Corporate earnings announcements and economic activity. *

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Abstract

Are corporate earnings (CE) announcements important for economic activity? To examine this question we employ a novel identification method that combines the valuable information embedded in strategic CE announcements with the heteroscedasticity of shocks experienced on these particular days. Our results demonstrate that CE announcements have a significant impact on the macroeconomy, exhibiting dynamics akin to traditional financial disruptions. We establish that the identified shocks from CE announcements can be classified as financial shocks, highlighting their critical role in the financial system.

JEL Classification: *C32, F3, G01*

Keywords: corporate earnings, event study, heteroscedasticity, structural VAR.

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1 Introduction

Corporate earnings (CE) announcements are one of the most important channels of communication between a firm's managers and outside investors. They provide valuable information about the prospects of not only the issuing firms but also their peers and more generally the entire economy (Savor and Wilson, 2016). Market participants, including analysts and investors, closely scrutinize earnings reports and adjust their expectations accordingly. Hence, CE announcements have a significant impact on how investors feel and how the market behaves, often leading to significant fluctuations in stock prices. Recent studies by Lian and Ma (2021) and Drechsel (2022) have highlighted the heightened significance of CE, revealing that they serve as collateral for approximately 80% of non-financial corporate borrowing in the United States. This implies that CE announcements also provide information about firms' borrowing constraints, which is an important aspect of macroeconomic models that incorporate financial disturbances. Despite their importance, the impact of these announcements on economic activity remains relatively unexplored.

The objective of this study is to examine the macroeconomic effects of CE announcements in the US. To detect the unpredictable component of these announcements, we employ an identification design that exploits the valuable information around days with significant CE announcements, and the heteroscedastic nature of shocks on these specific days. The methodology integrates the identification through heteroscedasticity introduced by Rigobon (2003) with event studies, as in Wright (2012). This methodology offers an advantage over the traditional event study approach by accommodating the occurrence of multiple shocks and announcements within the (daily) event window.

Our primary identifying assumption is that shocks surrounding CE announcements exhibit heteroscedasticity, with their variance notably higher on days when significant corporate profit news is disclosed. Exploiting the lumpy manner of news releases mitigates concerns of reverse causality, as it is unlikely that stock price changes would influence corporate profit announcements within short time windows, such as daily intervals. We demonstrate that on event days, the system's variance is substantially greater compared to non-event days, and this disparity can be attributed to a single orthogonal shock, termed the CE announcement shock. Finally, to evaluate the effects of CE announcements on key economic indicators, we employ the series of structural shocks from the daily vector autoregression (VAR) framework as an instrumental variable within a monthly large Bayesian VAR model.

CE announcements have significant effects on economic activity. Specifically, expansionary CE announcements that raise the S&P 500 index by 1 percent elicit immediate improvements in credit market conditions. This is evident in the decline of 5 basis points (bp) in credit spreads and a 3 bp reduction in the Excess Bond Premium (EBP). Furthermore, there is a notable drop of approximately 3 percent in the VIX index, which measures equity volatility. In terms of macroeconomic indicators, the shock leads to a statistically significant increase in GDP (0.06%) and industrial production (0.18%), accompanied by a rise in inflation (0.05%). These findings suggest that the aggregate demand effects of the shock outweigh the aggregate supply effects. In response to these expansionary and inflationary developments, monetary policy is notably tightened by 5 bp. Additionally, the term spread experiences a decrease of 3 bp, indicating a rise in short-term interest rates coupled with a smaller increase in long-term rates. One quarter after the shock, there is a robust and enduring upswing in business loans (0.23%) and a slighter increase in consumer loans (0.13%).

