of capital inflows, $k(t)$, to a shock to itself.

The first interesting result is that the impact effect on capital inflows of an unanticipated increase in the Fed Funds rate is different depending on the month it happens within the quarter, though the dynamic response is similar in the three cases. The effect is positive and significant when the interest-rate shock occurs in the first month of the quarter, positive but significant only after two quarters when the shock occurs in the second month, while it becomes negative when the shock takes place in the third month, i.e. at the end of the quarter. In other words, an unexpected monetary contraction, i.e. an increase in the Fed Funds rate, has a positive effect on capital inflows when it takes place at the beginning of the quarter while the effect is negative at the end of the quarter. Thus, it appears that monetary policy shocks take time to display their effect on capital flows. To the extent that changes in interest rates are persistent, an interest rate increase that occurs at the beginning of the quarter and lasts over three months is expected to have a larger effect on capital inflows as it affects the net sale of assets over the entire three-month period over which they are measured. On the other hand, an interest rate shock occurring at the end of the quarter barely affects capital inflows within that quarter

---

[14]The estimates become quasi-ML when the assumption of a Gaussian likelihood is not supported by the data. As a consequence, all LR tests should be interpreted as quasi-LR tests.

since the latter are predetermined for the most part by the market conditions prevailing in the previous two months. The delayed effect of interest rate shocks occurring in the second month of the quarter is consistent with this interpretation. While asset prices and exchange rates immediately react to interest rate shocks, US capital inflows, i.e. the net sale of US assets to foreign residents, is a flow variable whose dimension increases with the sampling period. An increase in the interest rate occurring at the beginning of the quarter –and lasting until the end of the quarter– that raises the sales of US assets can have a sizable/significant effect on capital flows simply because these higher sales cumulate over the entire three-month period.

This interpretation requires that monetary policy shocks be persistent; if they were short lived, in particular if they lasted just for one month, their impact on capital flows would be the same independently of the month they occurred. Figure 4 shows the response of the Fed Funds rate to its own shock. A monetary policy shock has a rather persistent effect on the interest rate. A shock occurring at the beginning of the quarter produces a significant effect on the following two months too, before capital inflows data are collected. Actually, the response of the Fed Funds rate is hump-shaped reaching a peak after two months which suggests the possibility of a delayed reaction of capital flows. The result that monetary policy has different effects depending on its timing within the quarter explains the evidence reported in Section 2 that the monetary policy has no (or at most very weak) impact on capital inflows. In fact, aggregating the three impulse responses of Figure 3 (left panel) makes the overall quarterly effect very weak.

This discussion explains why a shock observed at the beginning of the quarter has a stronger effect than shocks occurring in the other two months. On the other hand, it is unclear and somewhat unexpected that a shock in the third month of the quarter has a negative, though not significant, effect, and that the response of capital flows is negative in the medium-long run, independently of the month of the shock. We come back to this issue in Section 4.6.

The middle and right columns of Figure 3 show the different responses of capital inflows to the two uncertainty shocks for each of the months in the quarter. The results are qualitatively similar to those obtained with the quarterly SVAR described in Section 2 but the negative impact of uncertainty shocks on capital inflows is much stronger and significant. In particular, economic uncertainty has an immediate effect on capital inflows, independently of the month within the quarter it hits the economy, while policy uncertainty takes few quarters before reaching its strongest effect.

Figures 4-8 complete the first set of results. In Figure 4-6 we show the effect of monetary policy shocks on economic uncertainty (VIX) and policy uncertainty (EPU). Figure 5 reports the responses of the VIX to a monetary policy shock. Interestingly, a shock to the Fed Funds rate occurring in the first month of the quarter has no effect, while it significantly reduces financial-market uncertainty when it takes place in the second month. The effect, moreover, is highly persistent. Figure 6 shows the effect of a monetary policy shock on EPU. Interestingly, a

monetary contraction has practically no effect on policy uncertainty, i.e. on EPU, unlike what happens for financial-market uncertainty as captured by the VIX.

Figure 7 and 8 report the reaction of the Fed Funds rate to the two uncertainty shocks. Figure 7 shows that the Fed reacts to economic uncertainty by increasing the interest rates, especially when the shock to the VIX occurs at the beginning of the quarter. The effect of the VIX shock is significant and persistent. On the contrary, the responses reported in Figure 8 show that a policy uncertainty shock leads to a monetary expansion that appears to be significant especially when the shock hits the economy in the third month of the quarter.

In Table 3 we report the Forecast Error Variance Decomposition (FEVD) for the capital inflows subject to monetary policy, economic and policy uncertainty shocks in the AB-MIDAS-SVAR model (panel b), calculated at different horizons (0, 1, 4, 8, 20 quarters). Such results are compared to those obtained through the aggregate quarterly SVAR discussed in Section 2 (panel a). The monetary policy shocks in the AB-MIDAS-SVAR model, aggregately, account roughly the double of the variance of capital flows compared to the quarterly SVAR model, at all horizons. The results are even more striking when comparing the economic and policy uncertainty shocks with respect to the uncertainty shock in the quarterly SVAR. Taken together, the economic and policy uncertainty shocks explain more than one fourth of the variability of the capital-flows forecast error in the medium- and long-run against much less than the 5% for the uncertainty shock in the quarterly SVAR model.

All the previous results confirm that the MIDAS-SVAR model performs enormously better than the quarterly SVAR: All the identified structural shocks explain a much larger part of the forecast error variance and provide richer impulse responses exploiting the dynamics within the quarter.

4.6 US interest rates to international interest rates

We now turn to the puzzle of the negative response of capital inflows to interest-rate shocks that occur in the third month of the quarter and to the negative effect that such flows display in the medium-long run independently of the month when the monetary contraction takes place. A potential explanation for these results is the omitted consideration in our AB-MIDAS-SVAR model of the reaction by other major central banks to the Federal Reserve's policy actions.

In fact, there is substantial evidence that European interest rates are affected by US monetary policy (see, among others, Favero and Giavazzi (2008)) and it seems likely that the interest rates of many other economies are influenced by the Fed's policy actions. In Section 4, we saw that a US monetary contraction leads to a significant increase in capital inflows when the shock occurs at the beginning of the quarter. However, to the extent that foreign interest rates react to US policy shocks, we expect capital flows to the US to come to an halt as other low-risk countries follow the same monetary policy.

Hence, we repeat our analysis by including in all equations, as potential control (exogenous)

variables, lagged EU and Japanese short-term interest rates. The residuals of the MIDAS-VAR will thus be orthogonal to the two main foreign competitor policy rates. The resulting structural shocks, thus, will capture the domestic effects only. The impulse responses for the total capital inflows, reported in Figure 11 (Dot-Dash-black lines), show that the negative impact of the monetary policy shocks arising in the third month of the quarter previously detected (reported in Figure 3) switch to positive. Furthermore, the negative effect on capital inflows in the medium-long run disappears for all three interest-rate shocks within the quarter. This sort of correction also applies to the financial capital inflows too, as discussed in the next Section 5.1.

5 Further investigations

In this section we provide further evidence on the relationships between monetary policy, uncertainty and capital flows. We distinguish between: (a) Foreign Direct Investment (FDI) and; (b) Portfolio Investment and Bank Transfers. This distinction is potentially interesting because FDI is concerned with returns over a long horizon while portfolio investment and bank flows are of a more speculative nature and are more sensitive to short-term economic uncertainty.

5.1 FDI and "financial" capital flows

As mentioned in Section 2, Bruno and Shin (2015) investigate the dynamics linking monetary policy with bank leverage, and show that adjustments in leverage play a relevant role in the monetary transmission mechanism, especially through fluctuations in risk-taking. In particular they find that a decline in US dollar bank funding costs results in an increase in bank leverage. At the same time, they also show that banking sector leverage is closely tied to risk measures, like the VIX. In this section we distinguish between "real-economy" FDI, and "financial" inflows, given by the sum of portfolio investment and bank transfers. This decomposition aims at investigating whether the US monetary policy shocks from one side and the economic and policy uncertainty shocks from the other have a different impact on the two components of the US capital inflows. Differently from Bruno and Shin (2015), we do not consider the risk channel only (or the economic uncertainty, using our terminology) but include the further potential source of uncertainty, provided by the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016).

The decomposition between FDI and financial capital inflows is studied through two MIDAS-SVAR models to obtain more deepened results concerning the transmission of monetary policy shocks, and economic and policy uncertainty shocks. The structure of the two models is practically the same and consists in a MIDAS-VAR model like the one in Eqs. (16)-(17), where, differently from the previous model, $k(t)$ is in turn, financial capital inflows or FDI. As for the previous MIDAS-VAR model, we include the inflation rate $\pi(t,j)$ and the industrial production index $ip(t,j)$, with $j = 1,..,3$, observed at monthly frequency.

The structural MIDAS-SVAR is identical to the one provided in Eq. (18). In the A matrix we include the coefficients of all contemporaneous relations among the high- and low-frequency variables, the within quarter relations between low- and high-frequency variables and the within quarter dynamics between $x_H(t,i)$ and $x_H(t,j)$, with $i > j$. The B matrix, instead, contains the simultaneous effects of the structural shocks among the variables, and within the quarter. The ordering is $\tilde{x}(t)' = \Big(i(t,1), vix(t,1), epu(t,1), i(t,2), vix(t,2), epu(t,2),$ $i(t,3), vix(t,3), epu(t,3), k(t) \Big)$, where $k(t)$ is the FDI/GDP in the first model, while "financial" flows/GDP in the second one. This ordering of the variables allows to identify the high frequency monetary policy shocks $\varepsilon^{mp}(t,j)$, economic uncertainty shocks $\varepsilon^{eu}(t,j)$ and economic policy uncertainty shocks $\varepsilon^{epu}(t,j)$, and, depending on the model, either financial flows $\varepsilon^{fin}(t)$ or FDI shocks $\varepsilon^{fdi}(t)$.

Following the same strategy for the MIDAS-SVAR model in Section 16, we select two lags and confirm the stationarity of the series. In Figure 9, we report the impulse responses for the financial inflows. The effect of the three structural shocks is very similar to the ones observed for the total capital inflows. Specifically, the monetary policy impact is initially positive and significant when the shock occurs during the first two months of the quarter, while it is negative though not significant when the shock hits during the last month. Concerning the economic and uncertainty shocks, the effect on financial inflows is overall negative, apart a surprising, but only marginally significant, positive swing following a policy uncertainty shock in the last month of the quarter. These results are consistent with Bruno and Shin (2015) although we use a wider aggregate for "financial" inflows and a longer sample period (from 1988 to 2013 compared to the 1995-2007 period).

