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Financial Conditions for the US: Aggregate Supply or Aggregate Demand Shocks?

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It depends. We reply to this question by providing novel empirical evidence about the US economy. We identify the impact of financial high-frequency shocks on macroeconomic variables by estimating mixed- and common frequency VARs. The results from the mixed-frequency VAR show that economic output and inflation move in opposite directions in response to detrimental financial conditions, mimicking negative aggregate supply shocks. Oppositely, the results from the common-frequency VAR show that worsening financial conditions lead to a drop in output and inflation (and in the monetary policy rate), resembling negative aggregate demand shocks.

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JEL Classification

C32, C54, E44

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Financial Conditions for the US: Aggregate Supply or Aggregate Demand Shocks?

Alessia Paccagnini* Fabio Parla†

6th February 2023

Abstract

It depends. We reply to this question by providing novel empirical evidence about the US economy. We identify the impact of financial high-frequency shocks on macroeconomic variables by estimating mixed- and common frequency VARs. The results from the mixed-frequency VAR show that economic output and inflation move in opposite directions in response to detrimental financial conditions, mimicking negative aggregate supply shocks. Oppositely, the results from the common-frequency VAR show that worsening financial conditions lead to a drop in output and inflation (and in the monetary policy rate), resembling negative aggregate demand shocks.

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1 Introduction

The financial crisis of 2008 and the slowdown of the economy that followed showed how important financial markets were in explaining macroeconomic fluctuations. Recent empirical studies provide evidence of how financial variables or indicators have been particularly useful in predicting the behaviour of macroeconomic variables, over the last few years (see Jermann and Quadrini 2012, Gilchrist and Zakrajšek 2012, Colombo and Paccagnini 2020, among others). But how can we figure out what a financial shock means for the real economy when we observe one? How can we interpret the fact that macroeconomic variables change slowly (i.e., at a monthly or quarterly frequency) and financial variables change quickly (i.e., at a daily or weekly frequency)? We seek an answer

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to this question by estimating a Mixed-Frequency Vector Autoregressive (MF-VAR) model and a Common-Frequency Vector Autoregressive (CF-VAR) model, using US data observed over the $1973-2019$ period. This double econometric approach is motivated by the use of the financial condition indices which are high-frequency variables. These indicators, which summarize information derived from financial variables, are widely employed in the current macro-finance literature to study the effects of financial markets on the business cycle (see Hatzius, Hooper, Mishkin, Schoenholtz and Watson 2010, Matheson 2012, Koop and Korobilis 2014, Arrigoni, Bobasu and Venditti 2022, Ferriani and Gazzani 2022, among others). We identify the effects of negative financial conditions, proxied by an exogenous increase in the Chicago Fed's National Financial Conditions Index (NFCI), on a set of macroeconomic variables. While the negative response of economic output to financial shocks is well established in the empirical literature, the evidence on the response of inflation is mixed. Inflationary effects of financial shocks are found e.g., by Abbate, Eickmeier and Prieto (2016), Alessandri and Mumtaz (2017), Brianti (2021), while deflationary effects are documented e.g., in the studies of Alessandri and Mumtaz (2017), De Santis and Van der Veken (2022), among others.[1]

We contribute to the literature by showing how the response of the inflation rate (and of the monetary policy rate) depends on the frequency of the shocks hitting the VAR. The CF-VAR shows that an increase in NCFI is associated with a reduction in both prices and monetary policy rate, typical of negative aggregate demand shocks. Oppositely, the MF-VAR shows a positive response of inflation (and of short-term interest rate) as in negative aggregate supply shocks. These results generate an important policy suggestion to adopt mixed-frequency models that take into account the high frequency of the identified shock. The structure of the rest of the paper is organized as follows. Section 2 illustrates the empirical strategy with details on data and the estimated models. Section 3 discusses the results. Section 4 concludes.

[1] Furlanetto, Ravazzolo and Sarferaz (2019) find that while financial shocks play an important role in shaping business cycle fluctuations, their impact on prices is negligible.

2 Empirical Strategy

2.1 Data

We use data for the U.S. economy observed over the period spanning from March 1973 to December 2019.[2] The variables have been chosen following the empirical analysis presented in Alessandri and Mumtaz (2017). In particular, we use three monthly macroeconomic variables and a proxy of financial conditions available at a weekly frequency. The block of monthly macroeconomic variables includes industrial production (IP), consumer price index (CPI), and federal funds effective rate (FFR). Our proxy for financial conditions in the U.S. is the Chicago Fed's National Financial Conditions Index (NFCI) which is updated on a weekly basis.[3] To allow for the same number of four observations within each month, we remove the first observation in months that contains five weeks.[4] Figure 1 shows the resulting weekly series of NFCI.