Our findings show that the dynamics produced by CE announcements closely resemble those observed in the case of financial disturbances. This alignment is not surprising given the strong connection between CE and firms' borrowing capacity in the US. To further investigate the interpretation of the shock derived from CE announcements, we conduct a formal analysis. Firstly, we compare our shock series with the four financial disturbances identified by Brunnermeier et al. (2019)(hereafter BPSS). We discover a high correlation between the CE announcements shock and an exogenous increase in corporate spreads. Secondly, we employ the theoretical framework proposed by Ajello (2016), which incorporates financial frictions and nominal rigidities. The analysis reveals that the CE announcements shock is observationally equivalent to a model-based financial disturbance. Importantly, we show that our shock series exhibits no correlation with the remaining shocks in the Ajello (2016) model, namely a productivity shock, a preference-driven demand shock, and monetary and fiscal policy shocks. This reinforces the financial nature of our shock and provides evidence against its contamination by various demand and supply factors. We conclude that shocks derived from CE announcements can be interpreted as financial shocks.

A critical step in our identification design is the construction of the events list. To achieve identification, the variance of CE announcements 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 on 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 price jumps that have been triggered by non-financial firms' CE announcements.[1] Therefore, our selected event days encompass the corporate profit releases of significant and strategically important non-financial companies, resulting in a noticeable surge in the aggregate asset price index. Utilizing this methodology, we identify a total of 17 CE events spanning the period from 1996 to 2009.

We conducted various sensitivity checks to ensure the robustness of our findings across different dimensions, including estimation and identification strategies. To address concerns that our identification strategy might capture broader uncertainty, we performed a placebo exercise, randomly

[1]The exclusion of news pertaining to financial institutions is primarily due to the typical focus in the literature on earnings-based constraints for nonfinancial corporations.

selecting days with significant stock price movements for baseline analysis. As anticipated, this experiment yielded high noise levels due to the convolution of different shocks. To reinforce the financial nature of our CE announcements shocks and mitigate confounding factors like demand, uncertainty, and sentiment shocks, we conducted a joint identification analysis, imposing orthogonality between our shock and these additional factors. This analysis confirms the consistency of our results, providing further evidence that our findings on the impact of CE announcements on the economy are robust and not influenced by confounding factors.

Literature review.

Extensive research has been conducted on the impact of economic news on asset prices, interest rates, energy prices, and other economic indicators, employing both high-frequency and low-frequency models. Several studies (Faust et al., 2007, Kilian and Vega, 2011, Wright, 2012, Gilbert et al., 2017, Altavilla et al., 2017, Ai and Bansal, 2018, Gurkaynak et al., 2020, Känzig, 2020, and Gu et al., 2020) have explored this relationship in depth. In our investigation, we focus on a specific category of economic news, namely corporate earnings announcements, and establish their connection to the broader concept of financial disturbances.

This is not the first paper to look at corporate earnings news. Earnings announcements are a pivotal channel 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 (see Michaely et al., 2014, Patton and Verardo, 2012 Savor and Wilson, 2016, and Pevzner et al., 2015 among others). We contribute to this literature by providing novel evidence on the low-frequency macroeconomic effects of this type of announcement.

We show that shocks derived from CE announcements can be included in the broader category of financial shocks. Thus, we relate to the extensive literature analyzing the relevance of disturbances originating in the financial sector. [2] 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 Fornari and Stracca (2012), Abbate et al. (2016), 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) and Barnichon et al. (2018) 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, Mumtaz et al. (2018) rely on DSGE-generated data to identify credit supply shocks, while BPSS extracts financial disturbances using a heteroscedasticity approach to identification. Unlike the aforementioned contributions, our study focuses on the overall impacts of CE announcements, which we demonstrate to be observationally equivalent to financial disturbances in a subsequent analysis.

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 a daily frequency. We address this challenge by 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, and discuss the main results.

[2] 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 internationally (see Dedola and Lombardo, 2012 and Perri and Quadrini, 2018).

In Section 4 we provide a structural interpretation of the CE announcements shock as a financial shock. Section 5 concludes.

2 Identification strategy

Our strategy to isolate the exogenous part of CE announcements combines the identification through heteroscedasticity with the event study methodology, in line with what has been proposed by Wright (2012) for monetary policy shocks. The key identifying assumption is that there is a set of event days when the variance of CE announcements shocks is particularly high, while the variance of the other shocks remains unchanged. Other shocks can occur on the same days as 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 announcements shock based on this approach.