Figure 10 shows the impulse responses of FDI to the three high frequency shocks. The impact of monetary policy shocks is much smaller (and not significant) with respect to the financial and total capital inflows, although the path of the IRFs is similar. The main difference with previous results for total inflows concerns economic uncertainty shocks whose impact tends to be positive, though generally not significant, possibly indicating that a surge in financial-market risk shifts investors' preferences towards longer horizon FDI. By contrast, policy uncertainty shocks, when the effect is significant, lead to a contraction in FDI flows. The last two results are interesting in that differentiating between economic and economic policy uncertainty allows to understand the different reaction of long-horizon investments to the two types of uncertainty. While both economic and policy uncertainty act as deterrent to short-run investment and thus financial inflows, only economic policy uncertainty negatively affects long-run investment and FDI flows.

6   Robustness checks

In this section we provide some robustness check in order to validate our main empirical findings. We first include in the MIDAS-VAR model an additional set of exogenous regressors; next, we focus on the sub-sample obtained by excluding the global financial crisis, in which the policy interest rates showed practically no variability. Lastly, we use an alternative proxy of economic uncertainty.

6.1   Controlling for other explanatory variables

In the main specification discussed in Section 4.3 we included, among the exogenous regressors, the monthly industrial production index (growth rate) and the inflation rate. These variables help identify the monetary policy shocks. However, other variables are likely to be relevant in explaining the dynamics of the short-term interest rate, the uncertainty indexes and, more importantly, the different aggregates of capital inflows. We thus repeat the analysis by considering other control variables. In particular, we include an indicator of the global business cycle measured by the aggregate industrial production (growth rate) of the OECD+BRICST[15] countries, an indicator of the behavior of the US stock financial market measured by the S&P500 index (growth rate)[16], the US long-term interest rates measured through the 10-year maturity sovereign bond rates, the effective exchange rate and an alternative indicator for the US business cycle measured by the monthly civilian unemployment rate. All these new variables enter lagged one period (one month) in order to avoid endogeneity issues.

The results are reported in Figures 11-13, for the total capital inflows, financial capital inflows and FDI, respectively. In all figures we compare the IRFs of these last results (red lines) to the main ones previously discussed (dashed-blue lines). The graphs show that our main results are extremely robust to a different specification of the MIDAS-VAR models and that the monetary policy, the economic uncertainty and the economic policy uncertainty impact, over the three months characterizing the quarter, still remain.

6.2   Pre-crisis period

Just after the global financial crisis, the Federal Reserve started to implement unconventional monetary policies rather than acting on the short term interest rate that remained practically constant around zero. Given the absence of variability of the Fed Funds rate during the most recent period, we re-estimated the models over the pre-crises period, from 1988:1 to 2007:3.

The results for total capital inflows, financial inflows and FDIs are reported in Figures 11-13, respectively. The new IRFs (dot-dash-black) are shown together with all other results. All

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[15]Brazil, Russia, India, China, South Africa and Turkey.

[16]Practically indistinguishable results are obtained by using the MSCI-World Index or the levels of the variable instead of the growth rates.

IRFs are very similar and, once considering the natural uncertainty shown by the confidence bands (not reported here to simplify the visual impact of the curves), we can conclude that the results are extremely in line with the main findings presented in Section 4.5.

6.3 An alternative economic uncertainty proxy

Although the VIX has a forward-looking component, its one-month horizon is too short to proxy uncertainty over longer periods which are arguably more relevant for investment decisions yielding returns in the medium and long run. Jurado, Ludvigson, and Ng (2015, p.1178) start from the premise that *"what matters for economic decision making is not whether particular economic indicators have become more or less variable or disperse per se, but rather whether the economy has become more or less predictable; that is, less or more uncertain."*. This notion of uncertainty can be formalized as follows:

$$\mathcal{U}_{i,t}(h) \equiv \sqrt{E\left[(y_{it} - E[y_{it-h}|I_t])^2 | I_t\right]}.$$

Uncertainty is the conditional volatility of the unpredictable component of the series. A broad index of macroeconomic uncertainty can be therefore obtained by aggregating uncertainty for a large set of macroeconomic and financial variables, denoted by $\mathcal{U}_t(h)$ where h is the forecast horizon:

$$\mathcal{U}_t(h) \equiv \frac{1}{N}\sum_{i=1}^{N}\mathcal{U}_{i,t}(h).$$

An interesting feature of this index is its ability to track uncertainty at different horizons, unlike the VIX. This is particularly relevant for investment decisions that are affected by uncertainty over several years.

The results, both in terms of IRFs and FEVD, not reported here, are rather similar to those obtained with the VIX, whatever the horizon used $(h = 1, 3, 12)$[17].

7 Concluding remarks

The paper presented new evidences on the effects of monetary policy and uncertainty on US capital inflows. In particular we have shown that the so far weak evidences of monetary policy shocks on gross capital inflows are mainly due to the different impact of these shocks hitting the economy in the three months of the observed quarter.

The introduction of an appropriate multivariate model dealing with the different frequency at which the variables are observed, the MIDAS-VAR, allows to highlight these different effects. Specifically, a restrictive monetary policy shock has a strong positive impact on gross flows when appearing in the first two months of the quarter. The effect becomes negative when the

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[17]The complete set of results can be obtained from the authors upon request

shock strikes the economy in the last month. Similar evidences have been found for the two main components of the gross capital inflows, FDI and the sum of portfolio and bank transfer, called "financial" investment in the paper. The effect of the US monetary policy is stronger for the "financial" investments rather then for FDI.

The same approach has been used for detecting the effect of different uncertainty indicators on the US capital inflows. In particular, when jointly considering economic uncertainty and policy uncertainty, this latter has a negative impact on "financial" capital inflows, especially when these shocks happen at the beginning and ending of the quarter in which the flows are observed. The FDI, as expected, are less sensitive to uncertainty shocks.

Finally, the econometric approach, easily manageable through standard estimation and inferential tools, provides applied macro-econometricians/economists with a reference methodology for investigating the transmission of shocks when variables at different frequencies (monthly-quarterly, quarterly-annual) enter the model.

References

AMISANO, G., AND C. GIANNINI (1997): *Topics in structural VAR econometrics*. Springer-Verlag, 2nd edn.

ANDREU, A., E. GHYSELS, AND A. KOURTELLOS (2010): "Regression models with mixed sampling frequencies," *Journal of Econometrics*, 158, 246–261.

AROUBA, S. B., F. X. DIEBOLD, AND C. SCOTTI (2009): "Real-Time Measurement of Business Conditions," *Journal of Business & Economic Statistics*, 27(4), 417–427.

BACCHIOCCHI, E., E. CASTELNUOVO, AND L. FANELLI (2016): "Gimme a Break! Identification and Estimation of the Macroeconomic Effects of Monetary Policy Shocks in the U.S.," *Macroeconomic Dynamics*, forthcoming.

BACCHIOCCHI, E., AND L. FANELLI (2015): "Identification in Structural Vector Autoregressive Models with Structural Changes with an Application to U.S. Monetary Policy," *Oxford Bulletin of Economics and Statistics*, 77(6), 761–779.

BAKER, S. R., N. BLOOM, AND S. J. DAVIS (2016): "Measuring Economic Policy Uncertainty," *The Quarterly Journal of Economics*, forthcoming.

BAYAR, O. (2014): "Temporal aggregation and estimated monetary policy rules," *The B.E. Journal of Macroeconomics*, 14(1), 553–557.

BEKAERT, G., M. HOEROVA, AND M. LO DUCA (2013): "Risk, uncertainty and monetary policy," *Journal of Monetary Economics*, 60(7), 771–788.

BERNANKE, B. (1986): "Alternative explanations of the money-income correlation," *Carnegie-Rochester Conference Series on Public Policy*, 25(4), 49–99.

BLANCHARD, O. (1989): "A traditional interpretation of macroeconomic Fluctuations," *American Economic Review*, 79(4), 1146–1164.

BLANCHARD, O., AND R. PEROTTI (2002): "An empirical characterization of the dynamic effects of changes in government spending and taxes on output," *The Quarterly Journal of Economics*, 117(4), 1329–1368.

BLOOM, N. (2009): "The impact of uncertainty shocks," *Econometrica*, 77(3), 623 – 685.

——— (2014): "Fluctuations in uncertainty," *Journal of Economic Perspectives*, 28(2), 153 – 176.

BRUNO, V., AND H. S. SHIN (2015): "Capital flows and the risk-taking channel of monetary policy," *Journal of Monetary Economics*, 71(2), 119–132.

CARRIÈRE-SWALLOW, Y., AND L. F. CÉSPEDES (2013): "The impact of uncertainty shocks in emerging economies," *Journal of International Economics*, 90(2), 316 – 325.

CHRISTENSEN, B. J., O. POSCH, AND M. VAN DER WEL (2016): "Estimating dynamic equilibrium models using mixed frequency macro and financial data," *Journal of Econometrics*, 194(1), 116–137.

CHRISTIANO, L., M. EICHENBAUM, AND C. EVANS (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113(1), 1–45.

CHRISTIANO, L. J., AND M. EICHENBAUM (1987): "Temporal aggregation and structural inference in macroeconomics," *Carnegie-Rochester Conference Series on Public Policy*, 26, 63–130.

CHRISTIANO, L. J., M. EICHENBAUM, AND C. L. EVANS (1999): "Monetary Policy Shocks: What Have We Learned and to What End?," in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford. Amsterdam: North-Holland.

CLAESSENS, S., M. A. KOSE, AND M. E. TERRONES (2009): "What happens during recessions, crunches and busts?," *Economic Policy*, 24(60), 653–700.

——— (2012): "How do business and financial cycles interact?," *Journal of International Economics*, 87(1), 178–190.

CLEMENTS, M. P., AND A. B. GALVAO (2008): "Macroeconomic Forecasting With Mixed-Frequency Data," *Journal of Business & Economic Statistics*, 26, 546–554.

——— (2009): "Forecasting US output growth using leading indicators: an appraisal using MIDAS models," *Journal of Applied Econometrics*, 24(7), 1187–1206.

ERAKER, B., C. W. J. CHIU, A. T. FOERSTER, T. B. KIM, AND H. D. SEOANE (2015): "Bayesian Mixed Frequency VARs," *Journal of Financial Econometrics*, 13(3), 698–721.

FAVERO, C., AND F. GIAVAZZI (2008): "Should the Euro Area Be Run as a Closed Economy?," *The American Economic Review, Papers and Proceedings of the OneHundred Twentieth Annual Meeting of the American Economic Association*, 98, 138–145.

FERRARA, L., AND P. GUERIN (2015): "What Are The Macroeconomic Effects of High-Frequency Uncertainty Shocks?," EconomiX Working Papers 2015-12, University of Paris West - Nanterre la Defense, EconomiX.

FORBES, K. J., AND F. E. WARNOCK (2012): "Capital flow waves: Surges, stops, flight, and retrenchment," *Journal of International Economics*, 88(2), 235–251.

FORONI, C., E. GHYSELS, AND M. MARCELLINO (2014): "Mixed-frequency Vector Autoregressive Models," *Advances in Econometrics*, 32, 247–272.

