Corporate earnings shocks and economic activity. *

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Abstract

Around 80% of non-financial corporate loans in the US are earnings backed. Thus, shocks to corporate earnings relax firms' borrowing constraints and are crucial in understanding the macroeconomic effects of financial disturbances. In this paper we examine the effects of corporate earnings shocks on economic activity. The identification relies on the assumption that earnings shocks are more volatile than other disturbances on days with high profile corporate earning announcements. We find that a favorable shock to corporate earnings has substantial consequences for the US economy: stock prices increase, credit conditions improve, output, loans and prices rise considerably while the monetary policy tightens in face of the expansionary developments. The shock has powerful international effects.

JEL Classification: *C32, F3, G01*

Keywords: corporate earnings shock, event study, heteroscedasticity, borrowing constraints, structural VAR.

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1 Introduction

Borrowing constraints of firms are a cornerstone of the macroeconomic models featuring financial frictions and/or financial disturbances. The literature commonly links firm's borrowing constraints to the liquidation value of physical assets (Kiyotaki and Moore, 1997, Bernanke et al., 1998, Mendoza, 2010, Jermann and Quadrini, 2012, Liu et al., 2013, Becard and Gauthier (2020)). However, recent evidence in Lian and Ma (2021) and Drechsel (2019) suggests that around 80% of the non-financial corporate borrowing in the US is pledged by firms' cash flow measured by earnings (earning-based lending) and only 20% is backed by physical assets (asset-based lending). Furthermore, the two studies demonstrate that the type of credit constraints (i.e asset-based vs. earning-based) can have a substantial impact on both the credit dynamics and the central transmission mechanism in macro-finance models.

Since the lion's share of corporate lending in the US is cash-flow backed, the key constraint to firm's debt are corporate earnings rather than assets. Therefore, shocks to corporate earnings (CE) relax/tighten the borrowing constraints of firms and are thus (i) financial in nature; and (ii) pivotal in understanding business cycle fluctuations in the US. Nevertheless, little is known about the economic effects of this type of financial shocks on economic activity.

The objective of this study is to examine the macroeconomic effects of corporate earning (CE) shocks using data. This is a difficult task due to the well-known issues of endogeneity and simultaneity arising in empirical models that combine macroeconomic and financial data. We approach these challenges using a novel identification design that exploits the heteroscedasticity of CE shocks around high profile corporate earnings announcements in a daily VAR setting. The methodology integrates the identification through heteroscedasticity introduced by Rigobon (2003) with event studies, as in Wright (2012). Combining the event study method with the heteroskedasticity approach allows for the presence of multiple shocks during the event (daily) window.

Our key identifying assumption is that CE shocks are heteroscedastic and their variance is particularly large on days when important corporate profit news are reported. Moreover, we exploit the lumpy manner in which news are released to the public to rule out reverse causality since it is unlikely that changes in stock prices might cause corporate profit announcements during short windows (daily in our case). We show that on event days, the variance of the system is higher compared to non-event days, and that this difference can be attributed to a single, orthogonal shock, which we call the CE shock. Finally, to assess the effects of CE shocks on the main economic indicators, we use the series of structural shocks from the daily VAR framework as an instrumental variable in a monthly large Bayesian (B) VAR model.

Overall, our findings show that CE shocks are qualitatively aligned to the theoretical predictions for standard (asset-based) financial disturbances. CE shocks have considerable effects both domestically and internationally. An expansionary CE shock that increases S&P500 by 1 percent triggers a sharp and contemporaneous improvement in credit market conditions captured by a fall of 5 and 3 basis points (bp) in both credit spreads and the Excess Bond Premium (EBP), respectively. VIX index of equity volatility drops as well, by around 3 percent. The shock leads to a statistically significant rise in GDP (+0.06%) and industrial production (+0.16%) as well as to an increase in inflation (0.05%). Hence aggregate demand effects seem to dominate aggregate supply ones. Monetary policy is tightened substantially (+5 bp) in face of these expansionary and inflationary economic developments while the term spread drops (-3bp), consistent with a short rate rise accompanied by a smaller rise in long rates. A quarter after the shock there is a strong and persistent boom in business loans (+0.23%) and a slightly milder increase in consumer loans (+0.13%). We also show that EBF shocks are a key driver of the historical variations in real activity and are tightly linked to the onset of recessions.

Moreover, we document a powerful transmission channel of the US CE shock across the borders. In the empirical exercise, we focus on the CE shock transmission to the EA, which is one of the main financial and trade partners of the US. The financial expansion originating in the US induces a highly synchronized response in the financial and economic variables of the EA, and is thus crucial to explain the strong international comovement in macroeconomic variables that we observe in the data. But, importantly, the shock generates sizable fluctuations in financial activity on a global scale, triggering a significant increase in the global financial factor (GFF) developed by Miranda-Agrippino and Rey (2020). Furthermore, the shock explains 76% of the contemporaneous forecast error variation of the GFF. This result highlights the hegemonic role of the United States in the international financial system as well as the raising importance of financial integration in the transmission of (financial) disturbances across the borders. Finally, we show that US output responses change substantially if we remove the GFF from the baseline model. We interpret this result as bringing evidence in favor of a strong international financial feedback channel.

A critical step in our identification design is the construction of the events list. To achieve identification, the variance of CE shocks is expected to be higher on event days, while the variance of the other shocks should remain unchanged. We select the corporate profit announcements from the dataset developed by Baker et al. (2019), available at `www.stockmarketjumps.com`. In this study, the authors approximate the *cause* of stock market jumps by examining newspapers in the day following a jump in S&P500 higher than 2.5%. We select the events in Baker et al. (2019) dataset corresponding to asset prices jumps that have been triggered by corporate earning announcements. Put differently, our event days contain important corporate profit releases that are the primary announcement of the day. Based on this approach, we obtain 26 financial events between 1996 and 2009.

This is not the first paper to look at corporate earnings news. Earnings announcements represent one of the most important channels of communication between a firm's managers and investors. The effects of CE news on stock returns, equity premium and systemic risk have been extensively analyzed in the finance literature (Michaely et al., 2014, Savor and Wilson, 2016, Pevzner et al., 2015). To the best of our knowledge, however, this is the first paper to look at the macroeconomic effects of these announcements, combining the event study methodology with a VAR identified with heteroskedasticity.

We conduct a series of sensitivity checks that indicate that our findings are robust along a number of dimensions. In particular, our event days list contains corporate profit news pertaining to both financial and non financial institutions. Since earning-based lending is the prevalent tool in the non-financial sector, we show that our results are unaffected if we remove from the event list the corporate news related to financial firms. Moreover, a large share of our events belongs to the 2008-2009 Global Financial Crisis (GFC) period. This might raise concerns that some of the corporate earning news during GFC convey information on the macroeconomic outlook on top of the earning news. We show that our findings hold if we remove GFC events from the analysis. Furthermore, our event days might contain overlapping information for both first and second moment financial shocks. To address this matter we provide evidence that our results hold if we simultaneously identify first and second moment financial shocks. In addition, we show that on event days the difference in the volatility of the system is triggered by one orthogonal shock alone.

Literature review. This paper builds on the recent contributions of Lian and Ma (2021) and Drechsel (2019) who show that corporate borrowing in the US is predominantly earning-based rather than asset-based as commonly modeled in the literature. In particular, Lian and Ma (2021) provide empirical evidence on the effects of exogenous changes in corporate earnings on firms' borrowing using micro-level data. In change, we investigate the domestic and internatioal effects of CE shocks at aggregate level. We are also different from Drechsel (2019), where the focus is on the implications of earnings-based borrowing constraints for the transmission of investment shocks rather than looking at the effects of shocks to the different type of borrowing constraints.

Since CE shocks are part of the broader category of financial shocks, we also relate to the large macroeconomic literature analyzing the relevance of disturbances originating in the financial sector. This aspect has been widely assessed both domestically (see Gilchrist et al., 2009, Nolan and Thoenissen, 2009, Del Negro et al., 2011, Jermann and Quadrini, 2012, Christiano et al., 2014, Ajello, 2016 and Hirakata et al., 2017) and internationally (see Peek and Rosengren, 1997, Dedola and Lombardo, 2012, Perri and Quadrini, 2018, and Born and Enders, 2019).

Our work is, however, closer to studies that examine the impact of financial shocks using data. Most of the existing empirical analyses identify financial shocks with VAR models resorting to theoretically informed sign restrictions such as Jarocinski and Smets (2008), Helbling et al. (2011), Meeks (2012), Fornari and Stracca (2012), Eickmeier and Ng (2015), Abbate et al. (2016), Gambetti and Musso (2017), Cesa-Bianchi and Sokol (2017), Furlanetto et al. (2019) and Caggiano et al. (2021). Exceptions to this strand are Gilchrist and Zakrajšek (2012), Walentin (2014), Abbate et al. (2016), Barnichon et al. (2018) and Forni et al. (2021) who identify a financial shock using timing restrictions; Caldara et al. (2016) disentangle the macroeconomic implications of first and second moment financial shocks using a penalty function approach while Mumtaz et al. (2018) rely on DSGE generated data to identify credit shocks.

In contrast to these contributions, we focus on a specific type of financial shocks, the CE shocks, and we propose a novel identification approach. We construct an instrumental variable for CE shocks exploiting (i) the valuable information around days with strategic corporate profit news; and (ii) the higher variance of CE shocks on these days. Unlike the mainstream approach of sign restrictions which offers limited information on the magnitude of the estimates, our framework produces point identified results; moreover we can dispense from imposing timing restrictions which are particularly hard to justify in models combining macroeconomic and financial data.

In terms of the identification strategy, the closest contribution to our paper is provided by Brunnermeier et al. (2019) who analyze the role of several financial disturbances in a VAR model identified through heteroscedasticity. We differ from this study in a crucial aspect. Specifically, we integrate the identification through heteroscedasticity with the event study approach. This extension allows us to provide an explicit structural interpretation of the identified shock as a CE shock.

From a methodological perspective, our paper relates to the literature that employs a heteroscedasticity-based event study approach to detect causality in time series models, as in Wright (2012), Nakamura and Steinsson (2018), Gurkaynak et al. (2020) and Miescu and Rossi (2021). To refine the identification, this approach is usually employed in high frequency models (daily or intra-daily). This is an important limitation for macroeconomic analyses where the main indicators have scarce coverage at daily frequency. We address this challenge advancing the use of the structural shocks from the daily VAR model as an external instrument in lower frequency models.

The paper is organized as follows. In section 2 we introduce the identification strategy providing details on the selection of the events days and the methodology used to construct the instrumental variable. In section 3 we describe the econometric model and the data, while section 4 discusses the main results. Section 5 concludes.

2 Identification strategy

Our strategy to isolate exogenous CE disturbances is based on combining the identification through heteroscedasticity with the event study methodology, in line with what has been proposed by Wright (2012) in the context of monetary policy shocks. The key identifying assumption is that there is a set of event days when the variance of CE shocks is particularly high, while the variance of the other shocks remains unchanged. Other shocks can occur on the same days with the CE events and the variance of these shocks can change from day to day as long as their average volatility is the same on these and other days. Thus, the selection of the event days is a crucial step in our identification design.

In this section we describe in detail the events list, the econometric framework combining the heteroscedasticity with the event study approach and the construction of the instrumental variable for CE shocks based on this approach.

2.1 Corporate earnings events list

Our identification scheme is based on the observation that on specific days when high profile corporate profit announcements occur, the variance of CE shocks is higher than in other days, while the variance of the other shocks remains unchanged.

We select the set of corporate earning news using the dataset produced by Baker et al. (2019). In this dataset, the authors approximate the cause of stock market jumps (defined as movements in S&P500 bigger than 2.5%) reading the lead article about each jump in the next-day (or same-evening) newspapers. The 2.5% threshold is large enough to ensure the next day newspapers always contains articles discussing the prior day's jump. Each jump is randomly assigned to several coders who classify the stock market jumps into one of the sixteen pre-established categories. Based on this approach, we select the days in Baker et al. (2019) dataset in which the primary cause of the asset price jump has been attributed *by all coders* to "Corporate earnings & outlook news". This category contains "News relating to the release or impending release of information about corporate earnings, revenues, costs, or borrowings.". In this way we isolate 26 CE event days as described in Table 1.

Baker et al. (2019) dataset has three desirable features for the purposes of our identification design. First, it focuses exclusively on high profile events related to jumps in asset prices and this should trigger an increase in the volatility of the system by construction. Second, it assigns primary causes to each asset price jump; as such, we minimize the risk that on event days other shocks might record an increase in variance. Third, it precludes the use of intra-daily data which is costly to acquire and can have limited coverage.