2.1 CE announcements 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 announcements shocks is higher than on 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 determine the cause of all stock market jumps that occurred from 1990 to the end of 2020, which are defined as movements in the S&P500 exceeding 2.5% in absolute value. They achieve this by reviewing the lead article of each jump in the next day (or same-evening) newspapers. The 2.5% threshold is large enough to ensure the next day's 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 or more of the seventeen pre-established categories which include, among others, news about policy (monetary and fiscal), macroeconomic and outlook, corporate earnings, elections, commodities, terrorist attacks and wars, and so on. They classify the primary reason for each jump into one of the seventeen categories and, when warranted by the article's discussion, a secondary reason as well. If an article mentions multiple reasons for a given jump but does not clearly identify the most important one, the order of appearance in the article is treated as a tiebreaker.

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." Next, we eliminate news related to financial institutions by carefully reviewing the articles. In this way, we isolate 17 event days that contain CE news of non-financial firms, 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, as required by our identification design. Second, the asset price jumps can be attributed to several causes but we pick the events for which all coders agree that the primary cause of the jump is related to the CE announcement. As such, we minimize the risk that on event days other shocks might record an increase in variance.[3]

[3]For example, if in the same day with the CE event, a piece of important policy news is released, at least some of the coders would record this news as the primary news of the day, hence this type of events are not selected by our approach.

Table 1 – Corporate earnings events list

Date	S&P500 % jump	Brief Explanation
15/07/1996	-2.5	Weak earnings reports of high-flying tech firms
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 everywhere, from chemicals to technology
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 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.

Third, Baker et al. (2019) dataset precludes the use of intra-daily data which is costly to acquire and can have limited coverage.

Most of our events are either firm-specific or sectoral news. The fact that idiosyncratic shocks have aggregate effects is lending evidence to the granular shock theory put forward by Gabaix (2011) and Acemoglu et al. (2012). These studies show that in the presence of intersectoral input–output linkages, microeconomic idiosyncratic shocks of strategic firms lead to aggregate fluctuations. Thus, firm-level shocks provide a microfoundation for aggregate shocks. Furthermore, a related strand of the finance literature focusing on CE announcements suggests that earnings news provides valuable information about the prospects of not only the issuing firms but also their peers and more generally the entire economy. Thus, investors use individual firm announcements to update their expectations about aggregate earnings, and this effect is stronger for larger firms, as described in Michaely et al. (2014) and Savor and Wilson (2016) and references therein.

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:

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

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 announcements 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 announcements 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 announcements shock. We verify this requirement by computing, for each saved draw, the statistical distance

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

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).