FORONI, C., P. GUÉRIN, AND M. MARCELLINO (2015): "Using low frequency information for predicting high frequency variables," Discussion Paper 2015/13, Norges Bank Working Paper.

FORONI, C., AND M. MARCELLINO (2014): "Mixed-Frequency structural models: Identification, estimation, and policy analysis," *Journal of Applied Econometrics*, 29(7), 1118–1144.

FORONI, C., M. MARCELLINO, AND C. SCHUMACHER (2014): "Unrestricted mixed data sampling (UMIDAS): MIDAS regressions with unrestricted lag polynomials," *Journal of the Royal Statistical Society A*, 178(1), 57–82.

GHYSELS, E. (2016): "Macroeconomics and the Reality of Mixed Frequency Data," *Journal of Econometrics*, 193(2), 294–314.

GIANNONE, D., L. REICHLIN, AND D. SMALL (2008): "Nowcasting: The real-time informational content of macroeconomic data," *Journal of Monetary Economics*, 55(4), 665–676.

JORDÀ, Ò., M. SCHULARICK, AND A. M. TAYLOR (2011): "Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons," *IMF Economic Review*, 59(2), 340–378.

JURADO, K., S. C. LUDVIGSON, AND S. NG (2015): "Measuring uncertainty," *American Economic Review*, 105(3), 1177–1216.

LÜTKEPOHL, H. (ed.) (2006): *New Introduction to Multiple Time Series*. Springer.

MARCELLINO, M. (1999): "Some Consequences of Temporal Aggregation in Empirical Analysis," *Journal of Business & Economic Statistics*, 17(1), 129–136.

MARIANO, R., AND Y. MURASAWA (2003): "A new coincident index of business cycles based on monthly and quarterly series," *Journal of Applied Econometrics*, 18(4), 427–443.

MILESI-FERRETTI, G.-M., AND C. TILLE (2011): "The great retrenchment: international capital flows during the global financial crisis," *Economic Policy*, 26(66), 289–346.

REINHART, C., AND V. REINHART (2009): "Capital Flow Bonanzas: An Encompassing View of the Past and Present," in *NBER International Seminar on Macroeconomics 2008*, ed. by J. Frankel, and C. Pissarides, chap. 1, pp. 9–62. University of Chicago Press.

REY, H. (2015): "Dilemma, not Trilemma: The global financial cycle and monetary policy independence," Working Paper 21162, National Bureau of Economic Research.

ROSSI, B., AND T. SEKHPOSYAN (2015): "Macroeconomic uncertainty indices based on nowcast and forecast error distributions," *American Economic Review: Papers and Proceedings*, 105(5), 650–655.

ROTHENBERG, T. J. (1971): "Identification in parametric models," *Econometrica*, 39, 577–591.

SCHORFHEIDE, F., AND D. SONG (2015): "Real-Time Forecasting with a Mixed-Frequency VAR," *Journal of Business & Economic Statistics*, 33(3), 366–380.

SEGAL, G., I. SHALIASTOVICH, AND A. YARON (2015): "Good and bad uncertainty: Macroeconomic and financial market implications," *Journal of Financial Economics*, 117(2), 369–397.

TAYLOR, J. (1993): "Discretion versus Policy Rules in Practice," *Carnegie-Rochester Conference Series on Public Policy*, 39, 195–214.

ZADROZNY, P. A. (1990): "Forecasting US GNP at monthly intervals with an estimated bivariate time series model," *Federal Reserve Bank of Atlanta Economic Review*, 75, 2–15.

A Appendix: Mapping from MIDAS-VAR to VAR: Some details and further results

Consider the MIDAS-VAR models in Eq. (8) with potential exogenous variables included:

$$
\begin{pmatrix} x_H^1(t,1) \\ x_H^1(t,2) \\ x_H^1(t,3) \\ x_L^2(t) \end{pmatrix} = \begin{pmatrix} A_{11}^1 & A_{12}^1 & A_{13}^1 & A_1^1 \\ A_{21}^1 & A_{22}^1 & A_{23}^1 & A_2^1 \\ A_{31}^1 & A_{32}^1 & A_{33}^1 & A_3^1 \\ A_{L1}^1 & A_{L2}^1 & A_{L3}^1 & A_L^1 \end{pmatrix} \begin{pmatrix} x_H^1(t-1,1) \\ x_H^1(t-1,2) \\ x_H^1(t-1,3) \\ x_L^2(t-1) \end{pmatrix} +
$$

$$
+ \begin{pmatrix} C_{11}^1 & C_{12}^1 & C_{13}^1 & C_1^1 \\ C_{21}^1 & C_{22}^1 & C_{23}^1 & C_2^1 \\ C_{31}^1 & C_{32}^1 & C_{33}^1 & C_3^1 \\ C_{L1}^1 & C_{L2}^1 & C_{L3}^1 & C_L^1 \end{pmatrix} \begin{pmatrix} z_H(t,1) \\ z_H(t,2) \\ z_H(t,3) \\ z_L(t) \end{pmatrix} + \begin{pmatrix} u_H^1(t,1) \\ u_H^1(t,2) \\ u_H^1(t,3) \\ u_L^2(t) \end{pmatrix} \tag{19}
$$

where $z_H(t,i)$ is the vector of high-frequency exogenous variables for the i-th month of quarter t and $z_L(t)$ is the vector of low-frequency exogenous variables at quarter t. If we continue to suppose that the monthly data are aggregated to obtain quarterly data, pre-multiplying both sides by the G matrix defined in Eq. (11), we obtain

$$
\begin{pmatrix} \bar{x}_L^1(t) \\ \bar{x}_L^2(t) \end{pmatrix} = \begin{pmatrix} \bar{A}_{11}^1 & \bar{A}_{12}^1 \\ \bar{A}_{21}^1 & \bar{A}_{22}^1 \end{pmatrix} \begin{pmatrix} x_H^1(t-1,1) \\ x_H^1(t-1,2) \\ x_H^1(t-1,3) \\ x_L^2(t-1) \end{pmatrix} + \begin{pmatrix} \bar{C}_{11}^1 & \bar{C}_{12}^1 \\ \bar{C}_{21}^1 & \bar{C}_{22}^1 \end{pmatrix} \begin{pmatrix} z_H^1(t-1,1) \\ z_H^1(t-1,2) \\ z_H^1(t-1,3) \\ z_L^2(t) \end{pmatrix} + \begin{pmatrix} \bar{u}_L^1(t) \\ \bar{u}_L^2(t) \end{pmatrix} \tag{20}
$$

with

$$
\begin{aligned}
\bar{A}_{11}^1 &= \begin{pmatrix} A_{11}^1 + A_{21}^1 + A_{31}^1 & A_{12}^1 + A_{22}^1 + A_{32}^1 & A_{13}^1 + A_{23}^1 + A_{33}^1 \end{pmatrix} \\
\bar{A}_{21}^1 &= \begin{pmatrix} A_{L1}^1 & A_{L2}^1 & A_{L3}^1 \end{pmatrix} \\
\bar{A}_{12}^1 &= A_1^1 + A_2^1 + A_3^1 \\
\bar{A}_{22}^1 &= A_L^1 \\
\bar{C}_{11}^1 &= \begin{pmatrix} C_{11}^1 + C_{21}^1 + C_{31}^1 & C_{12}^1 + C_{22}^1 + C_{32}^1 & C_{13}^1 + C_{23}^1 + C_{33}^1 \end{pmatrix} \\
\bar{C}_{21}^1 &= \begin{pmatrix} C_{L1}^1 & C_{L2}^1 & C_{L3}^1 \end{pmatrix} \\
\bar{C}_{12}^1 &= C_1^1 + C_2^1 + C_3^1 \\
\bar{C}_{22}^1 &= C_L^1
\end{aligned} \tag{21}
$$

When there are no exogenous variables, it immediately emerges that the VAR and the MIDAS-VAR will be equivalent when the null hypothesis in Eq. (12) is supported by the data. In the case of included exogenous variables, as in the empirical application presented in the paper, the null hypothesis for testing the mapping between the two specification must include the following

relations

$$H_0^3 \quad : \quad \left(C_{11}^1 + C_{21}^1 + C_{31}^1\right) = \left(C_{21}^1 + C_{22}^1 + C_{32}^1\right) = \left(C_{31}^1 + C_{32}^1 + C_{33}^1\right)$$
$$H_0^4 \quad : \quad C_{L1}^1 = C_{L2}^1 = C_{L3}^1. \tag{22}$$

Concerning the matching between the two structural representations, it can be easily proved by pre-multiplying both sides of Eq. (13) by the G matrix defined before, irregardless the presence or not of exogenous variables. The null hypothesis in Eq. (15) immediately follows.

A.1 Different aggregation schemes

The use of the selection matrix G allows to evaluate the differences between MIDAS-SVARs and traditional SVARs when alternative aggregations of the high frequency variables occur. If, for example, the aggregation scheme consists in taking the first observation of the quarter only, the G matrix becomes:

$$G = \begin{pmatrix} I_{n_H} & 0 & 0 & 0 \\ 0 & 0 & 0 & I_{n_L} \end{pmatrix} \tag{23}$$

and the associated null hypothesis for testing the equivalence between the two specifications (without exogenous variables, for simplicity) reduces to

$$H_0^1 \quad : \quad A_{12}^1 = A_{13}^1 = 0$$
$$H_0^2 \quad : \quad A_{L2}^1 = A_{L3}^1 = 0. \tag{24}$$

for the dynamic part of the model, and

$$H_0^1 \quad : \quad A_{12} = A_{13} = 0$$
$$H_0^2 \quad : \quad A_{L2} = A_{L3} = 0$$
$$H_0^3 \quad : \quad B_{12} = B_{13} =$$
$$H_0^4 \quad : \quad B_{L2} = B_{L3} = 0 \tag{25}$$

for the structural one. A very similar situation might occur when the aggregation scheme for high-frequency variables reduces to select the last observation of the quarter.

Extremely interesting, as it would reasonably be in many empirical applications, is the case where the high-frequency variables are aggregated differently with respect to their nature. As an example, interest rates and uncertainty measures could be selected at the beginning of the quarter, while inflation and industrial production could be aggregated by taking the quarter mean. Were this the case, for an hypothetical vector of high-frequency variables defined by $x_H(t,j) = \left(i\left(t,j\right), vix\left(t,j\right), epu\left(t,j\right), \pi\left(t,j\right), ip\left(t,j\right) \right)'$, and one single low-frequency variable

$k(t)$, the associated selection matrix would be

$$
G = \begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1/3 & 0 & 0 & 0 & 0 & 1/3 & 0 & 0 & 0 & 0 & 1/3 & 0 & 0 \\
0 & 0 & 0 & 0 & 1/3 & 0 & 0 & 0 & 0 & 1/3 & 0 & 0 & 0 & 0 & 1/3 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
\tag{26}
$$

with related null hypothesis obtained through the same reasoning as explained before.