Table 1 – Corporate earnings events list

Date	S&P500 % jump	Brief Explanation
15/07/1996	-2.5	Weak earnings reports
23/03/1999	-2.7	Tech companies earnings expected to disappoint
07/03/2000	-2.7	Profit warning by P&G
25/04/2000	3.4	Positive earnings reports
13/10/2000	3.5	Optimistic news about third-quarter profit performances for tech
19/10/2000	3.5	Strong earnings report by Microsoft
05/01/2001	-2.7	Derivative losses at large banks
03/04/2001	-3.4	Tech stocks down on bad earnings news
05/04/2001	4.4	Good earnings news for Dell, Alcoa, Yahoo rating upgraded
29/01/2002	-2.9	Enron-like accounting troubles expected in more firms
08/05/2002	3.8	Cisco hints about business recovery
14/08/2002	4	More confidence in financial statements after Enron scandal
27/09/2002	-3.2	Woes in Brazil and Argentina hurt Citigroup/JP Morgan
11/10/2002	3.9	On-target earnings report from GE
15/10/2002	4.7	Citigroup, GM show good earnings
16/07/2008	2.5	Wells Fargo reports better- than-expected earnings
09/09/2008	-3.4	Failed negotiations between Lehman and Korean investors
21/10/2008	-3.1	Tech companies reported weak quarterly results
22/10/2008	-5.9	Weak corporate earnings
14/01/2009	-3.3	Citigroup plans to dismantle itself
20/01/2009	-5.2	Fears about banking system
21/01/2009	4.3	Bank of America directors reported to have bought own stock
10/03/2009	6.3	Good news for Citi profits
12/03/2009	4.1	Good news for Bank of America, GM and GE
09/04/2009	3.7	Wells Fargo reports better- than-expected earnings
15/07/2009	3	Intel reports strong sales

Notes. The table reports the stock market jumps due to corporate earning news as reported by Baker et al. (2019). The brief explanation column is the outcome of the authors' reading of the articles. GE and GM are acronyms for General Electric and General Motors, respectively.

2.2 Daily heteroscedastic VAR framework

The baseline VAR model is defined as:

$$Y_t = X_t B + u_t \tag{1}$$

where Y_t is $1 \times N$ matrix of endogenous variables, $\underbrace{X_t}_{1\times(NP+1)} = [Y_{t-1}, .., Y_{t-P}, 1]$ denotes the regressors in each equation and B is a $(NP+1) \times N$ matrix of coefficients. The error term is heteroscedastic:

$$
\begin{aligned}
u_t &\sim \mathcal{N}(0, \Sigma_1) \text{ periods of CE events} \\
u_t &\sim \mathcal{N}(0, \Sigma_0) \text{ all other periods}
\end{aligned}
$$

The reduced form errors u_t are linked to the structural shocks ε_t through matrix A

$$u_t = A\varepsilon_t \tag{2}$$

Event-based identification through heteroscedasticity. The standard identification through heteroscedasticity relies on the assumption that different shocks' relative variance changes across relevant episodes in recent history (*e.g.*, the Volcker disinflation versus the Great Moderation) while macro dynamics remain constant. In the current application we assume that one specific shock, namely the CE shock, has variance σ_1 on event days and σ_0 on the remaining days while the other structural shocks have constant variance on all dates.

This assumption allows the identification of the column vector $A_{(1)}$ corresponding to the CE shock in the A matrix, from the following decomposition:

$$\Sigma_1 - \Sigma_0 = A_{(1)}A'_{(1)}\sigma_1 - A_{(1)}A'_{(1)}\sigma_0 = A_{(1)}A'_{(1)}(\sigma_1 - \sigma_0) \tag{3}$$

Since $A_{(1)}A'_{(1)}$ and $(\sigma_1 - \sigma_0)$ are not separately identified we adopt the normalization that $(\sigma_1 - \sigma_0)$ =1, as in Wright (2012). With the estimates of variance-covariance matrices $\hat{\Sigma}_1$ and $\hat{\Sigma}_0$ at hand, the impact vector $A_{(1)}$ is obtained by solving the minimum distance problem:

$$A_{(1)} = \underset{A_{(1)}}{argmin} \left[vech\left(\hat{\Sigma}_1 - \hat{\Sigma}_0\right) - vech\left(A_{(1)}A_{(1)}^{'}\right)\right]^{'} \left[\hat{V}_0 + \hat{V}_1\right]^{-1} \left[vech\left(\hat{\Sigma}_1 - \hat{\Sigma}_0\right) - vech\left(A_{(1)}A_{(1)}^{'}\right)\right] \tag{4}$$

where $\hat{V}_0$ and $\hat{V}_1$ are the estimates of the variance-covariance matrices of $vech(\hat{\Sigma}_0)$ and $vech(\hat{\Sigma}_1)$ respectively.

We adopt a Bayesian approach to estimation using a standard Gibbs sampler for a model with heteroscedastic errors. A detailed description of the algorithm is provided in Appendix A.

Validation of our identification. Our identification strategy is based on two requirements. First, we require that the variance-covariance matrix of residuals is higher on event days compared to non-event days, that is $\Sigma_1 \neq \Sigma_0$. This is necessary to achieve identification as it signals heteroscedasticity on event days. To verify this requirement we compute for each saved draw in the Gibbs-sampler, the following statistical distance

$$\hat{T}_1 = vech\left(\hat{\Sigma}_1 - \hat{\Sigma}_0\right) vech\left(\hat{\Sigma}_1 - \hat{\Sigma}_0\right)^{'} \tag{5}$$

If the two variance-covariance matrices are not statistically different, we expect a posterior distribution concentrated around zero. Figure 1 (left-quadrant) shows that this is not the case, as the Kernel distribution is not centered at zero. This brings supporting evidence to our identification assumption.

Second, we require that the difference in the variance-covariance matrices can be factored in the form of one vector, that is $\Gamma_1\Gamma_1^{'}$, i.e. $\Sigma_1 - \Sigma_0 = \Gamma_1\Gamma_1^{'}$. This would indicate that the difference in the variance-covariance matrices between event and non-event days can be explained by one orthogonal shock, which we call CE shock. We verify this requirement by computing, for each saved draw, the statistical distance

$$\hat{T}_2 = \left[vech\left(\hat{\Sigma}_1 - \hat{\Sigma}_0\right) - vech\left(\hat{\Gamma}_1\hat{\Gamma}_1^{'}\right)\right]^{'} \left[vech\left(\hat{\Sigma}_1 - \hat{\Sigma}_0\right) - vech\left(\hat{\Gamma}_1\hat{\Gamma}_1^{'}\right)\right] \tag{6}$$

The second requirement is verified if the posterior distribution of $\hat{T}_2$ is concentrated around zero, as it is suggested by Figure 1 (right-quadrant).

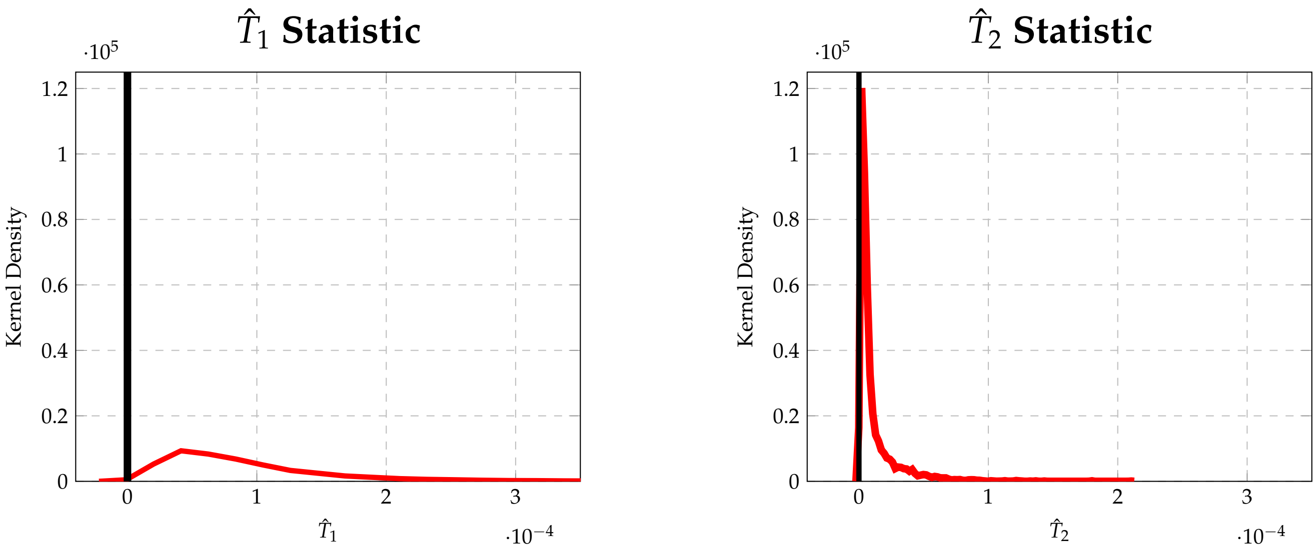

Figure 1 – Kernel density functions calculated on 5000 posterior draws of the statistics $\hat{T}_1$ and $\hat{T}_2$.

2.3 Data and results

We use data at daily frequency from January 1, 1990 to October 16, 2020. The sample choice is motivated by the daily data availability together with the concentration of events in the post 90's era. The baseline model contains five variables,

$$X_t = [ln\,(VIX_t)\,,\, ln\,(S\&P500_t)\,,\, DGS1_t,\, BAA_t,\, Sentiment_t]\,, \tag{7}$$

$ln\,(S\&P500_t)$ is the (log of) the S&P 500 Index, the main US stock market indicator meant to capture a number of first-order effects. $ln\,(VIX_t)$ is the (log of) VIX index[1], commonly used as a proxy for economic uncertainty, *e.g.* Bloom (2009). $DGS1_t$ is the 1-Year Treasury

[1]We follow Baker et al. (2016) and use the VIX index in logs to have a clear interpretation in percent terms of the IRFs of the VIX index. However, the results remain, for all practical purposes, identical in an alternative model with the VIX index in levels (result available upon request)

Constant Maturity Rate which is a more appropriate proxy for monetary policy when the sample includes the zero lower bound, as argued by Gertler and Karadi (2015) . BAA_t is the corporate bond spread over the 10 year treasury rate and it is a measure of external finance premium, while $Sentiment_t$ is a recent text-based measure of daily economic sentiment from economic and financial newspaper articles, see Shapiro et al. (2020). The number of lags is set to 10. A detailed description of the data is available in the Appendix B.

Impulse response analysis. Now we turn our attention to the effects of the identified CE shock in the daily VAR model. For each variable, we report the posterior median and the 68 and 90 credibility intervals responses to a CE shock scaled to increase the S&P 500 index by 1 percent. The scaling is without loss of generality and exclusively for expositional purposes.

As can be seen in Figure 2, the CE expansionary shoock triggers an increase in stock prices (+1%) and an improvement in credit conditions, captured by the fall in BAA credit spread (-2bp). The persistent increase in stock prices and the substantial rise in the sentiment index could suggest a generalized increase in financial confidence. Regarding the relation between first and second moment financial variables, the predictions of the empirical studies are rather mixed. In agreement with Mumtaz et al. (2018) and Caggiano et al. (2021), we find that the stock market expansion is accompanied by a fall in uncertainty (-2.2%). In contrast, Caldara et al. (2016) and Furlanetto et al. (2019) report a mild or insignificant response of uncertainty to financial disruptions. Finally, the monetary authority raises short rates consistent with a central bank reaction to an expansionary shock. Overall, the results of the impulse response analysis are in line with standard definitions of financial shocks.

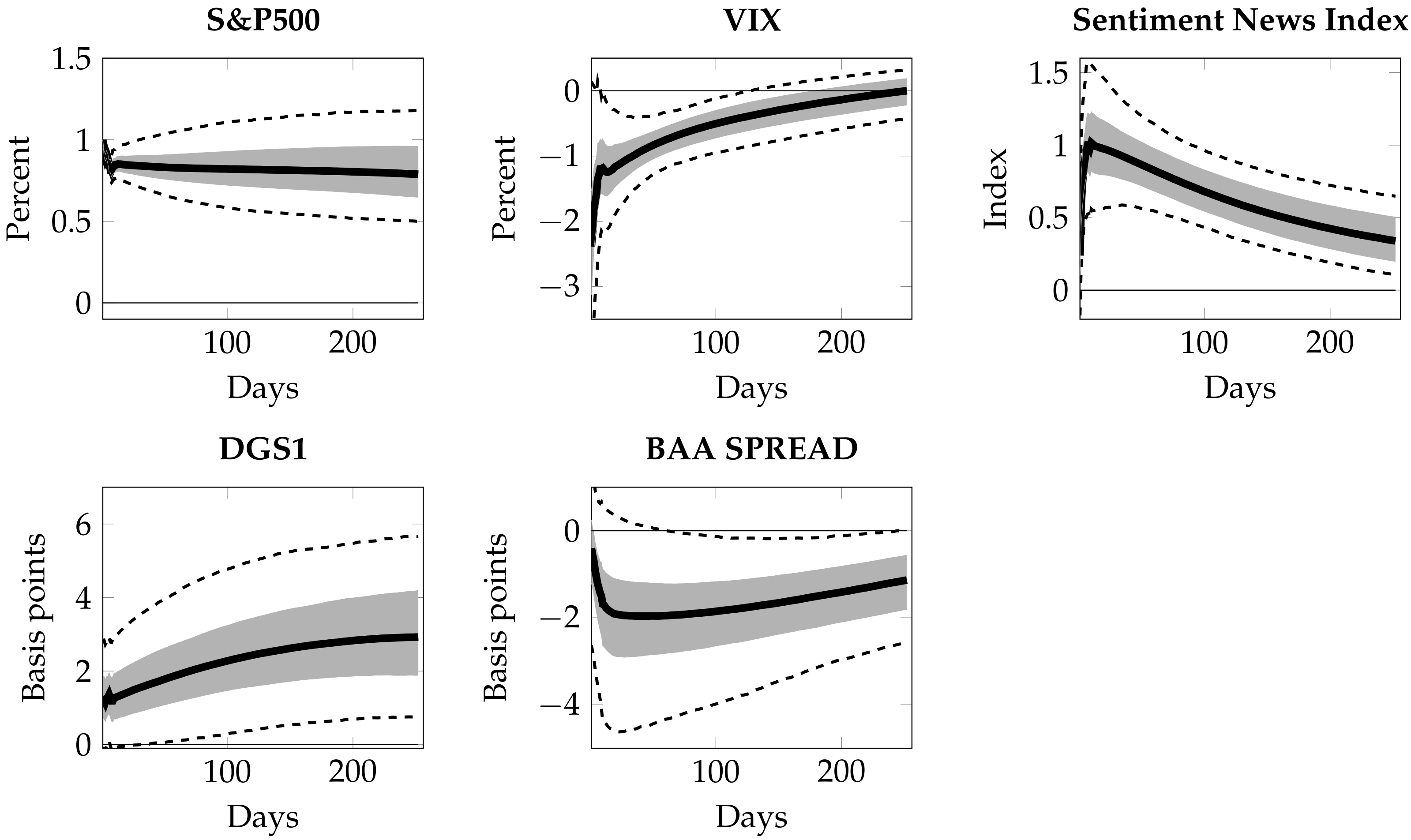

Figure 2 – IRFs to a CE shock increasing S&P 500 by 1 percent in the daily BVAR setting. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