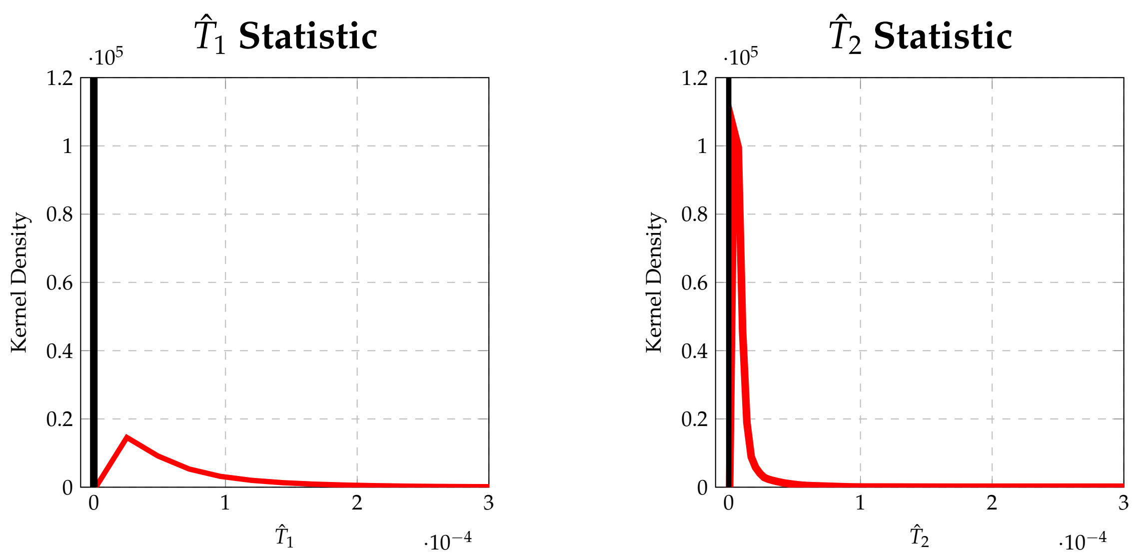

Figure 1 – Kernel density functions calculated on 5000 posterior draws of the statistics $\hat{T}_1$ and $\hat{T}_2$.

2.3 Data and results

We use data at a daily frequency from January 1, 1990, to October 16, 2020. We selected January 1990 as the starting point for the daily VAR model sample for several reasons. Firstly, it corresponds to the availability of the CBOE VIX index. Additionally, our event definition poses a constraint. Only one event in 1981 complies with our criteria between 1980 and 1996. Including this single event would create a 15-year gap in daily event data, disrupting the continuity of event history. To maintain consistency, we chose to begin the sample in 1990.

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[4], commonly used as a proxy for economic uncertainty, *e.g.* Bloom (2009). $DGS1_t$ is the 1-Year Treasury 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 Appendix B.

Impulse response analysis. Now we turn our attention to the effects CE announcements in the daily VAR model. For each variable, we report the posterior median and the 68 and 90 credibility intervals responses to the 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 expansionary CE announcement triggers an increase in stock prices (+1%) and an improvement in credit conditions,

[4] 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)

captured by the fall in BAA credit spread (-2bp). The impact of the shock on stock prices and short-term interest rates extends beyond a four-year period following the initial shock. The persistent increase in stock prices and the substantial rise in the sentiment index could suggest a generalized increase in financial confidence. We also find that the stock market expansion triggered by the CE announcements shock is accompanied by a fall in uncertainty (-2.2%) while the short rates increase. This last result is compatible with the investors' expectations of a tightening in the monetary policy as a response to the expansionary developments.