To compare the results obtained using mixed-frequency data with those obtained from the estimation of a CF-VAR, we aggregate the raw series (i.e., the original series from FRED) of weekly NFCI to a monthly frequency by computing the intra-month average and we estimate a monthly CF-VAR. The variables used in our empirical analysis are downloaded from the Federal Reserve Bank of St. Louis (FRED) Database.

2.2 Empirical methodology

We estimate a MF-VAR and a CF-VAR. The former is a stacked MF-VAR (introduced by Ghysels 2016) fitted to a weekly series of the U.S. NFCI (i.e., $K_h = 1$ high-frequency variable) and to three macroeconomic variables: industrial production, consumer price index, and federal funds rate, sampled at a monthly frequency (i.e., $K_l = 3$ low-frequency variables):

$$Y_t = \sum_{\ell=1}^{p} A_\ell Y_{t-\ell} + c + u_t \tag{1}$$

[2]As a robustness check, we estimate the model also using a recent sample period ($1973m3 - 2022m8$), including the COVID-19 periods. The results, available upon request, remain qualitatively and quantitatively similar to those discussed in the rest of the paper.

[3]The NFCI is a composite indicator that aggregates 105 financial market series, representative of money, debt, equity, and (traditional and "shadow") banking markets. For more details on the construction of the NFCI, see Brave and Butters (2012).

[4]Götz, Hecq and Smeekes (2016) use the same approach to construct a daily measure of realized volatility using the S&P500 stock index.

where $Y_t = \left(\Delta\mathrm{IP}', \Delta\mathrm{CPI}', \mathrm{FFR}', \mathrm{NFCI}'_{week1}, \mathrm{NFCI}'_{week2}, \mathrm{NFCI}'_{week3}, \mathrm{NFCI}'_{week4}\right)'$ is the 7×1 stacked vector of endogenous variables sampled at a different frequency. This includes the log changes of monthly industrial production (ΔIP), the log changes of monthly consumer price index (ΔCPI), the level of the monthly federal funds effective rate (FFR), and the $m = 4$ weekly series of NFCI (in levels).[5] According to equation (1), the ($K = 7$)-dimensional vector of mixed-frequency variables, with $K = Kl + (m \times Kh)$, evolves as a monthly VAR.[6] Furthermore, A_ℓ, for $\ell = 1, \ldots, p$, is a 7×7 matrix of slope coefficients, c is a 7×1 vector of intercepts, and u_t is a 7×1 vector of reduced form innovations, with $u_t \sim \mathcal{N}(0, \Sigma)$. We also estimate a monthly CF-VAR, where the weekly series of NFCI is aggregated to a monthly frequency by computing the intra-month average.

The financial shock, proxied by an exogenous increase in the NFCI, is identified by computing the Cholesky decomposition of the residual covariance matrix (Σ):

$$\Sigma = B_0 B_0' \tag{2}$$

where B_0 is the 7×7 impact multiplier matrix containing the contemporaneous effects of the structural shocks on the endogenous variables. In line with Alessandri and Mumtaz (2017), the block of macroeconomic variables (i.e., ΔIP, ΔCPI, and FFR) is ordered before the NFCI, as specified in equation (1). Moreover, the intra-month ordering of the weekly NFCI series is consistent with a publication lag strategy followed by other studies on MF-VAR (see Ferrara and Guérin 2018, among others), which implies that financial shocks occurring in each week affect only the following weeks.

Both the MF-VAR and the CF-VAR are estimated using data over the period $1973m3 - 2019m12$.[7] For comparison, the lag length of the two models is set equal to 6.[8] The models are estimated using Bayesian estimation techniques by imposing a Normal-inverse Wishart distribution on the VAR coefficients and on the residual covariance matrix. In line with Götz et al. (2016) and, more recently, with Paccagnini and Parla (2021), the prior is

[5] We also estimate the models using data in levels (i.e., using the log transform of IP and CPI) and the results remain qualitatively and quantitatively similar (they are available upon request).

[6] See Ghysels (2016) for technical details on the construction of the stacked vector of mixed-frequency variables.

[7] In our empirical application, we prefer to exclude Covid-19 data from the estimation sample. As a robustness check, we estimate the models including also the most recent observations (that is up to August 2022). The results remain similar and they are available upon request.