2.4 The CE shock instrument

The daily BVAR framework described in this section has many desirable properties but it comes with an important drawback: it relies on high frequency models. This can be a weighty limitation in applications focusing on macroeconomic variables which are mainly available at monthly or lower frequency. To be able to quantify the effects of CE shocks on the primary economic indicators we proceed as follows: we extract the series of structural CE shocks from the daily BVAR model and use them as an instrumental variable in lower frequency models (monthly in our case). To reduce the noise, we set to zero

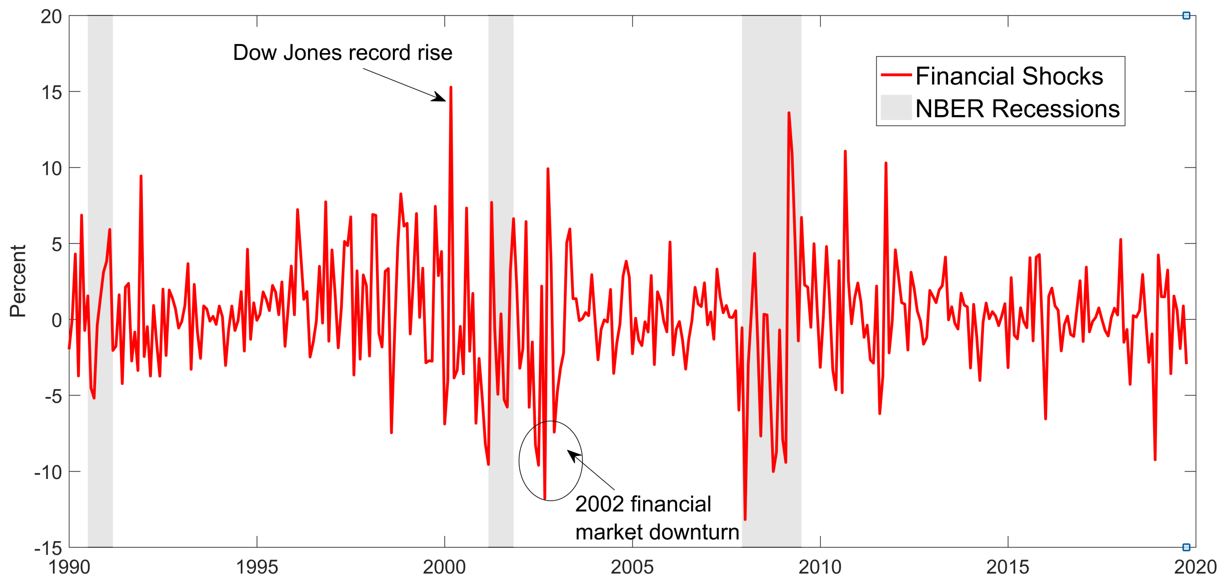

Figure 3 – This figure shows the monthly CE shock series constructed as the sum of the daily surprises. Shaded areas are NBER recession periods

the structural shocks that are not statistically different from zero at 90 HPDis. However, as reported in Figure C.7 this filtering has no effect on the results.

The structural CE shock series has several appealing features that make it an appropriate candidate for a CE shock instrument. Specifically, the shocks series is exogenous to the other disturbances in the model and it is not serially correlated by construction. Moreover, it inherits all the characteristics and assumptions of our identification design. It should thus capture exogenous CE disturbances. One drawback of this approach is that the shock series is subject to generated regressors problem. Nonetheless, using it as an instrument rather than directly in a model, minimizes the measurement error bias (see Stock and Watson, 2012 and Mertens and Ravn, 2013).

We aggregate the daily shocks to a monthly series taking the sum of the daily surprises in a given month. The monthly series of CE surprises covers the sample from 1990:2 to 2019:10 and is shown in Figure 3. The series tracks well the start of the early 90's recession, the Dot-com bubble recession as well as the Global Financial Crisis (GFC). In fact, the largest negative spike is recorded at the onset of the GFC. We observe other big negative shocks between June and September 2002 which correspond to the stock market downturn of 2002. A large positive CE (financial) shock is recorded in March 2000, in occasion to the record rise in Dow Jones industrial index as a result of the blue-chip euphoria. Overall, the shock series seems to account for the most relevant US financial events.

To reinforce the validity of the series, we perform a number of additional checks including the correlation with other instrumental variables available for different shocks and the sensitivity of the results to alternative specifications of the daily VAR model and of the event days. The outcome of these checks shows that the CE shock series is uncorrelated with the following instruments: the monetary policy instrument of Gertler and Karadi (2015), the uncertainty instrument of Piffer and Podstawski (2018), the housing credit instrument of Fieldhouse et al. (2018) and the oil supply news instrument of Känzig (2020). Moreover our main findings are unaffected if we increase the number of lags to 21 in the daily VAR model or if we remove from the events list the news related exclusively to financial institutions, as in Table C.2. The corresponding tables and figures are available in Appendix C.

3 Empirical model and data

In this section we describe the main empirical exercise. We first introduce the econometric method and the data used in the estimation phase.

3.1 Large BVAR model identified with external instruments

As discussed above, to minimize the background noise, the CE shock series from the daily VAR framework is used as an instrument in a large proxy BVAR model. The rich-information BVAR model is preferred to the small VAR alternative for two main reasons. First, it permits to jointly evaluate the response of several domestic and international variables. Second, it alleviates the potential bias due to non-invertibility of the small VAR model.[2] On the other side, relying on the instrumental variable identification, we preserve all the properties of the heteroscedasticity-based event study approach.

Consider again a standard VAR model:

$$Y_t = X_t B + u_t \tag{8}$$

where Y_t is $1 \times N$ matrix of endogenous variables, $\underbrace{X_t}_{1\times(NP+1)} = [Y_{t-1}, .., Y_{t-P}, 1]$ denotes the regressors in each equation and B is a $(NP+1) \times N$ matrix of coefficients. The reduced form errors u_t are linked to the structural shocks ε_t through matrix A

$$u_t = A\varepsilon_t \tag{9}$$

The external instruments identification assumes that there exists an instrument m that satisfies two conditions:

$$\mathbb{E}\left[m_t \epsilon_{1,t}\right] = \alpha \neq 0 \tag{10}$$

$$\mathbb{E}\left[m_t \epsilon_{2:n,t}\right] = 0 \tag{11}$$

Without loss of generality let us assume that $\epsilon_{1,t}$ is the CE shock while $\epsilon_{2:n,t}$ is the $(n-1) \times 1$ vector of the remaining shocks in the model. The assumption (10) is associated to the relevance of the instrument and is testable. Assumption (11) corresponds to the exogeneity of the instrument, is not testable and it requires that m is uncorrelated with the other shocks in the model. Conditional on the validity of our heteroskedasticity-based event study identification scheme, (11) should be verified by construction. If (10) and (11)

[2] The non-invertibility of a VAR model is essentially an omitted variable issue and is usually addressed by using a data-rich environment. See Stock and Watson (2018) and Miranda-Agrippino and Ricco (2019) for details.

hold, m is considered a valid instrument and the first column of A, *i.e.* $\mathbf{a_1}$, is identified up to scale as follows:

$$\tilde{a}_{1,1} \equiv \frac{a_{2:n,1,}}{a_{1,1}} = \frac{\mathbb{E}\left[m_t u_{2:n,t}\right]}{\mathbb{E}\left[m_t u_{1,t}\right]} \tag{12}$$

For ease of interpretation and consistency with the daily VAR framework, we assume that the normalization is such that it increases S&P500 by 1%, so that $a_{1,1} = 1$.

We estimate the model using Bayesian methods. Specifically, we impose a standard Normal-Wishart prior choosing the overall tightness parameter optimally as proposed by Giannone et al. (2015). Details on the estimation are provided in Appendix A. [3]

3.2 Data

We estimate two models, a US domestic BVAR model and an open economy BVAR model combining US and EA data. Both models contain monthly data on 12 time series (listed in Table 2). The sample covered by the domestic VAR goes from January 1980 to April 2019. Due to the limited availability of EA variables, data in the international model spans from February 1990 to April 2019 . The lag length P is set to 12. Variables are in log levels except for the GFF which is in original units; interest rates are expressed in basis points. The structure of the domestic VAR model follows Brunnermeier et al. (2019) and includes measures or real activity (GDP and Industrial Production), prices (PCE Deflator), consumer and business credit based on the Federal Reserve's weekly surveys of U.S. commercial banks, three spread measures that should capture credit stress along several dimensions (GZ Spread, EBP and the Term Spread) and 1-Year Treasury Rate as monetary policy variable.[4] We also include VIX index to account for second moment fluctuations, and the GFF as a proxy for the global asset prices. The inclusion of the GFF in the domestic BVAR model accounts for the international dimension of the shock and should capture

[3]For the estimation purposes we employ the codes provided in Miranda-Agrippino and Rey (2020).

[4]As described in Brunnermeier et al. (2019), GZ Spread detects tightness in business finance while the Term Spread accounts for inflation expectations and uncertainty about future fundamentals.

potential feedback effects from the international financial market. As for the specification of the international BVAR, we combine US and EA data as reported in Table 2. We follow Jarociński and Karadi (2020) in using the German one-year government bond yield to capture the safest one-year interest rate and we use the blue-chip STOXX 50 index as a proxy for EA stock prices. We add industrial production and consumer prices for the EA which are available for the whole sample as opposed to alternative measures (*e.g.* GDP and GDP deflator) attainable for shorter periods. Finally, we add Euro per USD exchange rate. [5]

Table 2 – Data series used in the model estimation

Variable name	Transformation	Source	Model 1 1980:01-2019:02	Model 2 1990:02-2019:04
S&P500	log	FRED data	✓	✓
US Gross domestic product (GDP)	log	Own source ∗	✓	✓
Personal Consumption Expenditure (PCE) deflator	log	FRED data	✓	✓
VIX index	log	FRED data	✓	✓
DGS1 (1Y US Treasury rate)	none	FRED data	✓	✓
GZ Spread (Gilchrist and Zakrajšek (2012) bond spread)	none	Gilchrist and Zakrajšek (2012)	✓	✓
Global Financial Factor (GFF)	none	Miranda-Agrippino and Rey (2020)	✓	✓
Industrial Production (IP)	log	FRED data	✓	
Consumer Loans (Commercial bank: real estate & consumer loans)	log	FRED data	✓	
Business Loans (Commercial bank: commercial & industrial loans)	log	FRED data	✓	
Term Spread (10Y- 1Y)	none	FRED data	✓	
Excess Bond Premium (EBP)	none	Gilchrist and Zakrajšek (2012)	✓	
Total industry excluding construction for EA (IP EA)	none	FRED data		✓
Consumer prices for EA (CPI EA)	log	BIS data		✓
Exchange rate (EUR to 1 USD)- Average over period	log	BIS data		✓
1Y Treasury rate for Germany (DGS1 Germany)	none	Bundesbank website		✓
STOXX50	none	Datastream		✓

Notes. The table lists the variables included in the baseline domestic and international BVARs. Models correspond to (1) the domestic BVAR (1980:01-2019:04) and (2) the international BVAR (1990:02-2019:04). ∗ Luca Benati kindly shared his monthly US GDP series with us.

[5] The exchange rate is defined such that an increase means appreciation of the USD versus Euro.

4 Results

In this section we discuss the main results of the empirical exercise. We report the first stage statistics, impulse responses from the domestic and international BVAR model, as well as the historical decomposition and variance decomposition for selected variables.

4.1 First stage statistics

We investigate the strength of our instrument computing the F statistics of the S&P500 residual on the instrument, as well as the reliability measure proposed by Mertens and Ravn (2013). If the F-statistic is well above the threshold level of 10 (see Stock et al., 2002), we are confident that there is no weak instrument problem. Following Mertens and Ravn (2013), Gertler and Karadi (2015) and Miranda-Agrippino and Rey (2020) we estimate the VAR using the whole data sample (*i.e.* 1980:01- 2019:04 for the domestic BVAR and 1990:02 - 2019:04 for the international BVAR) while the identification step (*i.e.* the projection of the VAR innovations on the instrument) and the first stage statistics are run over the common sample going from 1990:02 to 2019:04. Results in Table 3 show that our instrument attains levels of relevance far above the required threshold.

Table 3 – Tests for instrument relevance

Model	F-stat	90 HPDI	Reliability	90 HPDI
Domestic BVAR	150	[112 163]	42	[38 47]
International BVAR	155	[110 165]	46	[41 50]

Notes. The table reports first-stage F statistics, statistical reliability and 90% HPDIs. VAR innovations are computed from the sample going from 1980 to 2019 for the domestic BVAR and from 1990 to 2019 for the international BVAR. The first stage regressions are obtained from the sample 1990 to 2019, which is the overlapping sample between VAR data and the instrument.