B   Appendix: MIDAS-SVAR *vs* SVAR, Test implementation

This section is dedicated to the empirical implementation of the test. We consider that the low-frequency variables, as previously stressed, are obtained by adding high frequency variables. Alternative aggregation schemes are however discussed in Appendix A. Furthermore, we first focus on the reduced form model, and then discuss the structural form.

The reference null hypothesis is that reported in Eq. (12) and can be empirically implemented through a LR test. The reduced form is estimated both unrestrictedly and restrictedly and the two log-likelihood values are 838.29 and 761.02, respectively. The test statistic $LR = -2(761.02 - 838.29)$ asymptotically follows a $\chi_{(64)}$, with a related p-value practically equal to 0, strongly suggesting to reject the null. Aggregating the high frequency series as in traditional VARs generates a loss of information that is statistically highly significant. The number of degrees of freedom is given by the number of restrictions on the parameters related to the dynamics of the VAR (first row of Eq. (12), i.e. 18 restrictions for each of the two lags), plus the restrictions on the relationships between low- and high-frequency variables (second row of Eq. (12), i.e. 6 restrictions for each of the two lags), plus a set of further 16 restrictions on the exogenous variables (the details are discussed in Appendix A).

Such incontrovertible result favoring the MIDAS-VAR model yields completely unnecessary the test on the matching between the structural part of the MIDAS-SVAR versus the SVAR model, whose implementation, however, would have followed the same LR principle, as postulated in Eq. (15).[18]

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[18]As suggested in the Appendix A, one might be interested in alternative aggregation schemes. We have therefore tested whether the MIDAS-VAR model is comparable with the traditional VAR model obtained by taking the first month of the high-frequency variables instead of the mean. The null hypothesis is strongly rejected. The results continue to confirm the better performances of the MIDAS-VAR model. See Appendix A for the details on the definition of the null hypothesis.

C   Appendix: Figures and Tables

Table 1: Cross-correlations between uncertainty and Industrial Production: 1/1986 - 5/2014.

					Corr (x_{t+k}, IP_t)				
x_{t+k}	-12	-6	-3	-1	0	1	3	6	12
EPU	-0.059	-0.263	-0.302	-0.288	-0.277	-0.265	-0.237	-0.230	-0.302
$\mathcal{U}_t(1)$	-0.461	-0.770	-0.795	-0.757	-0.725	-0.686	-0.592	-0.449	-0.222
$\mathcal{U}_t(3)$	-0.468	-0.781	-0.804	-0.763	-0.730	-0.689	-0.591	-0.443	-0.207
$\mathcal{U}_t(12)$	-0.473	-0.792	-0.807	-0.755	-0.715	-0.669	-0.561	-0.397	-0.153
VIX	-0.170	-0.364	-0.399	-0.374	-0.341	-0.314	-0.280	-0.209	-0.138

Notes: Cross-correlations between uncertainty proxies and 12-months backward moving average of the percentage growth in U.S. Industrial Production (Jan. 1986 - May 2014). x_{t+k} denotes leads ($k > 0$) and lags ($k < 0$) of: EPU, the Economic Policy Uncertainty of Baker, Bloom, and Davis (2016), $\mathcal{U}_t(h)$ for $h = 1, 3, 12$ months, the macroeconomic uncertainty index of Jurado, Ludvigson, and Ng (2015), or the VIX. Negative (positive) correlation indicates that x_{t+k} is counter-cyclical (pro-cyclical). A maximum correlation for $k < 0$ ($k > 0$) indicates that x_{t+k} leads (lags) the business cycle.

Table 2: Descriptive statistics, cross-correlations and predictive regressions for uncertainty proxies: 1/1986 - 5/2014.

Panel (a): Descriptive statistics and cross-correlations.

				correlation with	
	CV	$\hat{\rho}$	$\hat{HL}$	$\mathcal{U}_{t+k}(1)$	VIX_{t+k}
EPU_t	0.31	0.84	3.98	0.423 (-12)	0.444 (1)
$\mathcal{U}_t(1)$	0.13	0.99	52.31		0.560 (2)
VIX_t	0.38	0.82	3.46		

Panel (b): Marginal R^2 from predictive regressions.

$R^2_{EPU \leftarrow \mathcal{U}}$	$R^2_{EPU \rightarrow \mathcal{U}}$	$R^2_{EPU \leftarrow VIX}$	$R^2_{EPU \rightarrow VIX}$	$R^2_{\mathcal{U} \leftarrow VIX}$	$R^2_{\mathcal{U} \rightarrow VIX}$
1.89	0.08	1.08	5.36	0.02	5.09

Notes: For each uncertainty proxy, columns 2-4 in Panel (a) show the coefficient of variation (CV), the estimate of the first order autocorrelation ($\hat{\rho}$) and the half-life ($\hat{HL}$). $\hat{\rho}$ and $\hat{HL} \equiv \ln(0.5) / \ln(\hat{\rho})$ have been estimated with an $AR(1)$ model. Columns 5-6 of Panel (a) show the cross-correlation between the row variable and the variable heading the column. Each cell in columns 5-6 displays the maximum correlation and the corresponding lead ($k > 0$) or lag ($k < 0$). A maximum correlation between, say EPU_t and VIX_{t+k} for $k < 0$, means that the VIX leads EPU. Panel (b) shows the marginal R^2 from predictive regressions. The marginal R^2 is defined as $100 \times \left(R^2_{UM} - R^2_{RM}\right)$. R^2_{RM} is the coefficient of determination associated to a model including 12 lags of the dependent variable and a constant. R^2_{UM} is the coefficient of determination associated to a model that includes variables in model RM and 12 lags of another explanatory variable. The headers of columns 1-6 can be read as follows: $R_{x \leftarrow y}$ means that the dependent variable is x and the explanatory variable is y, vice-versa for $R_{x \rightarrow y}$. If $R_{x \leftarrow y} > R_{x \rightarrow y}$ it means that y has predictive power for x.

Table 3: FEVD Quarterly SVAR and MIDAS-SVAR for capital flows

Panel a. Quarterly SVAR					
h	0	1	4	8	20
$FFR(t)$	1.25	2.66	3.17	4.31	12.75
$VIX(t)$	1.06	1.21	1.95	2.45	3.32
$k(t)$	97.70	96.13	94.88	93.24	83.94
Panel b. MIDAS-SVAR					
h	0	1	4	8	20
$FFR(t,1)$	2.11	3.95	5.01	5.81	11.41
$FFR(t,2)$	0.66	0.57	2.11	2.48	6.07
$FFR(t,3)$	2.84	2.74	2.30	4.80	8.41
$\sum FFR(t,m)$	5.61	7.26	9.41	13.10	25.89
$VIX(t,1)$	0.46	3.95	3.93	4.39	3.78
$VIX(t,2)$	1.74	2.12	5.85	6.05	5.20
$VIX(t,3)$	0.53	0.96	2.43	2.67	2.44
$\sum VIX(t,m)$	2.73	7.03	12.22	13.12	11.43
$EPU(t,1)$	3.07	2.98	2.70	3.56	3.09
$EPU(t,2)$	0.11	0.93	6.42	9.96	9.00
$EPU(t,3)$	1.18	3.92	5.11	5.18	5.45
$\sum EPU(t,m)$	4.36	7.83	14.23	18.71	17.55
$k(t)$	87.30	77.88	64.14	55.07	45.13

*Notes*: Forecast Error Variance Decomposition (FEVD) for the capital inflows subject to monetary policy shocks, economic and policy uncertainty shocks and capital shocks in the AB-MIDAS-SVAR model calculated at different horizons (0, 1, 4, 8, 20 quarters) (panel b), and FEVD obtained through the aggregate quarterly SVAR discussed in Section 2 (panel a). The sample period is 1988:1-2013:3.

Table 4: FEVD MIDAS-SVAR financial flows and FDI

Panel a. MIDAS-SVAR for financial flows					
h	0	1	4	8	20
$FFR(t,1)$	1.18	2.06	1.96	2.92	6.13
$FFR(t,2)$	0.15	0.18	0.71	1.28	3.43
$FFR(t,3)$	0.70	0.64	0.80	1.19	2.56
$\sum FFR(t,m)$	2.02	2.88	3.47	5.39	12.12
$VIX(t,1)$	1.00	1.76	2.00	2.13	2.03
$VIX(t,2)$	3.49	3.74	9.11	9.39	8.72
$VIX(t,3)$	0.86	3.79	4.66	4.41	3.94
$\sum VIX(t,m)$	5.35	9.29	15.77	15.94	14.69
$EPU(t,1)$	2.56	3.47	3.46	4.11	3.81
$EPU(t,2)$	0.67	1.22	6.93	10.21	10.84
$EPU(t,3)$	1.50	4.48	6.03	6.14	5.60
$\sum EPU(t,m)$	4.73	9.17	16.43	20.45	20.25
$FIN(t)$	87.89	78.66	64.33	58.22	52.94
Panel b. MIDAS-SVAR for FDI					
h	0	1	4	8	20
$FFR(t,1)$	1.39	1.46	1.31	1.29	1.45
$FFR(t,2)$	0.70	1.10	1.58	1.57	1.82
$FFR(t,3)$	0.16	1.58	1.33	1.44	1.63
$\sum FFR(t,m)$	2.25	4.14	4.21	4.30	4.89
$VIX(t,1)$	0.01	2.55	2.22	2.07	2.09
$VIX(t,2)$	0.09	0.82	0.75	0.80	1.19
$VIX(t,3)$	1.03	1.33	1.63	2.05	1.99
$\sum VIX(t,m)$	1.13	4.69	4.61	4.92	5.26
$EPU(t,1)$	0.27	0.45	0.59	1.13	1.74
$EPU(t,2)$	1.60	1.51	4.62	8.45	12.26
$EPU(t,3)$	0.03	0.07	0.57	1.17	1.60
$\sum EPU(t,m)$	1.90	2.03	5.79	10.76	15.61
$FDI(t)$	94.72	89.14	85.39	80.03	74.23

Notes: Forecast Error Variance Decomposition (FEVD) for the financial inflows (panel a) and FDI (panel b) subject to monetary policy shocks, economic and policy uncertainty shocks and capital shocks in the AB-MIDAS-SVAR model calculated at different horizons (0, 1, 4, 8, 20 quarters). The sample period is 1988:1-2013:3.