[8] For both the MF-VAR and the CF-VAR, the Akaike information criterion suggests a lag length equal to 10, while the Bayesian information criterion suggests a number of lags equal to 3. We prefer to impose a half-year delay in the response of the variables. However, as a robustness check, we compare the results from MF- and CF-VARs using alternative lag lengths, that is 3 and 12 lags (see Section 3). The results are qualitatively and quantitatively similar across the different lag structures.

imposed by constructing artificial (dummy) observations tailored to take into account the different frequencies of the endogenous variables.[9] The overall tightness of the prior is selected by maximizing the marginal likelihood of the models.[10] We use a Gibbs sampling algorithm to simulate the posterior distribution, setting a total number of replications equal to 15000 and using the last 5000 for inference.

3 Results

Figure 2 shows the weekly impulse response of the macroeconomic variables to a one-standard deviation financial shock, proxied by an exogenous increase in NFCI. Each chart documents the median response of the MF-VAR (red line) and the CF-VAR (blue with asterisks). In addition, we include for the estimation of the MF-VAR the associated 68% (red shading) and 90% (grey shading) error bands, and for the estimation of the CF-VAR the associated 90% (blue dashed lines) error bands. The IRFs for the levels of the variables (cumulative sum for IP and CPI) are computed over a 36-month forecast horizon.

At a first glance, we find that the responses of the macroeconomic variables differ across weeks both in terms of magnitude and sign. For IP, we document how the magnitude of the response to financial shocks decreases over the third and fourth weeks. Moreover, the MF-VAR responses are less recessionary than those obtained from the common-frequency model and the difference between the two IRFs becomes larger towards the end of the month. The negative response of economic output to detrimental financial conditions (using both the MF-VAR and the CF-VAR) corroborates the existing findings in the literature (see Gilchrist and Zakrajšek 2012, Caldara, Fuentes-Albero, Gilchrist and Zakrajšek 2016, among others). For CPI and FFR, the responses of MF- and CF-VAR show an opposite sign, especially in the first and third weeks.

The results from the CF-VAR show that an increase in NCFI is associated with a reduction in IP, CPI and FFR, consistently with a negative aggregate demand shock. This result is in line with Alessandri and Mumtaz (2017) for the US. However, when financial shocks are estimated at a weekly frequency through the MF-VAR, the results provide a different economic interpretation: economic output and inflation rate move in opposite directions in response to financial shocks. In particular, the inflationary effect of financial shocks is more pronounced during the first and third weeks. Moreover, also the response of the

[9] In stacked MF-VAR, the dummy observations are constructed *ad-hoc* as they depend on the specification of the stacked vector of mixed-frequency variables.

[10] For more details on the estimation of a stacked MF-VAR using dummy observations prior, see Paccagnini and Parla (2021).

monetary policy rate tends to be positive, especially in those weeks when the inflation rate increases (i.e., the first and third week). Altogether, these findings suggest that financial shocks resemble negative aggregate supply shocks when we take into account the weekly frequency. To summarize, while the response of economic output to financial shocks remains negative in both the MF-VAR and the CF-VAR, the responses of inflation and monetary policy rate depend on whether we aggregate the high-frequency NFCI or not. While the use of aggregated monthly NFCI is associated with demand-type shocks (i.e., reducing output, price, and monetary rate), once we account for high-frequency data, financial shocks resemble negative aggregate supply shocks: central banks increase monetary policy rate in response to the supply shocks (see e.g. Hristov, Hülsewig and Wollmershäuser 2012).

We test the robustness of the findings in Figure 2 by estimating the CF- and MF- VAR with different lag lengths. Figure 3 documents the aggregate (average) responses across weeks for IP, CPI, and FFR. For each macroeconomic variable, we present the median response by estimating the MF-VAR using 6 (red line with asterisks), 3 (magenta line with crosses), and 12 (green line with circles) lags, together with the 90% error bands obtained from the MF-VAR with 6 lags (grey shadow area). The median response from a CF-VAR with 6 lags (blue line with asterisks) and the 90% error bands (blue dashed lines) are also included. Figure 3 suggests how the results provided by the benchmark MF-VAR with 6 lags are robust to different lag lengths.

4 Concluding remarks

We look into whether US financial conditions are inflationary or deflationary. To answer this question, we conduct an empirical study of the effects of worsening financial conditions (proxied by an increase in NFCI) on US macroeconomic variables. We compare the results from MF-VAR and CF-VAR. As main findings, we document how, for inflation and short-term monetary policy rate, the responses obtained from the two models display an opposite sign. While the CF-VAR shows that an increase in NCFI is linked to a drop in both CPI and FFR, similar to negative aggregate demand shocks, the MF-VAR shows a positive response of CPI and FFR, similar to negative aggregate supply shocks. These results provide an important policy suggestion to adopt mixed-frequency models that take into account high-frequency shocks.