4.2 Domestic effects of US CE shocks

We now introduce the results from the estimation of the domestic BVAR model. We first present the impulse responses, we then compare the magnitude effects of real activity estimates with previous findings, and finally we report the historical contribution of CE shocks to real activity.

4.2.1 Impulse response analysis

Figure 4 shows the impulse response functions of the identified CE shock scaled to increase the S&P500 index by 1 percent. We report the median over the saved draws, together with the 68 and 90 coverage set.

The expansionary CE shock triggers a sharp and significant increase in stock prices accompanied by a contemporaneous raise in the GDP with effects that persist for almost two years. The industrial production starts increasing shortly after the shock reinforcing the expansionary features of the disturbance. The resulting economic boom leads to substantial inflation over time. In response to these expansionary developments, monetary authority raises short rates. Term spread drops, consistent with a stronger effect of the monetary contraction at the short end of the yield curve.

The shock increases credit considerably, with a strong delayed effect on business loans and a more modest effect on consumer loans. VIX index, GZ spread and EBP decrease on impact indicating an improvement in credit and financial conditions. Importantly, the shock has a powerful effect on the global asset market raising substantially the GFF. This result highlights both the hegemonic role of US in the global financial market as well as the strong spillover effects triggered by the shock. The failure to account for the international dimension of the shock might lead to biased results.

Discussion. Overall, our findings fit well a theoretical setting combining asset-based financial frictions and financial disturbances with a monetary authority trying to offset these effects. In particular, our results are in line with the theoretical predictions of Christiano et al. (2014) and Ajello (2016) who associate favorable financial shocks to expansionary and inflationary developments, accompanied by a raise in the short rates and a drop in the slope of the term structure.

While the literature seems to agree on the response of output to financial shocks, the reaction of prices is less clear *a piori*. Several theoretical models predict a negative price reaction to contractionary financial shocks (*e.g.* Christiano et al., 2014, Ajello, 2016 and Curdia and Woodford, 2010), while other studies show that the interaction between financial frictions and customer markets can induce firms to raise prices in response to negative financial shocks (*e.g.* Gilchrist et al., 2017). In this respect, our estimates suggest a strong and significant co-movement between output and prices, in agreement with Gilchrist and Zakrajšek (2012) and Abbate et al. (2016). On the other side, the empirical evidence in Helbling et al. (2011), Caggiano et al. (2021), Fornari and Stracca (2012) and Furlanetto et al. (2019) attests a limited effect of financial shocks on prices. Notice that our results emerge naturally as we do not restrict in any way the sign of the responses. This is not the case in sign restricted models which predict a zero response of prices to financial shocks if the sign of prices is left unrestricted (see Meinen and Roehe, 2018). Moreover, the strong impact reaction of both prices and GDP detected by our identification scheme is incompatible with most empirical models imposing a zero contemporaneous response for slow movement variables.

Interestingly, our shock provides strikingly similar impulse responses to one of the four financial disturbances identified in Brunnermeier et al. (2019), and labeled by the authors as a GZ spread stress. This suggests that if we identified an exogenous GZ Spread shock through heteroscedasticity as in Brunnermeier et al. (2019), we would have obtained something similar to what we have found with the event-based heteroscedasticity method.

Summing up, from an empirical perspective, the corporate earning shock is observationally equivalent to the more general shock to corporate bond spreads. Moreover, our analysis does not unveil any substantial discrepancies between the CE shock and the theoretical predictions for standard financial disturbances that rely on asset based constraints.

4.2.2 Assessing the magnitude effects on real activity: the role of international feedbacks

To get a better understanding of the economic effects of US CE shocks, we compare the magnitude of our baseline estimates for GDP and IP with those of the literature, *i.e.* point identified VARs and estimated DGSE models. For ease of exposition, we scale the shock to increase EBP by 1% point, as in Barnichon et al. (2018). Moreover, we contrast the results obtained from the baseline domestic model with those obtained if we removed GFF from the baseline specification. This last exercise is meant to capture the relevance of an international feedback channel in the transmission of the financial shock.

In Figure 5, first row, we present the impulse responses of GDP, IP and EBP from the baseline model to a CE shock raising EBP by 1% point. The peak response of GDP (-2%) is in line with what reported by Gilchrist and Zakrajšek (2012) and Ajello (2016), while the peak reaction of IP of -5% is comparable to findings in Caldara et al. (2016) and somewhat higher than the estimates of Brunnermeier et al. (2019) for the GZ stress shock.

In a recent contribution, Barnichon et al. (2018) show that the presence of asymmetry in the effects of financial shocks leads to smaller and less persistent estimates in linear VAR models. Even though the GDP response in our model is indeed smaller and less persistent than what reported in Barnichon et al. (2018) —who account for the asymmetric effects of financial shocks —we take comfort from the fact that the magnitude of the IP response in our model (-5%) is actually stronger compared to their estimate of -4%.

In the second row of Figure 5, we report the same responses for GDP and IP, but this time the estimates come from the baseline model excluding the GFF. Notably, while the impulse response of EBP is similar across the two models, the behavior of output is quite different: compared to the baseline model estimates, the fall in output in the model

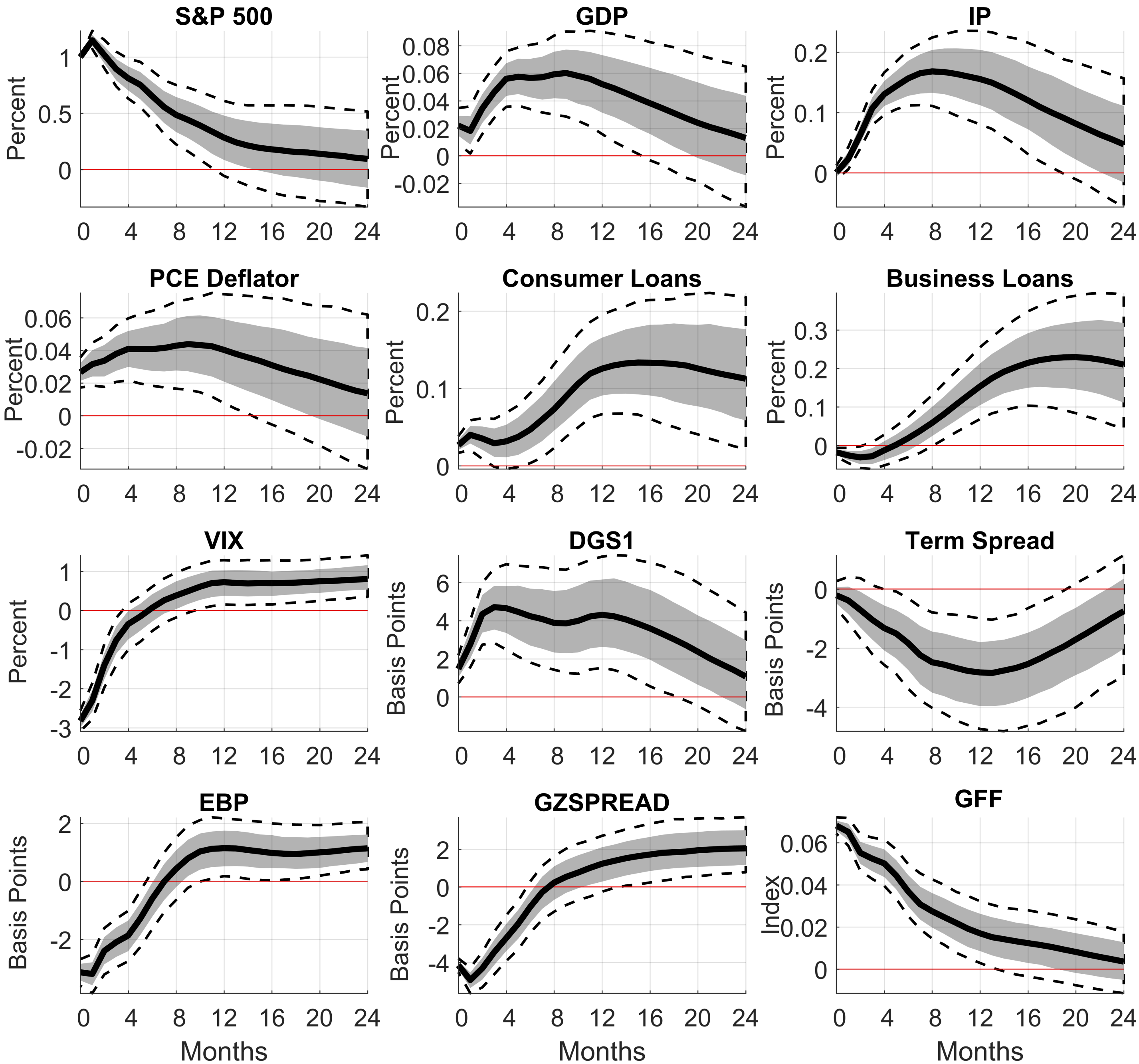

Figure 4 – IRFs of domestic US variables to a financial shock raising S&P 500 by 1 percent in the monthly BVAR model. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

without GFF is larger (-3 and -6 % for GDP and IP respectively) and much more persistent. It turns out that the results from this alternative specification are in fact comparable to the ones in Barnichon et al. (2018) in terms of both magnitude and persistence.

Taking stock, we have shown that (i) the magnitude of the real activity reaction to CE shocks is in line with findings pertaining to corporate spread shocks; and that (ii) the output response to CE shocks is substantially affected if the GFF factor is omitted from the model. We interpret this last result as evidence in favor of a powerful international financial feedback channel that (partly) offsets the effects of the shock. The failure to account for this channel leads to potentially inflated responses of domestic indicators to the CE shock.

4.2.3 Historical contribution of financial shocks to real activity

As we have seen, CE shocks can have substantial effects on the US economy. Nevertheless, an equally interesting question is how important CE shocks are in explaining the historical fluctuation of output. To answer this question, we compute a historical decomposition of the CE shocks.

Unlike structural impulse responses, historical decompositions are designed for stationary VAR models and should not be applied to integrated or co-integrated variables in levels without modifications (see Kilian and Lütkepohl (2017), Chapter 4). Thus, to perform this exercise we take the year on year growth rate of the variables in levels while leaving unchanged interest rates. We estimate the model using the common sample 1990:02:2019:04.

Figure 6 shows the cumulative historical contribution of CE shocks to the real activity, together with the actual value of the variables in percent deviations from the mean. In particular, we focus on GDP growth (left) and IP growth (right).

The shock is an important driver of the output drop in occasion of the National Bureau

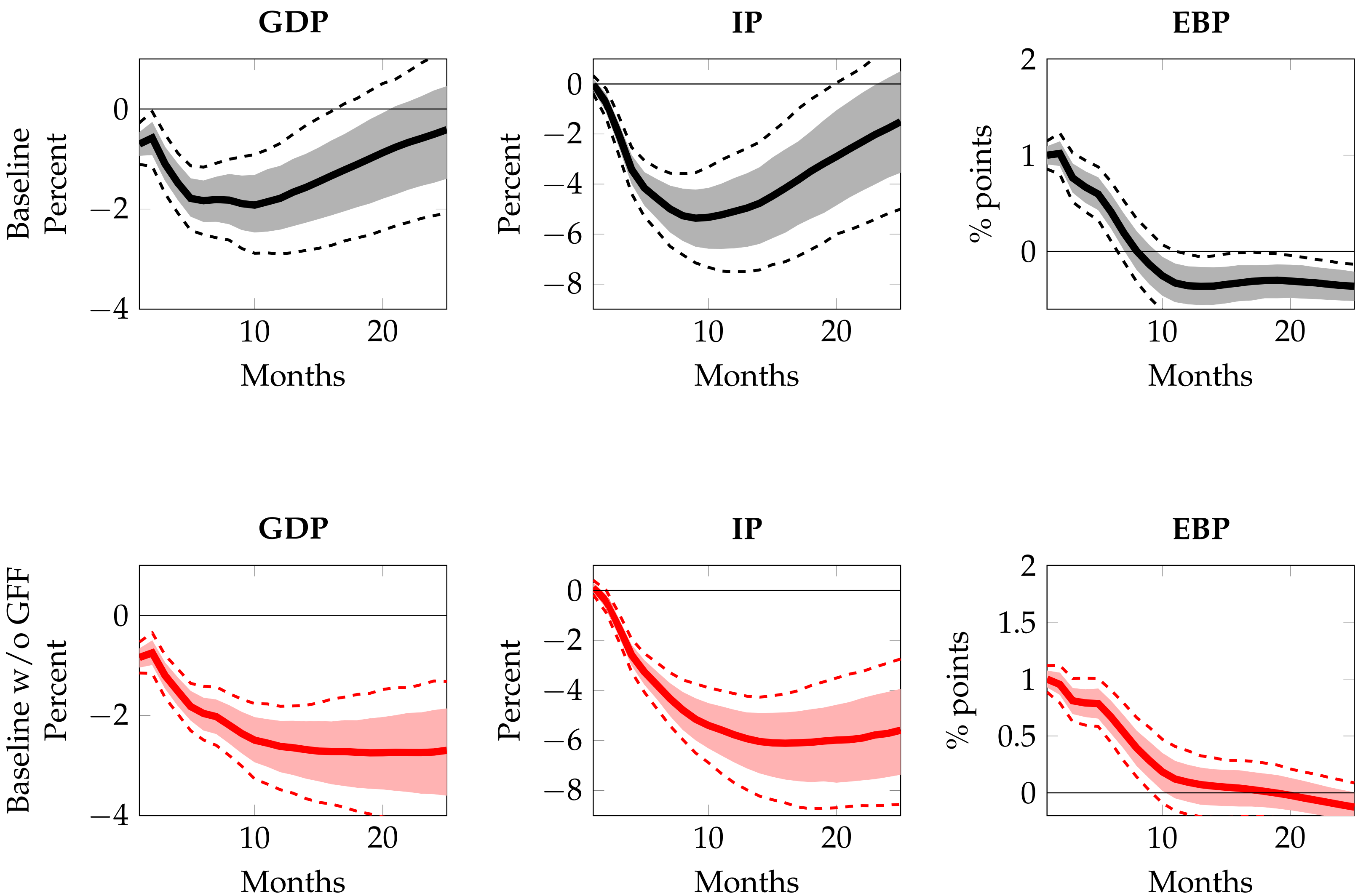

Figure 5 – IRFs of EBP and real activity variables to a CE shock raising EBP by 1 % point in the baseline domestic model (first row) and the baseline without GFF (second row). Solid line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

of Economic Research recessions, explaining around half of the GDP and IP drop during the Dot-com bubble crisis, and between 25 and 30% of the fall in real activity during the GFC. This is interesting considering that both episodes are characterized by disruptions on financial markets (*i.e.* the speculation of internet-related companies and the subprime crisis respectively). We signal the negative contribution of the CE shock during the Asian Crisis, even though it did not materialize in a recession. CE shocks track closely the historical fluctuations in output outside recessions periods as well, highlighting the relevance