Figure 1: Uncertainty proxies: Jan. 1986 - May 2014
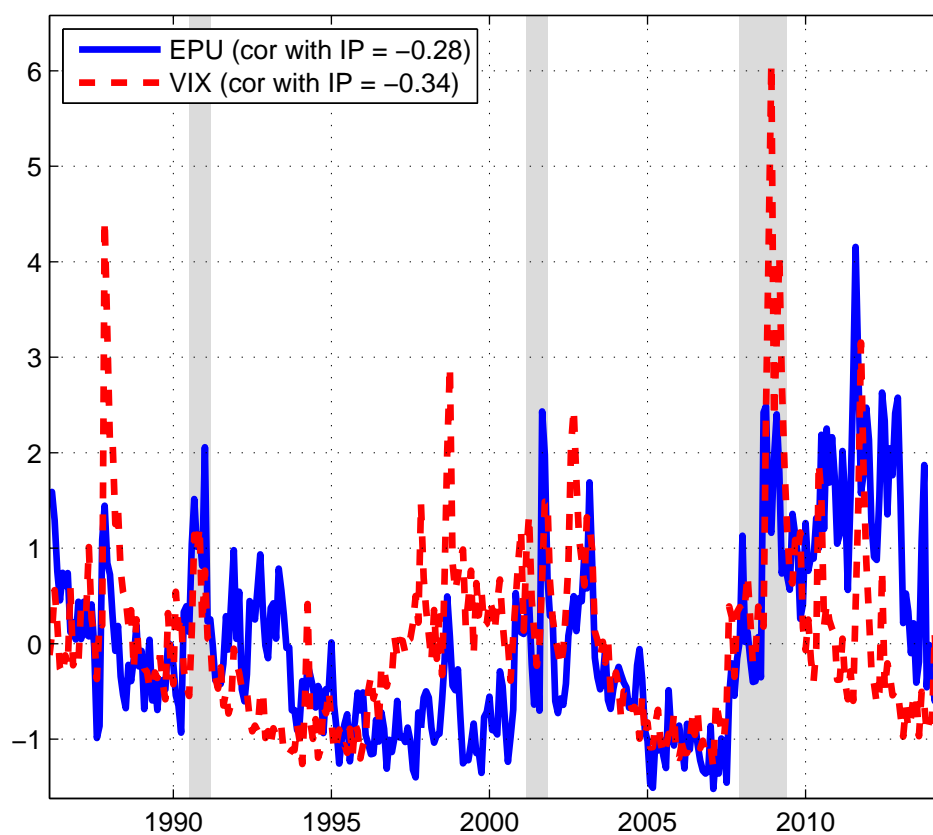
Notes: the figure shows the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016) and the VIX index. Both uncertainty indexes have been standardized to have zero sample mean and unit standard deviation. Their correlation with the 12 months backward moving average of the percentage growth in U.S. Industrial Production is shown in the legend. Shaded areas represent NBER recessions.

Figure 2: Monetary policy shocks, uncertainty shocks and gross capital flows: Quarterly VAR.
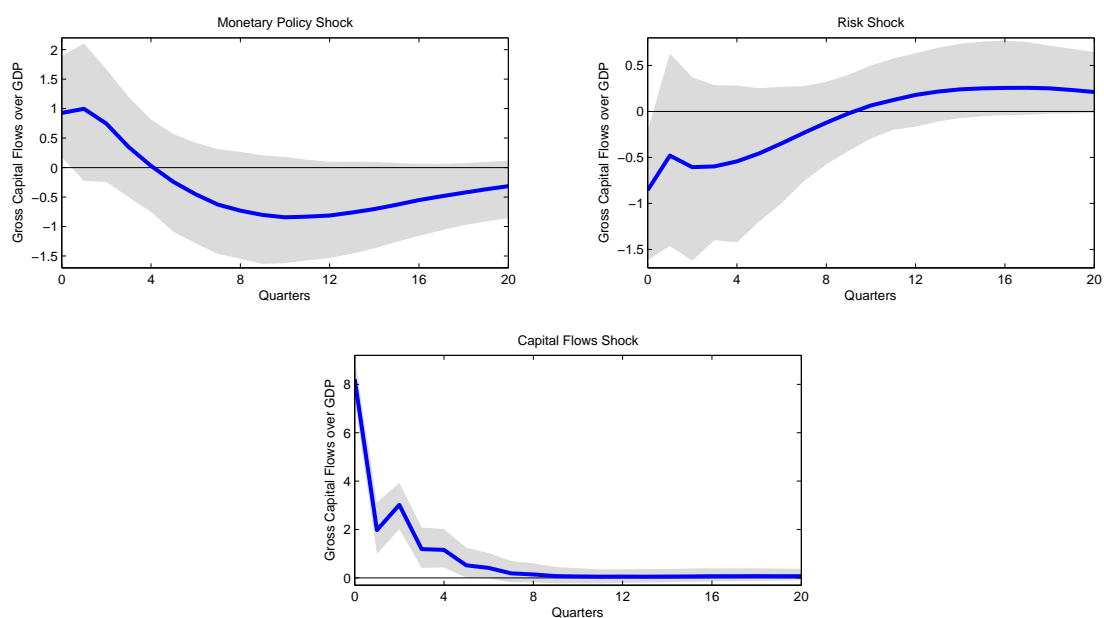
Notes: Impulse response functions and 90% bootstrapped confidence intervals for the SVAR model with quarterly observations. Response of gross capital flows over GDP to a monetary policy shock, an uncertainty shock and a capital shock. The sample period is 1988:1-2013:3.

Figure 3: Monetary policy shocks, economic uncertainty shocks, policy uncertainty shocks and **gross capital inflows**: MIDAS-SVAR model.
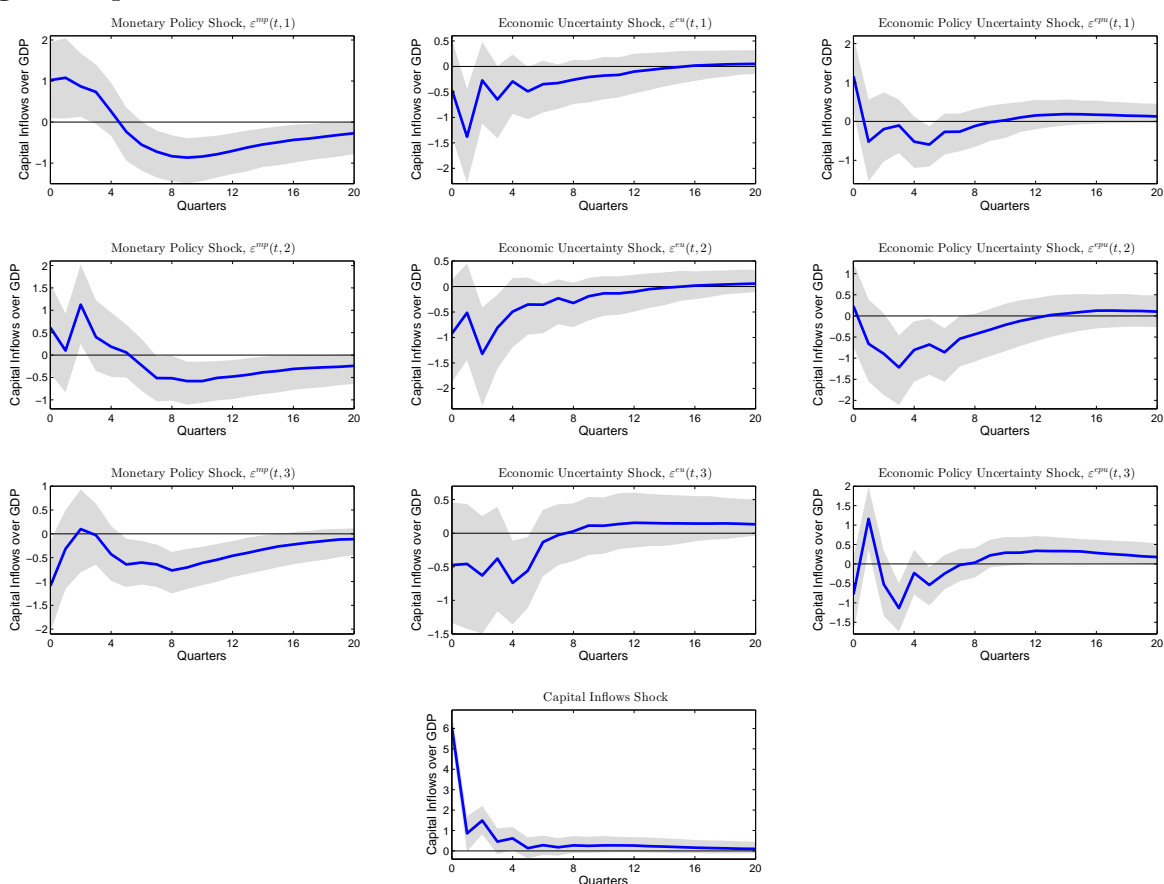
Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of gross capital flows over GDP $(k(t))$ to monetary policy shocks (left panel), economic uncertainty shocks (middle panel), policy uncertainty shocks (right panel) and capital shocks (bottom panel). "1", "2" and "3" indicate whether the shocks affect the low frequency $k(t)$ variable during the first, second and third month of the quarter, respectively. The sample period is 1988:1-2013:3.