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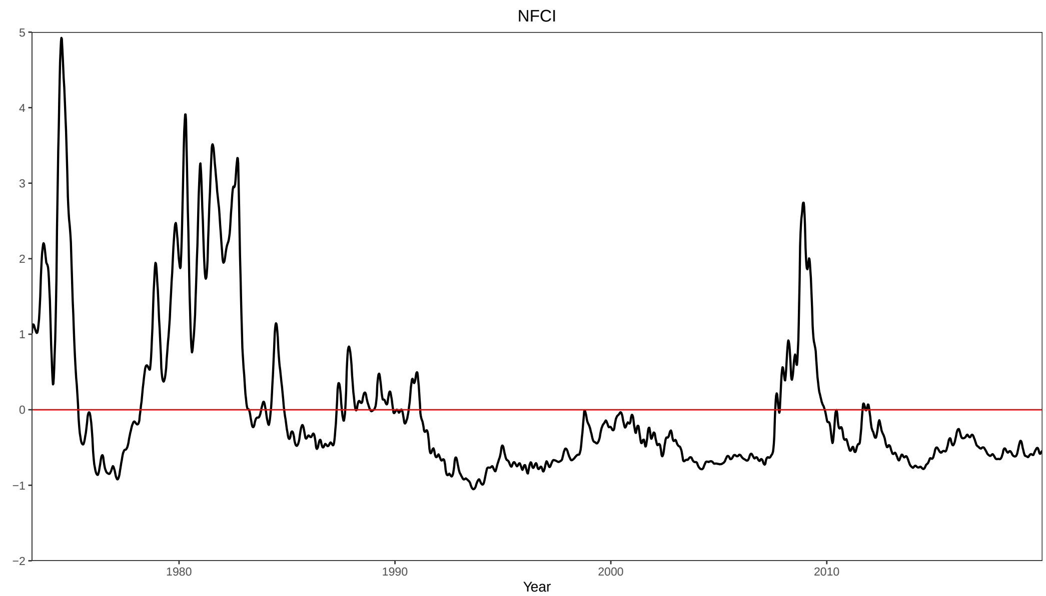
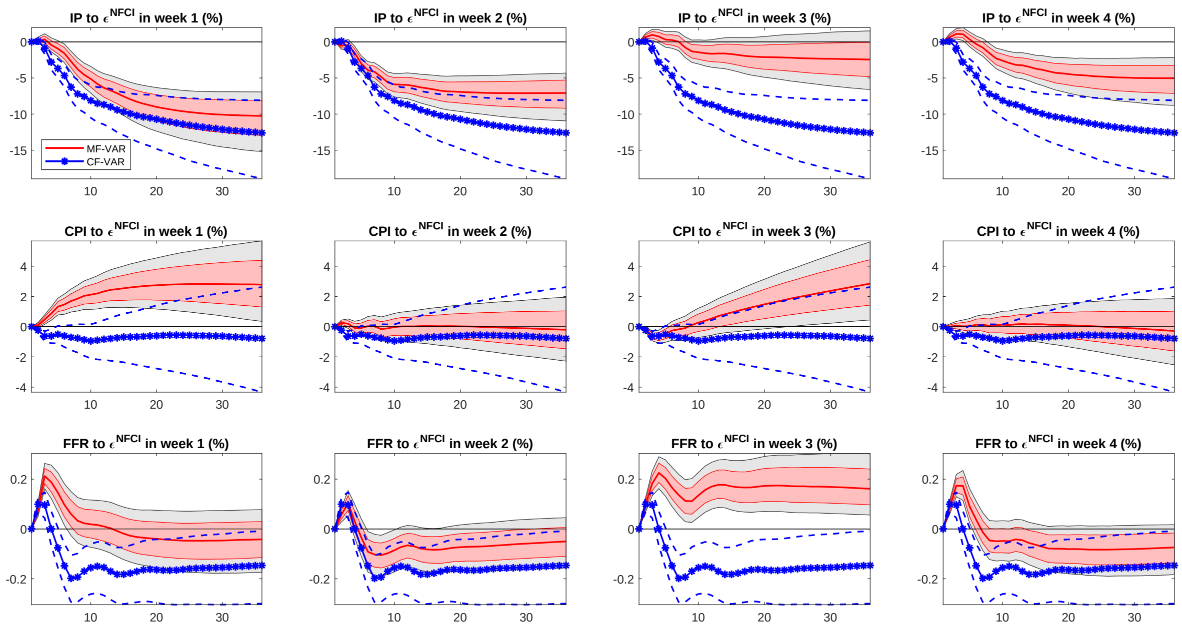
Appendix

Figure 1: Chicago Fed's National Financial Conditions Index (NFCI), weekly estimates.