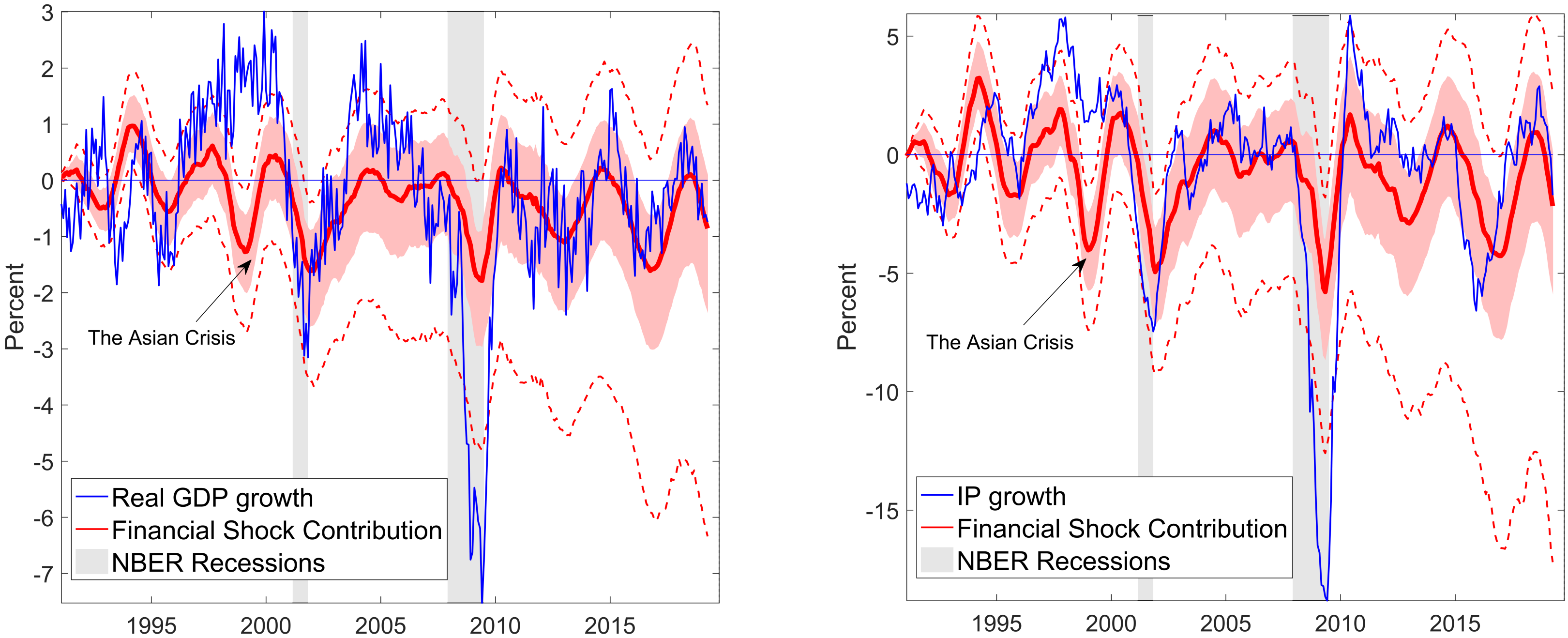

Figure 6 – Historical decomposition of US GDP growth (left) and US IP growth (right). The figure shows the cumulative historical contribution of CE shocks (red line) together with the actual variables (blue line) in percent deviations from mean. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

of financial disturbances in shaping real activity. Overall, our findings are in agreement with previous studies that point to financial shocks as important drivers of US recessions (see Ajello, 2016, Barnichon et al., 2018 and Caggiano et al., 2021).

4.3 International transmission of US CE shocks

Following the deep and synchronized recession experienced during the 2007-2009 financial crisis, the international transmission of financial shocks has received considerable attention from both theoretical studies (Dedola and Lombardo, 2012, Perri and Quadrini, 2018, Born and Enders, 2019) and empirical analyses (Helbling et al., 2011, Eickmeier and Ng, 2015, Abbate et al., 2016, Cesa-Bianchi and Sokol, 2017).

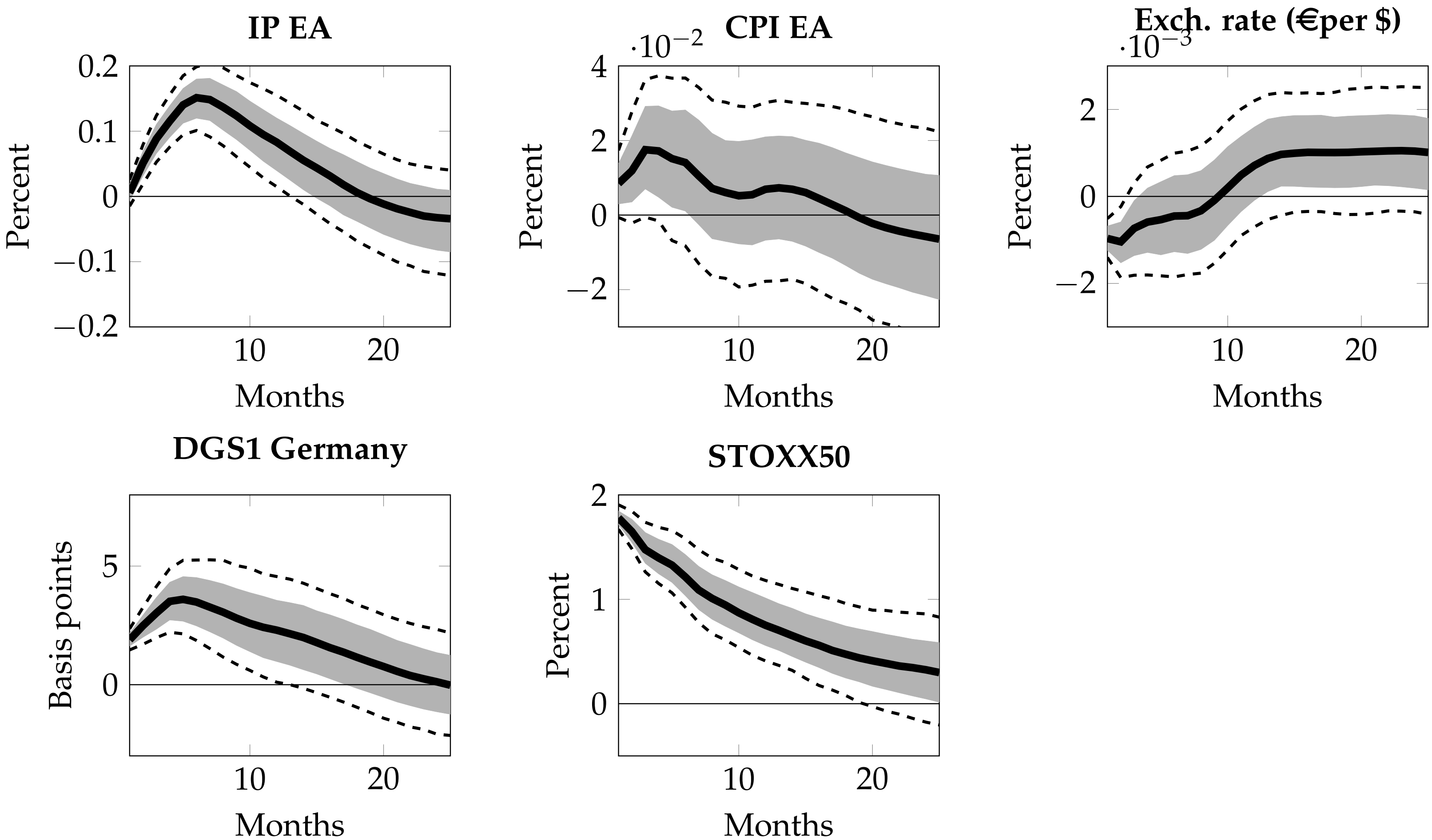

Figure 7 – IRFs of EA variables to a CE shock raising S&P 500 by 1 percent in the monthly international BVAR model. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

We contribute to this literature by examining the international transmission of the US CE shocks. In this exercise we focus on EA, which is the second world economic power, it has a unified monetary system and a floating exchange rate regime, and is one of the most important trade and financial partners of the US. In Figure 7 we report the IRFs for the EA variables only. The full set of IRFs is available in Figure C.2 in the Appendix.

The expansionary US CE shock triggers a large and synchronized increase in the asset prices in the EA and the output effect is about as large as on the US itself. The shock has inflationary effects, although less persistent than the one recorded domestically. Interest rates in the EA increase substantially, in line with a stabilizing monetary policy response to the expansionary (demand-like) developments. Finally, the USD depreciates with respect to the euro, but the effect is small and short lived. Overall, our results are consistent with findings in Eickmeier and Ng (2015).

Discussion. The US CE shock induces a strong co-movement in asset prices, output, interest rates and consumer prices in the EA, as implied by two-countries theoretical models featuring financial frictions and a high degree of financial integration (see Dedola and Lombardo, 2012 and Perri and Quadrini, 2018 among others). Thus, we show that earning-based financial shocks are indeed pivotal in explaining the high degree of international co-movement in economic indicators observed in the data.

The sharp and strong reaction in both the foreign asset prices and the GFF supports the existence of a powerful international financial channel, which can be associated to the global financial cycle hypothesis put forward by Rey (2015) and Miranda-Agrippino and Rey (2020) and further analyzed by Jordà et al. (2019). On the other side, the mild and short-lived reaction of the exchange rates suggests a less relevant trade channel in the transatlantic transmission of US financial shocks.

4.4 Variance decomposition analysis

A different way to asses the economic relevance of CE shocks is by computing the share of forecast error variance explained by these shocks. The estimates from this exercise are reported in Table 4.

Consistent with the financial nature of the disturbance, the highest shares explained by the shock correspond to S&P500 and the GFF, with an impact estimate of 66 and 76%, respectively. Notice that the impact estimate for VIX (+ 22%) is far smaller than the ones corresponding to stock prices and GFF. This finding together with the test in equation 6 —which shows that on event days the higher variance of the system is triggered by one orthogonal shock—bring evidence in favor of a first moment (financial) shock rather than

Table 4 – Forecast error variance decomposition

Part A: US variables

	S&P500	GDP	IP	PCE deflator	DGS1	VIX	GFF
0	0.66	0.01	0	0.03	0.01	0.22	0.76
	(0.61 0.7)	(0 0.02)	(0 0)	(0.01 0.04)	(0 0.02)	(0.18 0.25)	(0.71 0.79)
6	0.51	0.11	0.18	0.09	0.10	0.17	0.57
	(0.40 0.57)	(0.05 0.15)	(0.10 0.24)	(0.03 0.14)	(0.03 0.15)	(0.12 0.22)	(0.46 0.64)
12	0.29	0.12	0.20	0.09	0.11	0.16	0.42
	(0.19 0.436)	(0.04 0.18)	(0.09 0.29)	(0.02 0.16)	(0.03 0.18)	(0.11 0.20)	(0.30 0.50)
24	0.15	0.07	0.13	0.05	0.11	0.17	0.30
	(0.08 0.21)	(0.02 0.13)	(0.04 0.21)	(0.01 0.11)	(0.03 0.18)	(0.11 0.22)	(0.19 0.38)

Part B: EA variables

	Stoxx50	IP EA	CPI EA	Euro-dollar ex. rate	DGS1 Germany
0	0.69	0	0	0.01	0.06
	(0.63 0.72)	(0 0)	(0 0.01)	(0 0.01)	(0.03 0.08)
6	0.59	0.15	0.02	0.01	0.12
	(0.46 0.65)	(0.07 0.20)	(0 0.05)	(0.01 0.05)	(0.05 0.18)
12	0.46	0.14	0.02	0.02	0.11
	(0.32 0.56)	(0.06 0.20)	(0 0.05)	(0.01 0.05)	(0.03 0.18)
24	0.29	0.09	0.02	0.04	0.09
	(0.17 0.39)	(0.04 0.13)	(0 0.05)	(0.01 0.05)	(0.03 0.15)

Notes. The table shows the forecast error variance of the key US and international variables explained by US CE shocks at horizons 0,6, 12 and 24 months. The 90 credibility sets are displayed in brackets.

a second moment one. [6]

The CE disturbance accounts for a share of 12 and 20% for GDP and IP respectively, with the peak effect reached a year after the shock. As for prices and interest rates the portion of the variation explained is around 10%. These results are comparable to previous analyses (see Gilchrist and Zakrajšek, 2012, Eickmeier and Ng, 2015, Ajello, 2016 and Furlanetto et al., 2019 among others).