Figure 4: Response of interest rate to monetary policy shocks: MIDAS-SVAR model.
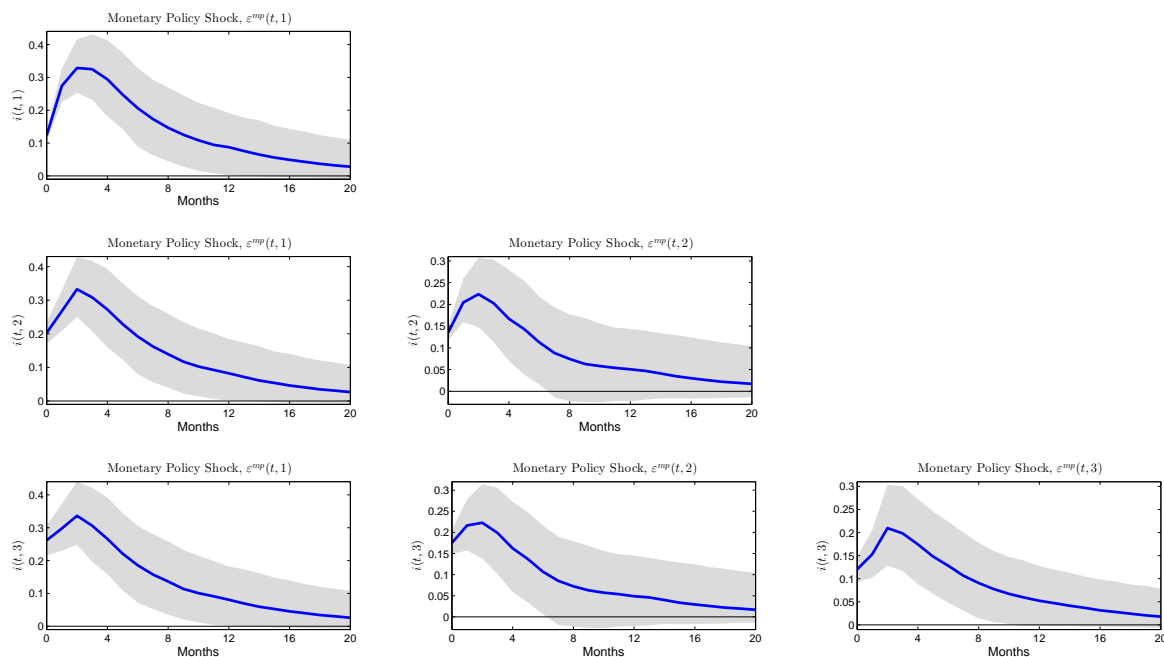
Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of Fed Funds rates $i(t,1)$ (upper row), $i(t,2)$ (middle row), $i(t,3)$ (lower row) to monetary policy shocks $\varepsilon^{mp}(t,1)$ (left panel), $\varepsilon^{mp}(t,2)$ (middle column) and $\varepsilon^{mp}(t,3)$ (right column). The sample period is 1988:1-2013:3.
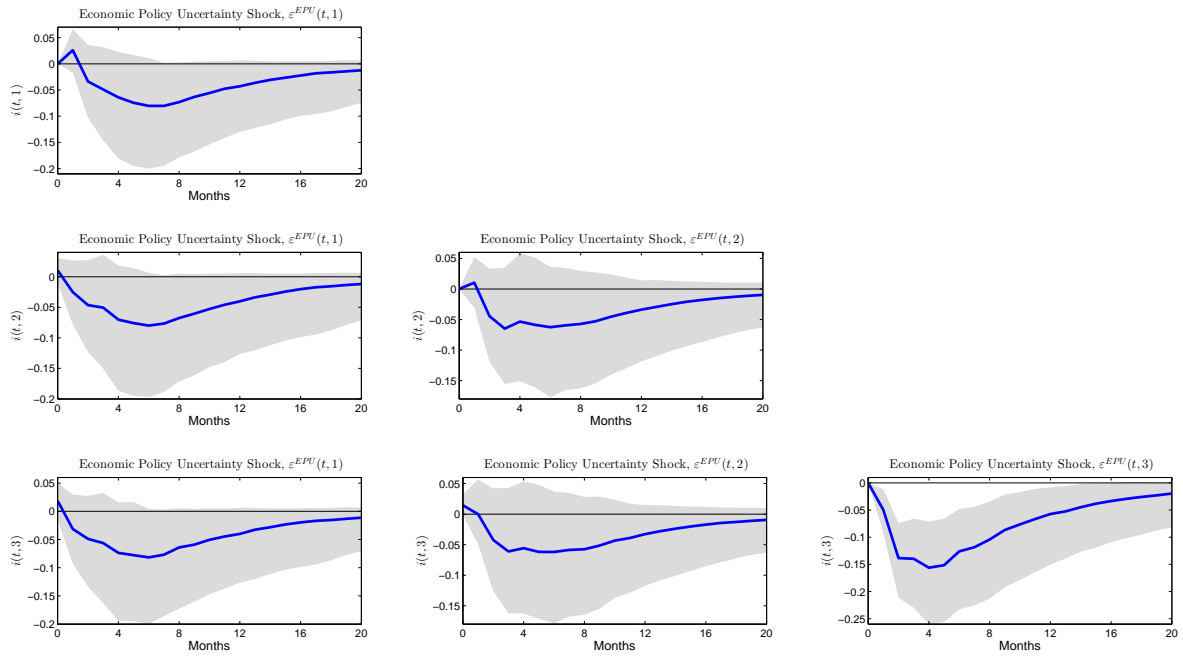
Figure 5: Response of VIX to monetary policy shocks: MIDAS-SVAR model.
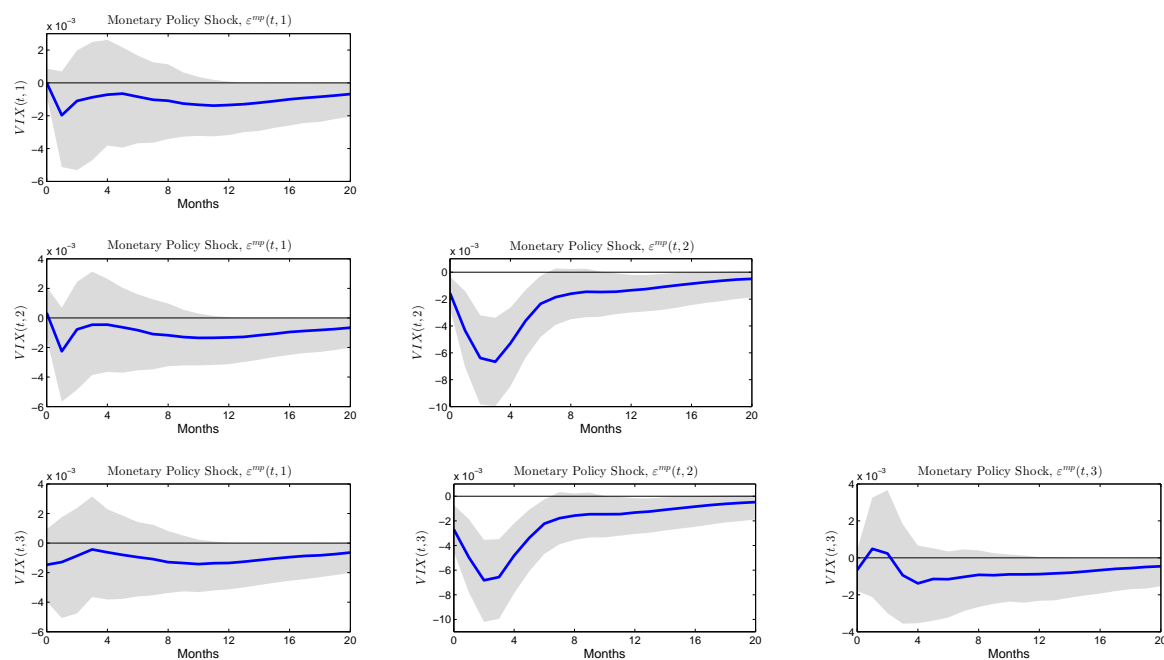
Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of $vix(t,1)$ (upper row), $vix(t,2)$ (middle row), $vix(t,3)$ (lower row) to monetary policy shocks $\varepsilon^{mp}(t,1)$ (left panel), $\varepsilon^{mp}(t,2)$ (middle column) and $\varepsilon^{mp}(t,3)$ (right column). The sample period is 1988:1-2013:3.
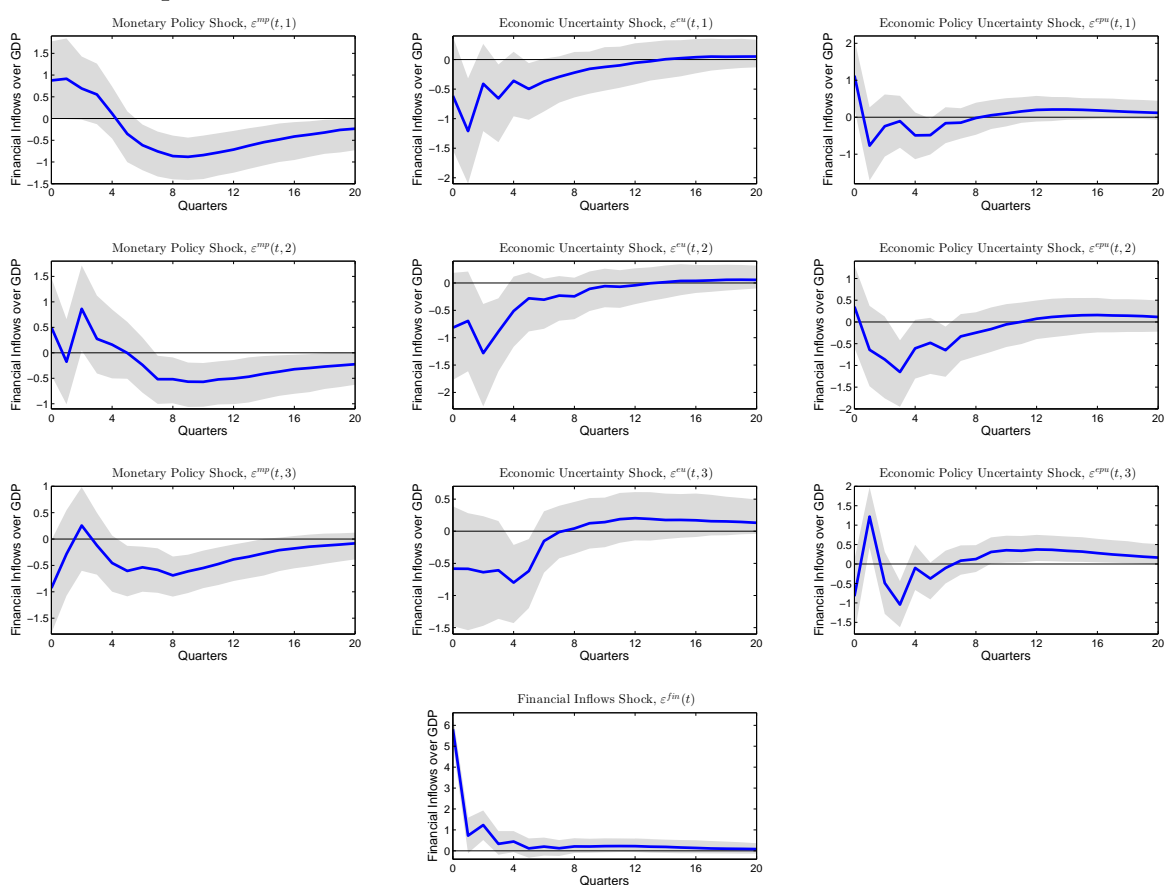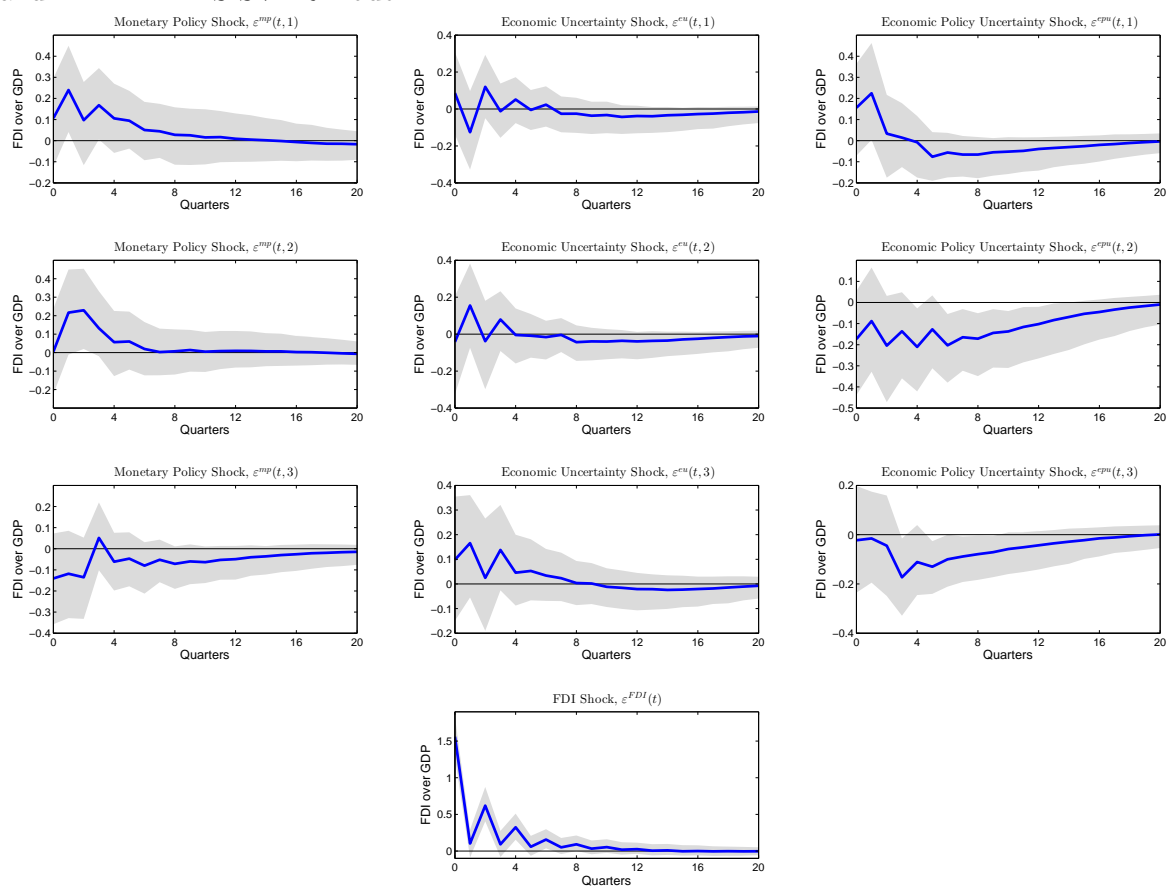
Figure 6: Response of EPU to monetary policy shocks: MIDAS-SVAR model.
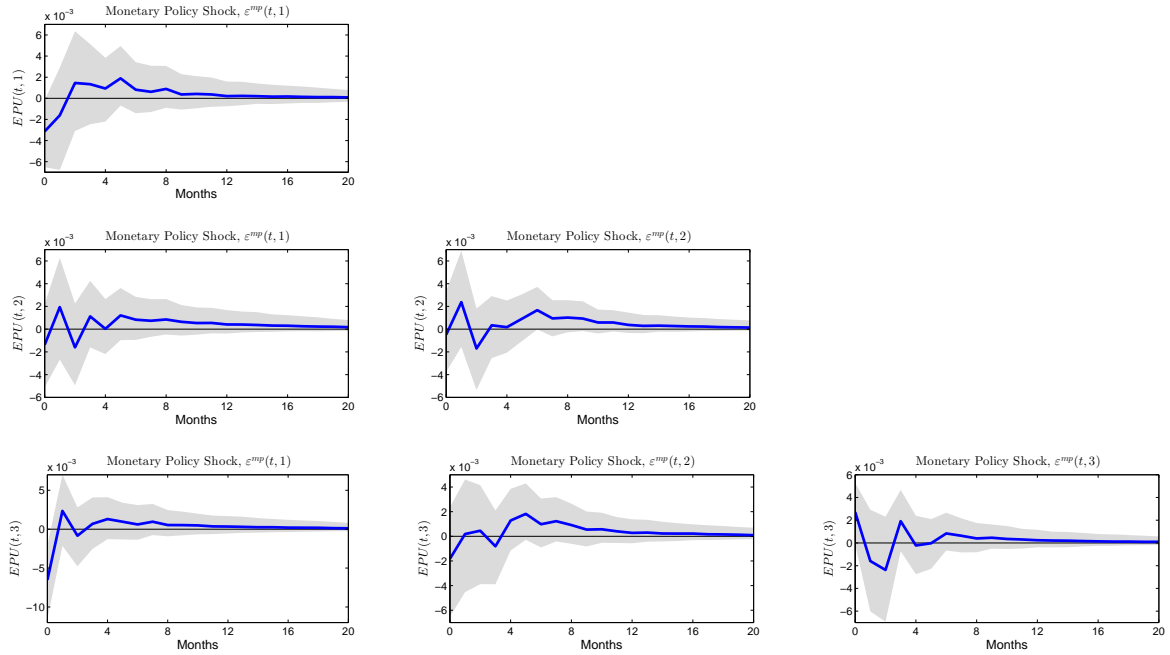
Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of $epu\,(t,1)$ (upper row), $epu\,(t,2)$ (middle row), $epu\,(t,3)$ (lower row) to monetary policy shocks $\varepsilon^{mp}\,(t,1)$ (left panel), $\varepsilon^{mp}\,(t,2)$ (middle column) and $\varepsilon^{mp}\,(t,3)$ (right column). The sample period is 1988:1-2013:3.