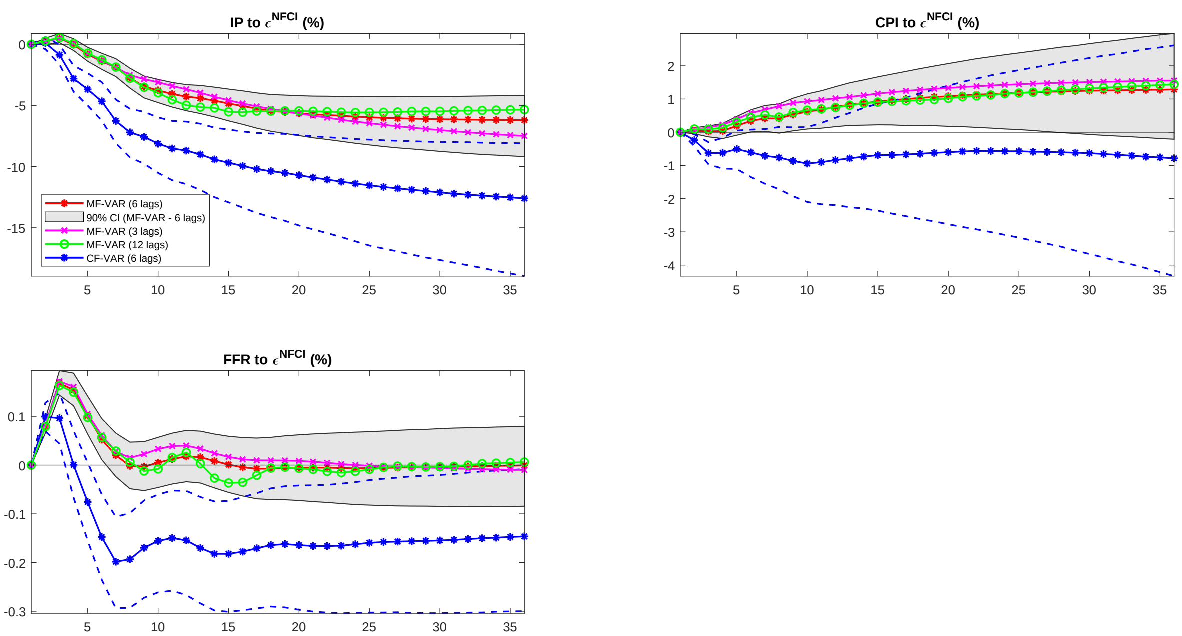
Notes. Weekly series of Chicago Fed's National Financial Conditions Index (NFCI) observed over the period $1973m3 - 2019m12$. The series is constructed such that each month contains four weekly observations (see Section 2.1).

Figure 2: Weekly responses of macroeconomic variables to financial shocks



Notes. Impulse responses of the industrial production (IP), consumer price index (CPI), and federal funds rate (FFR) in levels to a one standard deviation financial shock, computed over a 36-month forecast horizon. The charts show the impulse responses of the macroeconomic variables in weeks 1, 2, 3, and 4. Each chart shows the median response from the MF-VAR (red line) and the corresponding 68% (red shadow area) and 90% (grey shadow area) error bands. The median response obtained from a CF-VAR (blue line with asterisks) and the 90% error bands (blue dashed lines) are also reported. Estimation sample: $1973M3 - 2019M12$.

Figure 3: Responses of macroeconomic variables to financial shocks using alternative lag structure



Notes. Impulse responses of the industrial production (IP), consumer price index (CPI), and federal funds rate (FFR) in levels to a one standard deviation financial shock, computed over a 36-month forecast horizon, using different lag lengths. The weekly responses are aggregated by computing the mean over the four weeks for each forecast horizon. Each chart shows the median response of the macroeconomic variable by estimating the MF-VAR using 6 (red line with asterisks), 3 (magenta line with crosses), and 12 (green line with circles) lags, together with the 90% error bands obtained from a MF-VAR with 6 lags (grey shadow area). The median response from a CF-VAR with 6 lags (blue line with asterisks) and the 90% error bands (blue dashed lines) are also reported. Estimation sample: $1973M3 - 2019M12$.