[6] In addition, a robustness exercise described next, shows that orthogonalizing the shock with respect to uncertainty leaves our results unchanged.

In the second part of Table 4 we report the values for the EA variables. The variance decomposition analysis delivers a similar message to the impulse responses. Specifically, the portion accounted by the US CE shock in the variance of stock prices, output and interest rates in the EA is about the same as the US one. This result further supports the hypothesis of a strong international co-movement generated by the US earning-based financial shock. On the other side, the shock accounts for a negligible share in the EA prices and the USD per Euro exchange rate variation.

Taking stock, according to the model and the identification scheme proposed in this paper, the CE shock is responsible for most of the impact variation of domestic and foreign stock prices and the GFF. This confirms not only the financial nature of the CE shock but also its crucial role in shaping the global financial cycle. The US CE shock is pivotal in explaining both business cycle fluctuations as well as the international co-movement in macroeconomic variables.

4.5 Robustness checks

We test the robustness of our results along a number of dimensions. To preclude that our instrument is confounded with second moment factors, we estimate the baseline model identifying both earning-based financial shocks and uncertainty shocks. We employ our instrument and the uncertainty instrument proposed by Piffer and Podstawski (2018). The two shocks are orthogonalized by means of sign restrictions. Specifically, we follow Nguyen et al. (2021) and impose that the CE shock instrument is more correlated on impact with S&P500 than the uncertainty shock instrument, which instead, is more correlated to the financial uncertainty measure proposed by Ludvigson et al. (2015). The estimation sample is 1990:2-2015:7 for both the VAR coefficients and the identification matrix. The results from this experiment presented in Figure C.3 are in line with the baseline model estimates.

Figure C.5 describes the impulse responses from the baseline model estimated over the overlapping sample between the VAR data and the instrument, *i.e.* 1990:2-2019:4. Except from few responses that are less persistent, qualitatively the results are very similar.

In the construction of the CE shock instrument we employ corporate profit news related to both financial and non-financial institutions. Since most of the earning-based lending pertains to the non-financial sector, there might be concerns that corporate profit news from the financial sector rely on a different transmission mechanism. We run the baseline model with the instrument constructed using only non-financial institutions related news, as described in Table C.2. Estimates are presented in Figure C.2 and they are by all practical purposes unchanged.

Finally, several of our CE events occur during the GFC. Thus, it might be the case that CE events in this high-instability period might convey information on the macroeconomic outlook as well, on top of corporate earnings. In Figure C.6 we show that if we remove the GFC events, our result hold.

5 Conclusion

Corporate lending in the US is predominantly backed by earnings rather than physical assets, as commonly modelled in the literature. Thus, shocks to corporate earnings affect firms' capacity to borrow and are fundamental in understanding business cycle fluctuations. Despite that, little is known about the effects of these shocks on economic activity. We provide novel evidence on the macroeconomic effects of these shocks using an identification design that exploits the valuable information around days with corporate profit releases and the higher variance of CE shocks on these days. We find that CE shocks have significant effects on the macroeconomy and contribute substantially to historical variation in output. We document the existence of a powerful international dimension of the shock which interacts with both domestic and foreign variables.

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A The Econometric Framework

A.1 Heteroskedastic VAR model.

The baseline model is defined as:

$$Y_t = X_t \beta + \mu_t \tag{A.1}$$

where Y_t is $1 \times N$ matrix of endogenous variables, $\underbrace{X_t}_{1\times(NP+1)} = [X_{t-1}, .., X_{t-P}, 1]$ denotes the regressors in each equation and β is a $(NP+1) \times N$ matrix of coefficients. The error term is heteroscedastic:

$$\mu_t \sim \mathcal{N}(0, \Sigma_1) \text{ financial events}$$
$$\mu_t \sim \mathcal{N}(0, \Sigma_0) \text{ all other periods}$$

We use a natural conjugate prior for the VAR parameters implemented via dummy observations, see Bańbura et al. (2010):

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1\sigma_1...\gamma_N\Sigma_0)}{\tau} \\ 0_{N\times(P-1)\times N} \\ .... \\ diag(\sigma_1...\Sigma_0) \\ .... \\ 0_{1\times N} \end{pmatrix}, and\ X_{D,1} = \begin{pmatrix} \frac{J_P\otimes diag(\sigma_1...\Sigma_0)}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP+1} & \\ .... & \\ 0_{1\times NP} & I_1 \times c \end{pmatrix} \tag{A.2}$$

where γ_1 to γ_N denote the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients and c is the tightness of the prior on the constant. In our application, the prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable. We set $\tau = 1$. The scaling factors σ_i are set using the standard deviation of the error terms from these preliminary

AR(1) regressions. Finally we set $c = 1/10000$ in our implementation indicating a flat prior on the constant. We also introduce a prior on the sum of the lagged dependent variables by adding the following dummy observations:

$$Y_{D,2} = \frac{diag\left(\gamma_1\mu_1...\gamma_N\mu_N\right)}{\lambda},\ X_{D,2} = \begin{pmatrix} \frac{(1_{1\times P})\otimes diag(\gamma_1\mu_1...\gamma_N\mu_N)}{\lambda} & 0_{N\times 1} \end{pmatrix} \tag{A.3}$$

where μ_i denotes the sample means of the endogenous variables calculated using AR(1) preliminary regressions. As stamdard in the literature, we set the prior of $\lambda = 10\tau$.

The baseline VAR model is estimated via Gibbs sampling. Conditional on Σ_1 and Σ_0, the posterior distribution of $b = vec\left(\beta\right)$ is normal with mean M^* and variance V^* where

$$V^* = \left(\sum_{t=1}^{T}\left(R_t^{-1}\otimes X_t X_t'\right) + S_0^{-1}\right)^{-1} \tag{A.4}$$

$$M^* = V^*\left(vec\left(\sum_{t=1}^{T}\left(X_t Y_t' R_t^{-1}\right)\right) + S_0^{-1}\tilde{\beta}_0'\right) \tag{A.5}$$

where $R_t = \Sigma_1$ over periods characterized by the financial shock and $R_t = \Sigma_0$, otherwise. The prior for the VAR coefficients based on dummy observations is $N\left(\tilde{B}_0, S_0\right)$. Conditional on a draw for β, the conditional posterior for $\Sigma_i, i = 0, 1$ is inverse Wishart: $IW\left(\mu_i'\mu_i + s_0, T + t_0\right)$ where μ_i denotes the residuals associated with period of higher variance of financial shocks when $i = 1$ and all other periods when $i = 0$. The prior for the VAR error covariance implied by the dummy observations is $IW\left(s_0, t_0\right)$. The lag is set to 10.

A.2 Bayesian VAR model

Consider a standard VAR model:

$$Y_t = X_t B + u_t \tag{A.6}$$

where Y_t is $1 \times N$ matrix of endogenous variables, $\underbrace{X_t}_{1\times(NP+1)} = [Y_{t-1}, .., Y_{t-P}, 1]$ denotes the regressors in each equation and B is a $(NP + 1) \times N$ matrix of coefficients. The reduced form errors u_t are normally distributed with mean zero and variance Σ and are linked to the structural shocks ε_t through matrix A

$$u_t = A\varepsilon_t \tag{A.7}$$

We estimate the VAR following Miranda-Agrippino and Rey (2020), thus using a standard Normal-Inverse Wishart prior for the VAR coefficients which takes the following form:

$$\Sigma \sim \mathcal{IW}(s, v) \tag{A.8}$$

$$B|\Sigma \sim \mathcal{N}(b, \Sigma \otimes \Omega) \tag{A.9}$$

where B is a vector collecting all VAR parameters. The degrees of freedom of the Inverse-Wishart are set such that the mean of the distribution exists and are equal to $v = n + 2$, s is diagonal with elements which are chosen to be a function of the residual variance of the regression of each variable onto its own first P lags. More specifically, the parameters in Eq. A.8 and Eq. A.9 are chosen to match the moments for the distribution of the coefficients in Eq. A.6 defined by the Minnesota priors:

$$\mathbb{E}\left[(B_i)_{jk}\right] = \begin{cases} \delta_j & \text{for } i = 1, j = k \\ 0 & \text{otherwise} \end{cases} \tag{A.10}$$

$$\mathbb{V}\left[(B_i)_{jk}\right] = \begin{cases} \frac{\lambda^2}{i^2} & \text{for } j = k \\ \frac{\lambda^2}{i^2}\frac{\sigma_k^2}{\sigma_j^2} & \text{otherwise} \end{cases} \tag{A.11}$$

where $(B_i)_{jk}$ denotes the element in row (equation) j and column(variables) k of the coefficients matrix B at lag i $(i = 1, ..., P)$. When $\delta_j = 1$ the random walk prior is strictly imposed on all variables; however, for those variables for which this prior is not suitable we set $\delta_j = 0$ as recommended in Bańbura et al. (2010). In Eq. A.11 the variance of the elements in B_i is assumed to be proportional to the (inverse of the) square of the lag (i^2) and to the relative variance of the variables.

Importantly, λ is the hyperparameter that governs the overall tightness of the priors in the model. We treat λ as an additional parameter and we estimate it following Giannone et al. (2015). The lag is set to 12.

B Description of the daily VAR data

- the S&P500 index at daily frequency, transformed in logs. FRED link `https://fred.stlouisfed.org/series/SP500`
- the VIX index at daily frequency, transformed in logs. FRED link `https://fred.stlouisfed.org/series/VIXCLS`.
- the DGS1 index is the 1-year Treasury Constant Maturity Rate, FRED link `https://fred.stlouisfed.org/series/DGS1`
- the BAA Spread is Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity, FRED link `https://fred.stlouisfed.org/series/BAA10Y`
- Sentiment index is the Daily News Sentiment Index, a high frequency measure of economic sentiment based on lexical analysis of economics-related news articles, see Shapiro et al. (2020), link `https://www.frbsf.org/daily-news-sentiment-index/`.

Table C.1 – Correlation of the structural financial shock series with other instruments

Shock	Instrument	Frequency	Correlation coefficient	p-value
Uncertainty	Piffer and Podstawski (2018)	Daily	-.0001	0.92
Monetary policy	Gertler and Karadi (2015)	Daily	0.008	0.45
Oil supply news	Känzig (2020)	Daily	0.004	0.73
Housing credit	Fieldhouse et al. (2018)	Monthly	0.01	0.82

Notes. The table reports the correlation of the financial shock instrument with other instrumental variables, all the remaining instruments are at daily frequency, except for the housing credit instrument available at monthly frequency.

Table C.2 – Financial events list excluding news about non financial institutions

Date	S&P500 % jump	Brief Explanation
15/07/1996	-2.5	Weak earnings reports
23/03/1999	-2.7	Tech companies earnings expected to disappoint
07/03/2000	-2.7	Profit warning by P&G
25/04/2000	3.4	Positive earnings reports
13/10/2000	3.5	Optimistic news about third-quarter profit performances for tech
19/10/2000	3.5	Strong earnings report by Microsoft
03/04/2001	-3.4	Tech stocks down on bad earnings news
05/04/2001	4.4	Good earnings news for Dell, Alcoa, Yahoo rating upgraded
29/01/2002	-2.9	Enron-like accounting troubles expected in more firms
08/05/2002	3.8	Cisco hints about business recovery
14/08/2002	4	More confidence in financial statements after Enron scandal
11/10/2002	3.9	On-target earnings report from GE
15/10/2002	4.7	Citigroup, GM show good earnings
21/10/2008	-3.1	Tech companies reported weak quarterly results
22/10/2008	-5.9	Weak corporate earnings
12/03/2009	4.1	Good news for Bank of America, GM and GE
15/07/2009	3	Intel reports strong sales

Notes. The table reports the stock market jumps due to corporate earning news excluding announcements regarding financial institutions. The brief explanation column is the outcome of the authors' reading of the articles. GE and GM are acronyms for General Electric and General Motors, respectively.