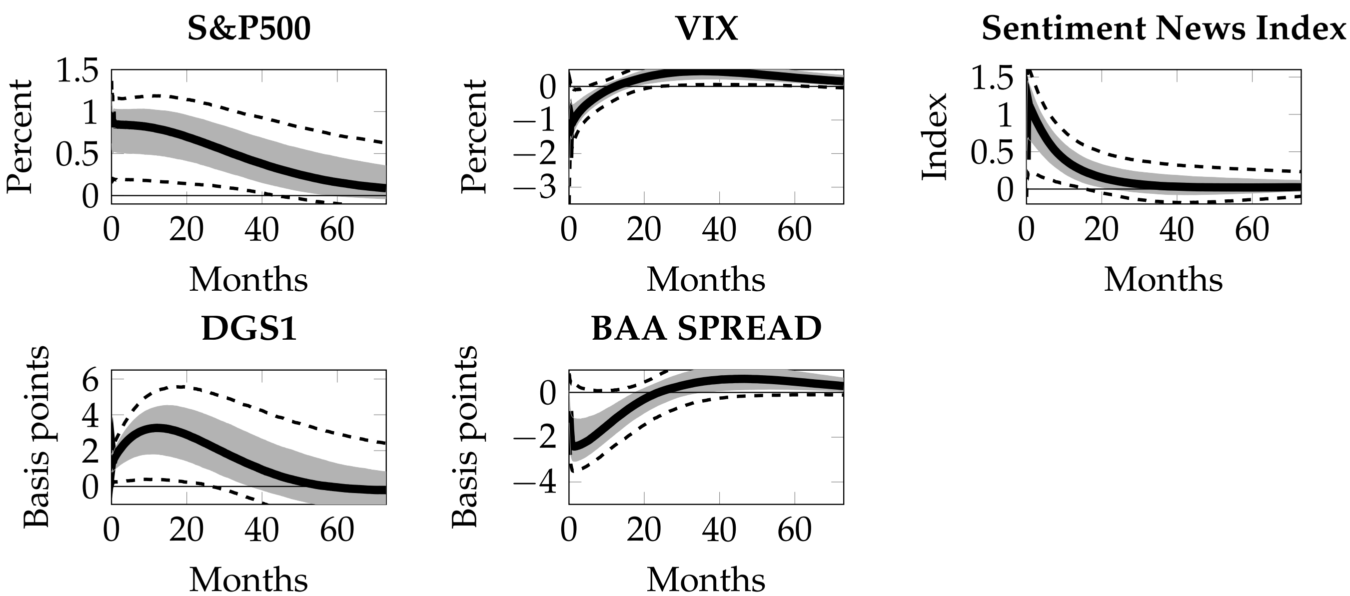

Figure 2 – IRFs to a CE announcements shock increasing S&P 500 by 1 percent in the daily BVAR setting. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

Placebo test. Since we focus on days with large movements in stock prices, an important concern is that the identification strategy may be picking up broader economic uncertainty as well. To reassure the reader that the identification strategy is picking up corporate earnings news, we perform a placebo exercise in which we randomly select 17 events from all days in Baker et al. (2019) dataset in which stock markets moved in excess of 2.5%, excluding any events that involve CE announcements. We then perform the daily VAR exercise and the Monthly BVAR analysis as in the baseline case across 1000 iterations. As expected, the results produced by this experiment (reported in Figures D.2 and D.3) are very noisy since they reflect a convolution of different shocks rather than the ones specific to CE announcements.

2.4 The CE announcements shock instrument

The daily BVAR framework used in this section has desirable properties but relies on high-frequency models, limiting its applicability to macroeconomic variables available at monthly or lower frequencies. To address this, we extract structural shocks from the daily BVAR model and utilize them as instrumental variables in lower frequency models. Similar techniques have been employed by Alessandri et al. (2023), with their extensive Monte Carlo analysis validating the approach. The structural shock series, exogenous and uncorrelated by construction, serves as a suitable instrument for capturing the exogenous component of Corporate Earnings (CE) announcements. Although the generated regressors problem is a potential drawback, using the shock series as an instrument mitigates biases from measurement errors (Stock and Watson, 2012, Mertens and Ravn, 2013).

We aggregate daily shocks into a monthly series, summing daily surprises within each month.[5] The resulting series of CE surprises spans from 1990:2 to 2019:10, tracking major economic events, including recessions and financial crises. Additional checks, such as correlation analyses and sensitivity tests to changing the number of lags or extending the number of events, validate the shock series. Our main findings remain robust across various model specifications, as demonstrated in the Appendix D.

[5] Alessandri et al. (2023) utilize monthly averages of daily shocks rather than sum. However, we have demonstrated in Figure D.9 that using averages instead of sums has a negligible impact on our results.

3 Low-frequency analysis

In this section, we examine the effects of CE announcements on macroeconomic indicators. We first introduce the econometric method and the data used in the estimation phase and then interpret the main findings.

3.1 Large BVAR model identified with external instruments

As discussed above, to minimize the background noise, the CE announcements 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 the non-invertibility of the small VAR model.[6] 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:

[6] 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.

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

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

Without loss of generality let us assume that $\epsilon_{1,t}$ is the CE announcements 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 heteroscedasticity-based event study identification scheme, (11) should be verified by construction. If (10) and (11) 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 and we choose the overall tightness parameter optimally as proposed by Giannone et al. (2015). Details on the estimation are provided in Appendix A. [7]

3.2 Data

We estimate BVAR model containing monthly data on 12-time series (listed in Table C.1). The sample covered goes from January 1980 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 VAR

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

model includes measures of real activity (GDP and Industrial Production), prices (PCE Deflator), consumer and business credit based on the Federal Reserve's weekly surveys of US 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 a monetary policy variable.[8] 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 potential feedback effects from the international financial market.