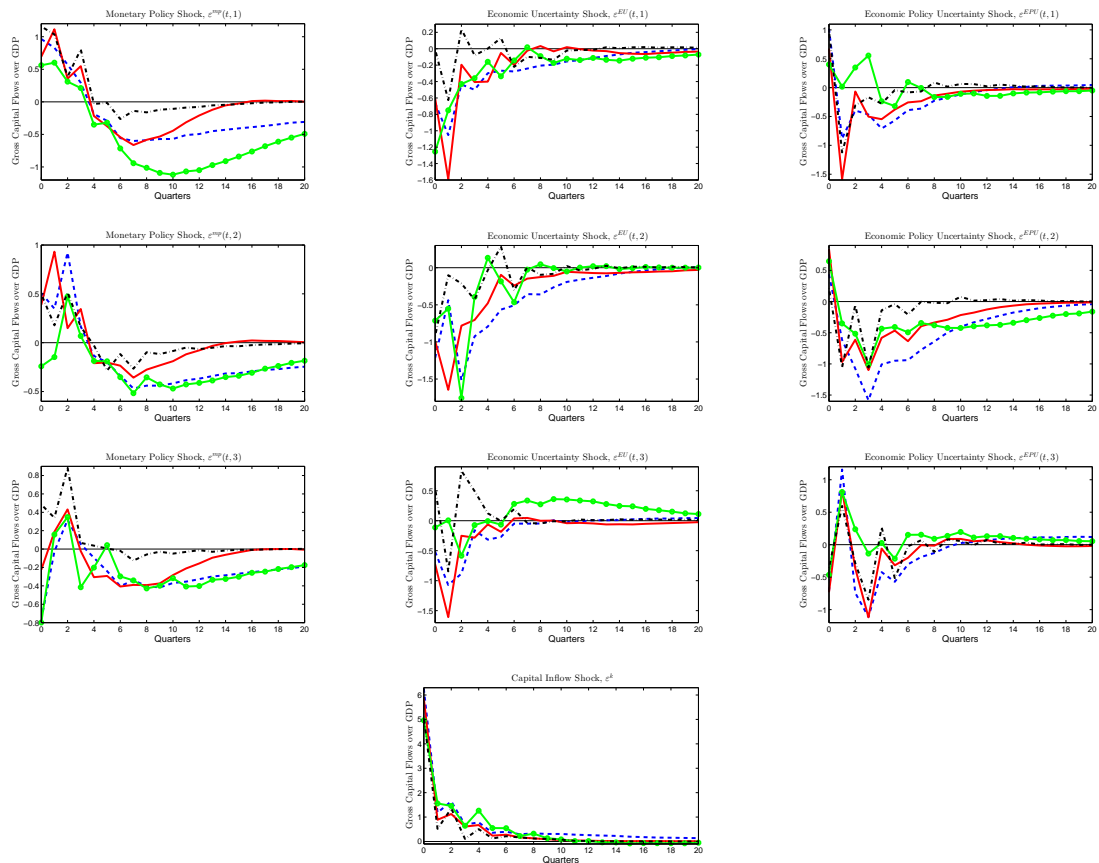Figure 7: Response of interest rate to economic uncertainty shocks: MIDAS-SVAR model.
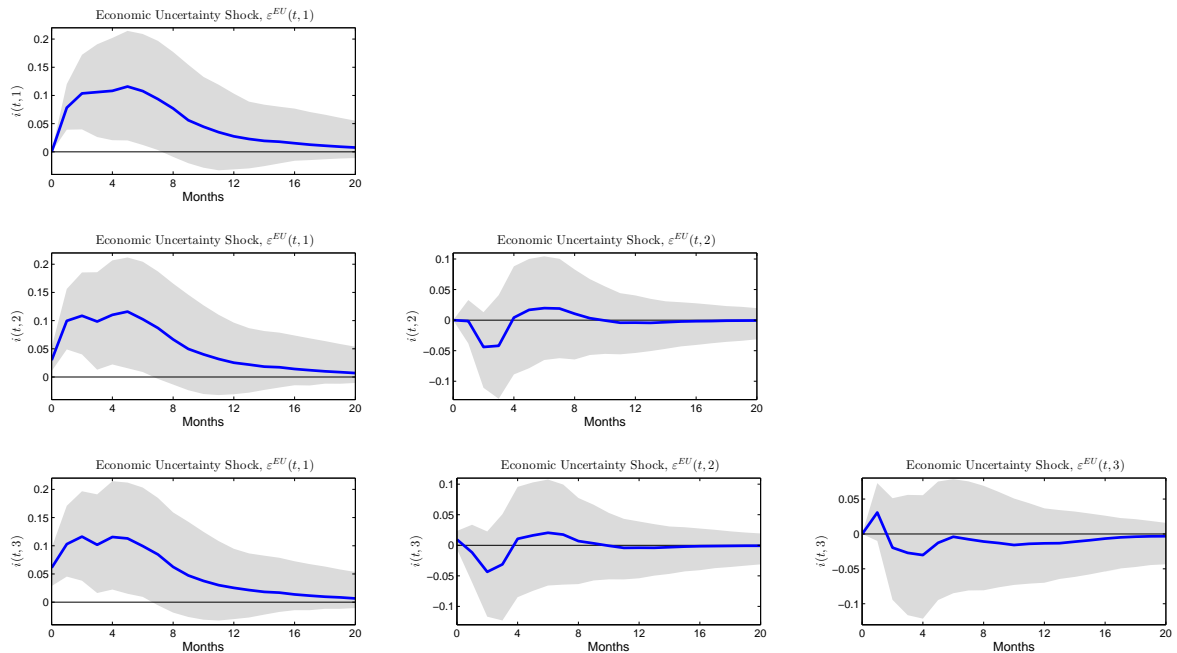
Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of Fed Funds rates $i\,(t,1)$ (upper row), $i\,(t,2)$ (middle row), $i\,(t,3)$ (lower row) to economic uncertainty shocks $\varepsilon^{eu}\,(t,1)$ (left panel), $\varepsilon^{eu}\,(t,2)$ (middle column) and $\varepsilon^{eu}\,(t,3)$ (right column). The sample period is 1988:1-2013:3.