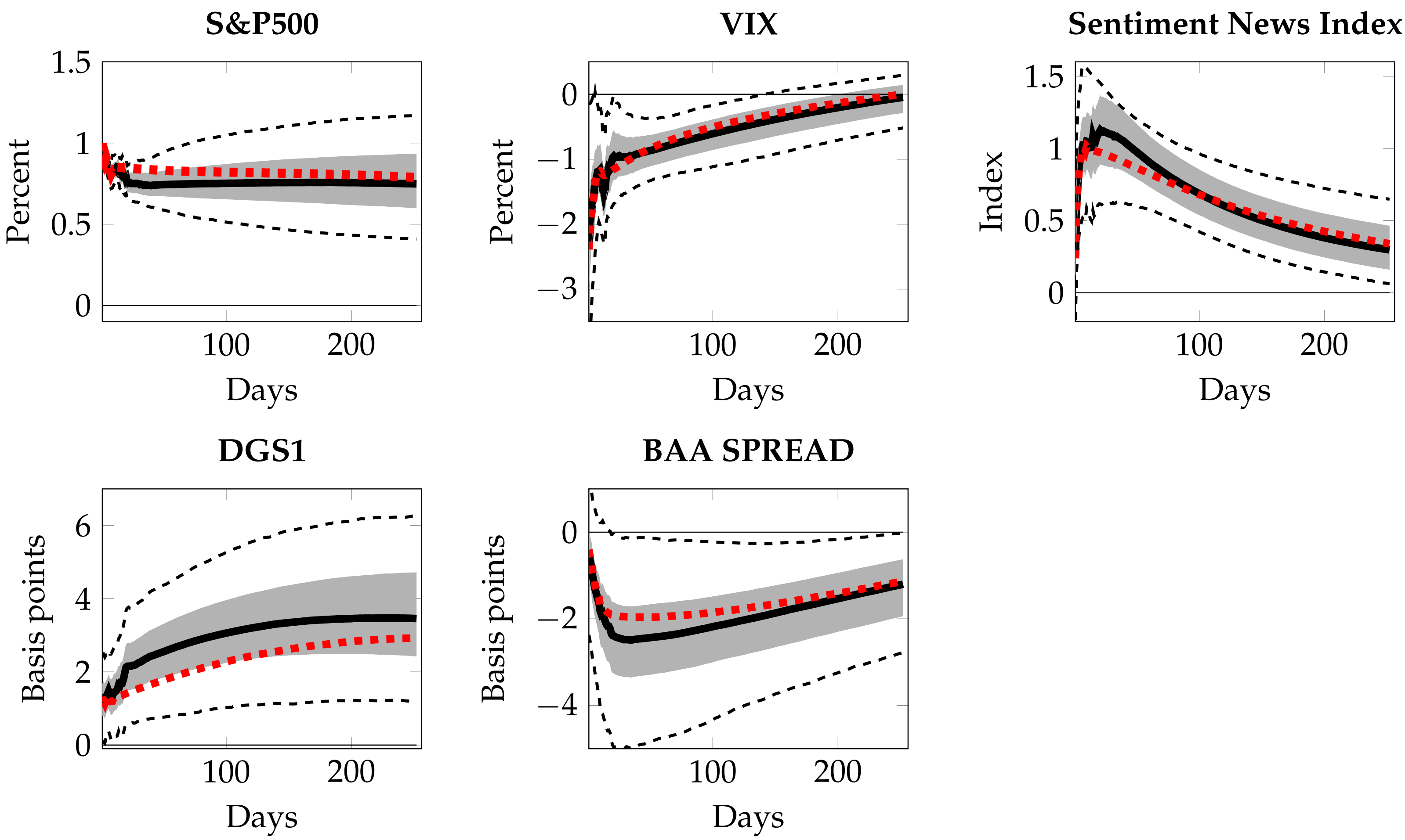

Figure C.1 – IRFs to a financial shock increasing S&P 500 by 1 percent in the daily BVAR setting with 21 lags. Solid black line, shaded areas and dotted lines are the median, 68 and 90 credibility sets. Red dashed line is the median in the baseline model with 10 lags.

C Robustness checks

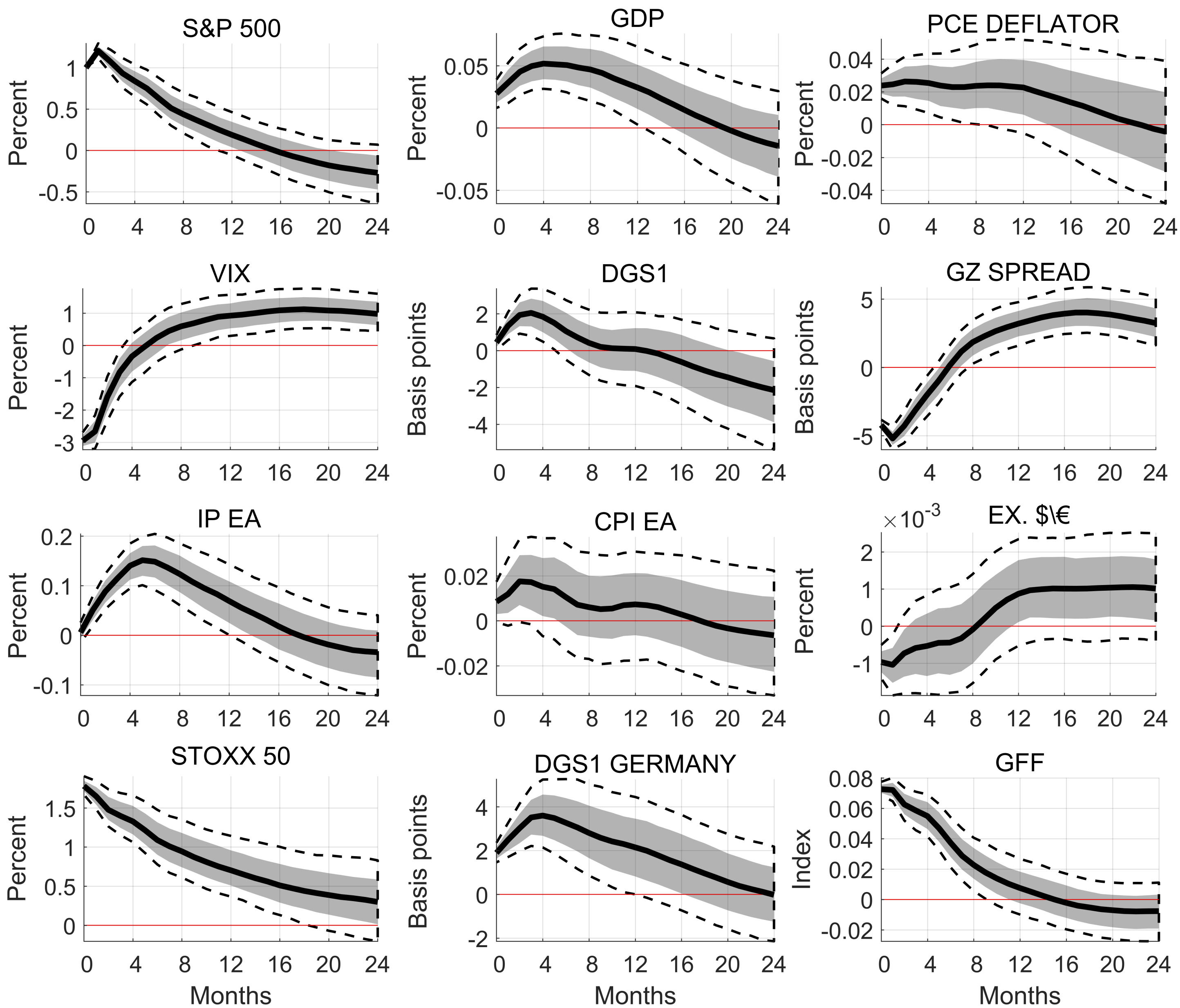

Figure C.2 – IRFs of US and EA variables to a financial shock raising S&P 500 by 1 percent in the monthly BVAR model. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

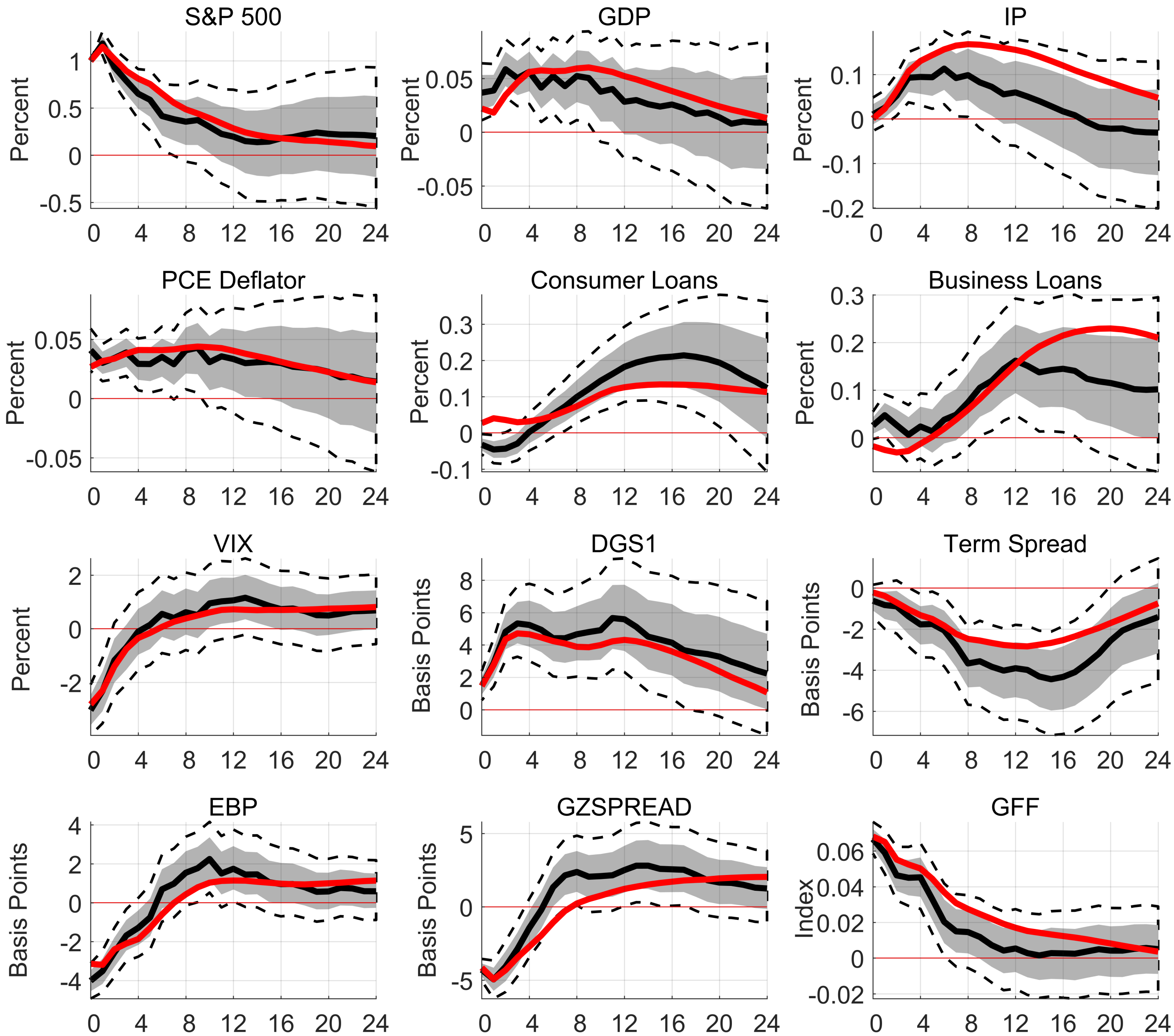

Figure C.3 – IRFs to a financial shock raising S&P 500 by 1 percent in the two shocks model in which the financial shock is orthogonal to the uncertainty shock. Solid black line, shaded areas and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.

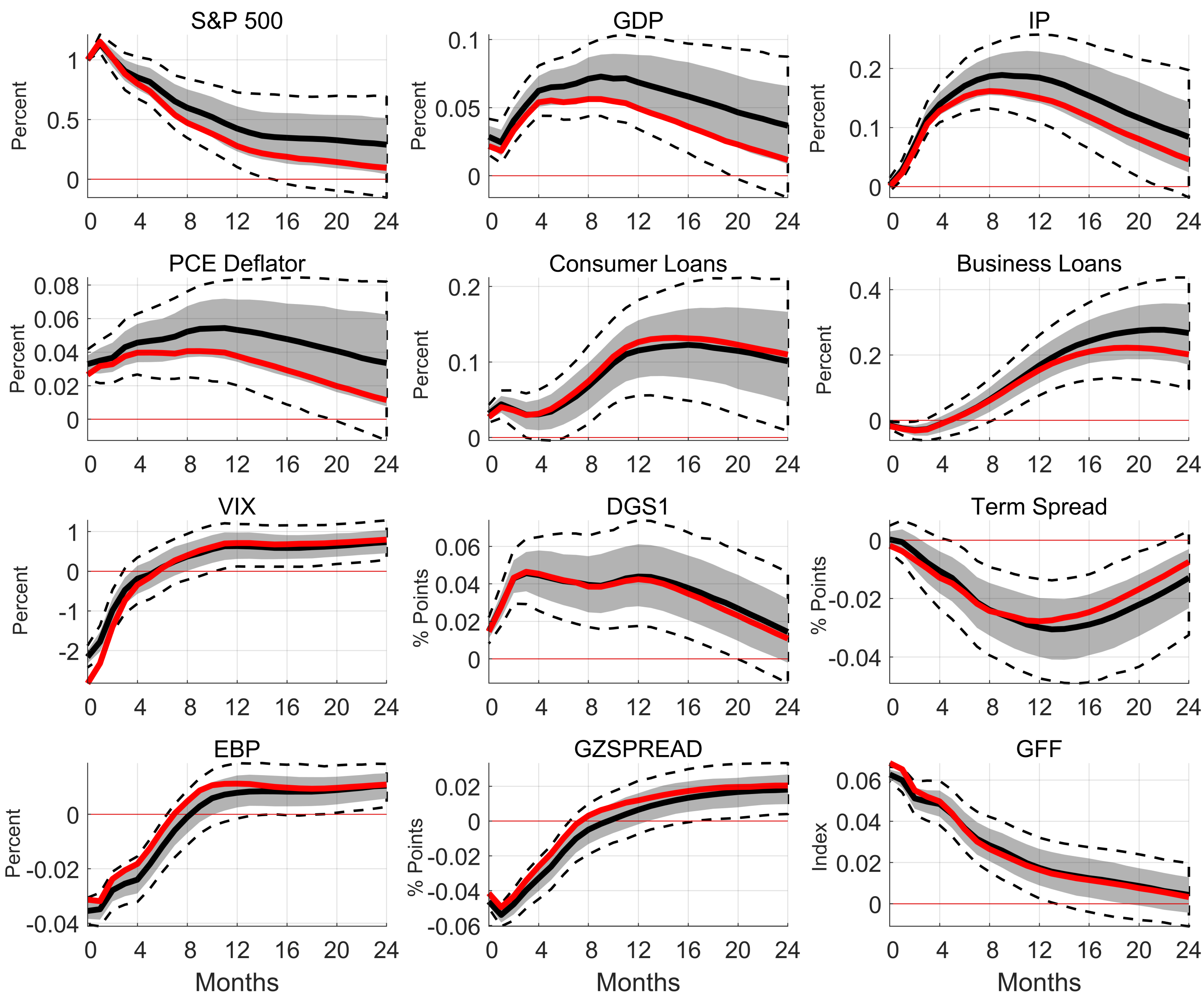

Figure C.4 – IRFs to a financial shock raising S&P 500 by 1 percent with the instrument constructed excluding financial sector events, as reported in Table C.2. Solid black line, shaded areas and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.

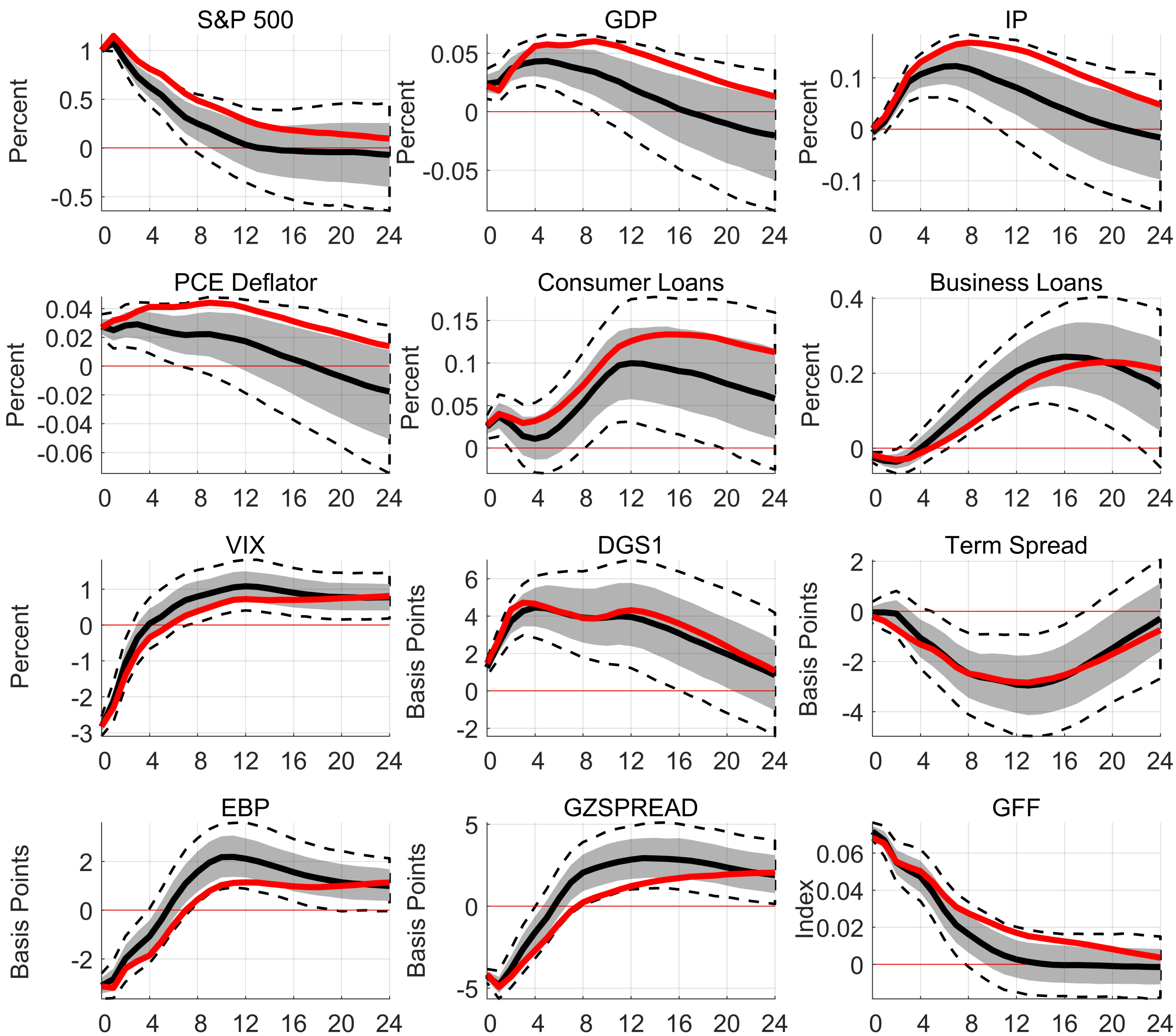

Figure C.5 – IRFs to a financial shock raising S&P 500 by 1 percent with estimation sample 1990:2-2019:4. Solid black line, shaded areas and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.

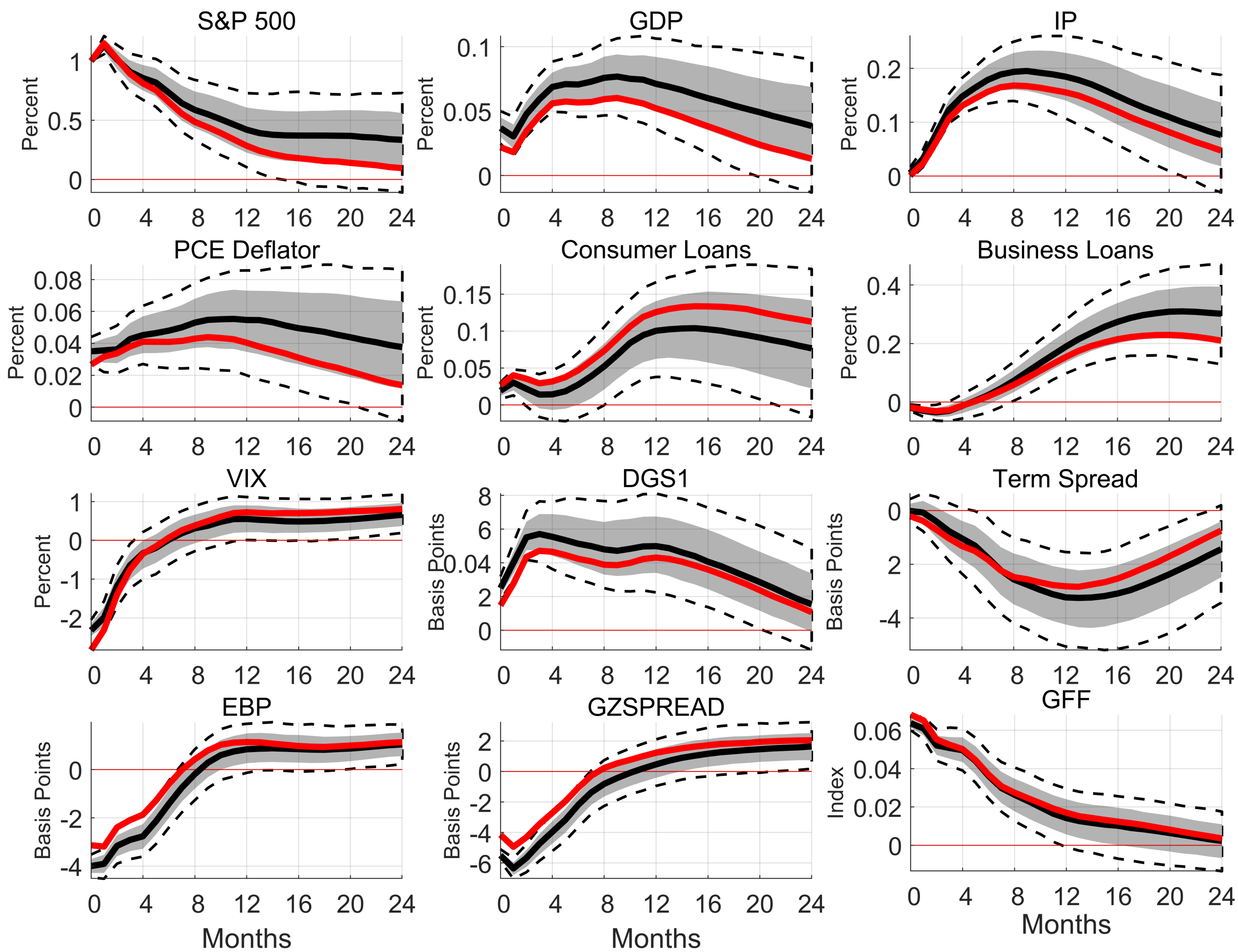

Figure C.6 – IRFs to a financial shock raising S&P 500 by 1 percent with the instrument constructed excluding the GFC events occurring between September 2008 and May 2009. Solid black line, shaded areas and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.

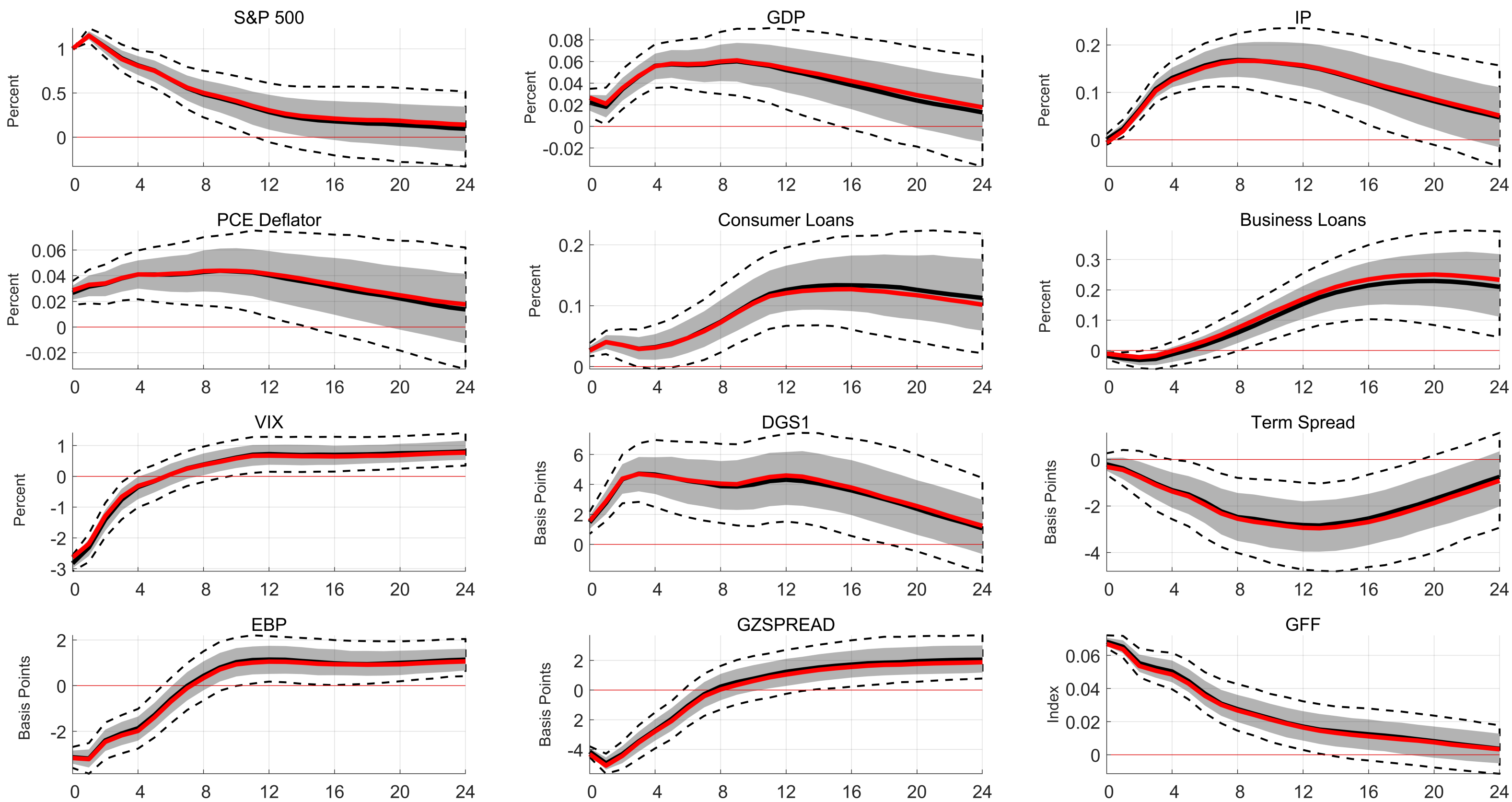

Figure C.7 – IRFs to a financial shock raising S&P 500 by 1 percent with the instrument constructed without removing the shocks that are not signifincant at 90 HPDIs. Solid black line, shaded areas and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.