Figure 8: Response of interest rate to economic policy uncertainty shocks: MIDAS-SVAR model.

Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of Fed Funds rates $i(t,1)$ (upper row), $i(t,2)$ (middle row), $i(t,3)$ (lower row) to economic policy uncertainty shocks $\varepsilon^{epu}(t,1)$ (left panel), $\varepsilon^{epu}(t,2)$ (middle column) and $\varepsilon^{epu}(t,3)$ (right column). The sample period is 1988:1-2013:3.

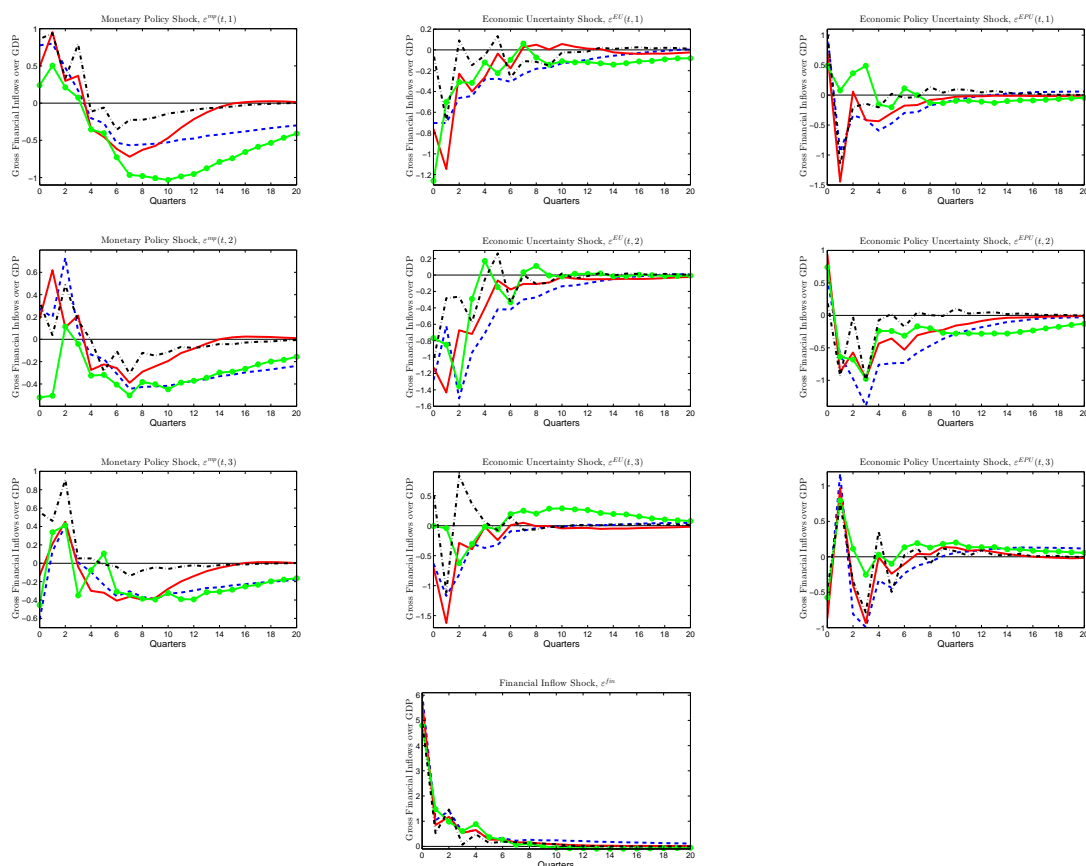Figure 9: Monetary policy shocks, economics uncertainty shocks, policy uncertainty shocks and **financial capital inflows**: MIDAS-SVAR model.

Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of financial inflows over GDP to monetary policy shocks (left panel), economic uncertainty shocks (middle panel), policy uncertainty shocks (right panel) and capital shocks (bottom panel). "1", "2" and "3" indicate whether the shocks affect the low frequency $k(t)$ variable during the first, second and third month of the quarter, respectively. The sample period is 1988:1-2013:3.

Figure 10: Monetary policy shocks, economics uncertainty shocks, policy uncertainty shocks and **FDI**: MIDAS-SVAR model.

Notes: Impulse response functions and 90% bootstrapped confidence intervals for the MIDAS-SVAR model. Response of FDI over GDP to monetary policy shocks (left panel), economic uncertainty shocks (middle panel), policy uncertainty shocks (right panel) and capital shocks (bottom panel). "1", "2" and "3" indicate whether the shocks affect the low frequency $k(t)$ variable during the first, second and third month of the quarter, respectively. The sample period is 1988:1-2013:3.

Figure 11: Robustness checks: Monetary policy shocks, economics uncertainty shocks, policy uncertainty shocks and **gross capital inflows**: MIDAS-SVAR model.
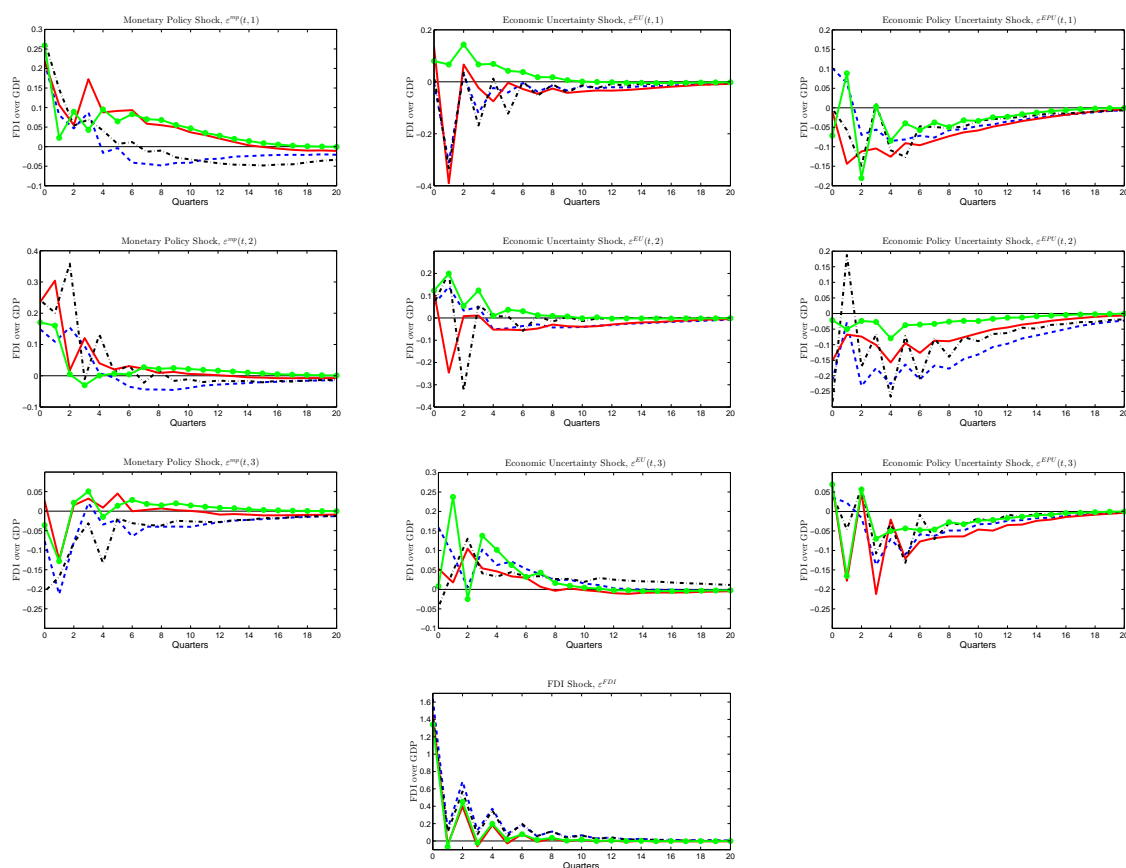

Notes: Impulse response functions for the MIDAS-SVAR model with different specifications. Response of gross capital flows over GDP $(k(t))$ to monetary policy shocks (left panel), economic uncertainty shocks (middle panel), policy uncertainty shocks (right panel) and capital shocks (bottom panel). "1", "2" and "3" indicate whether the shocks affect the low frequency $k(t)$ variable during the first, second and third month of the quarter, respectively. Dashed-blue lines: Median responses using the main specification of Section 4.4; Red lines: Median responses using the specification with more control variables as in Section 6.1; Dot-Dash-black lines: Median responses using the specification with more control variables and international interest rates as in Section 4.6; Green with circles: Median responses for the pre-crisis period as in Section 6.2.

Figure 12: Robustness checks: Monetary policy shocks, economics uncertainty shocks, policy uncertainty shocks and **gross financial inflows**: MIDAS-SVAR model.

Notes: Impulse response functions for the MIDAS-SVAR model with different specifications. Response of financial flows over GDP ($k(t)$) to monetary policy shocks (left panel), economic uncertainty shocks (middle panel), policy uncertainty shocks (right panel) and capital shocks (bottom panel). "1", "2" and "3" indicate whether the shocks affect the low frequency $k(t)$ variable during the first, second and third month of the quarter, respectively. Dashed-blue lines: Median responses using the main specification of Section 4.4; Red lines: Median responses using the specification with more control variables as in Section 6.1; Dot-Dash-black lines: Median responses using the specification with more control variables and international interest rates as in Section 4.6; Green with circles: Median responses for the pre-crisis period as in Section 6.2.

Figure 13: Monetary policy shocks, economics uncertainty shocks, policy uncertainty shocks and **FDI**: MIDAS-SVAR model.

Notes: Impulse response functions for the MIDAS-SVAR model with different specifications. Response of FDI over GDP $(k(t))$ to monetary policy shocks (left panel), economic uncertainty shocks (middle panel), policy uncertainty shocks (right panel) and capital shocks (bottom panel). "1", "2" and "3" indicate whether the shocks affect the low frequency $k(t)$ variable during the first, second and third month of the quarter, respectively. Dashed-blue lines: Median responses using the main specification of Section 4.4; Red lines: Median responses using the specification with more control variables as in Section 6.1; Dot-Dash-black lines: Median responses using the specification with more control variables and international interest rates as in Section 4.6; Green with circles: Median responses for the pre-crisis period as in Section 6.2.

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