3.3 Results

In this section, we discuss the main results of the empirical exercise. We report the first-stage statistics, and the low-frequency effects of the CE announcements shock.

3.3.1 First stage statistics

We investigate the strength of our instrument computing the reliability measure proposed by Mertens and Ravn (2013). Despite its inconsistency with the Bayesian framework, we also report F statistics of the S&P500 residual on the instrument. 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) 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. In Figure D.8 we show that results hold if we use the same sample for both the impact matrix identification and the VAR coefficients. Results in Table 2 show that our instrument performs well in terms of relevance.

[8] As described in BPSS, GZ Spread detects tightness in business finance while the Term Spread accounts for inflation expectations and uncertainty about future fundamentals.

Table 2 – Tests for instrument relevance

Model	F-stat	90 HPDI	Reliability	90 HPDI
Monthly BVAR	161	[120 174]	46	[39 48]

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. The first stage regressions are obtained from the sample 1990 to 2019, which is the overlapping sample between VAR data and the instrument.

3.3.2 Macroeconomic effects of CE announcements

We now introduce the results from the estimation of the domestic BVAR model. We present the impulse responses and the historical contribution of CE announcements shocks to real activity.

Impulse response analysis. Figure 3 shows the impulse response functions of the identified CE announcements shock scaled to increase the S&P500 index by 1 percent.[9] We report the median over the saved draws, together with the 68 and 90 coverage set.

Expansionary CE announcements trigger a sharp and significant increase in stock prices accompanied by a contemporaneous raise in the GDP with effects that persist for almost two years. 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 slightly delayed but strong effect on business loans and a more modest effect on consumer loans.[10] VIX

[9] The scaling is without loss of generality and is meant to be consistent with the daily VAR framework. However, the results hold if instead of stock prices we link the instrument to the residuals of the corporate spreads as shown in Section 4.

[10] Delayed responses of business loans to shocks compared to output and prices have

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 financial frictions and financial disturbances with a monetary authority trying to offset these effects. In particular, our results are aligned with the theoretical predictions of Christiano et al. (2014) and Ajello (2016) for financial shocks. Specifically, consistent with our findings regarding the effects of CE announcements, these studies 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.

The reaction of prices to financial disturbances is less clear in the literature. If some theoretical models predict a negative price reaction to contractionary financial shocks (*e.g.* Christiano et al., 2014, Ajello, 2016), 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 and our results emerge naturally as we do not restrict in any way the sign of the responses.

Interestingly, our shock provides highly similar impulse responses to one of the four financial disturbances identified in BPSS, and labeled by the authors as a GZ spread shock. This suggests that a generic (financial) shock to the corporate bond spread could have its origins in shocks to the firm's

been observed in previous studies as well, notably in response to shocks to the GZ Spread (see Brunnermeier et al., 2019) and to lending standards shocks (Lown and Morgan, 2006). Figure D.10 illustrates that similar dynamics are evident in the case of monetary policy shocks.

earnings.

Summing up, the impulse response analysis shows that CE announcements substantially affect macroeconomic and financial indicators in the US, and the effects triggered by the shock are strikingly aligned with the dynamics produced by traditional financial disturbances.

Robustness checks and additional results. To ensure the robustness of our instrument to confounding influences, we impose orthogonality between our shocks and external factors such as sentiment shocks, second-moment factors, and important demand shocks. Results from these experiments confirm the robustness of our estimates to sentiment, uncertainty, and demand-side confounding factors, as shown in Figures D.5, D.6, and D.7. Figure D.8 illustrates impulse responses from the baseline monthly model estimated over the overlapping sample between VAR data and the instrument (1990:2-2019:4) while Figure D.11 further confirms our results using Bayesian local projections instead of a BVAR model to obtain impulse response functions (IRFs).

In addition, we conducted further analyses exploring the economic effects of CE announcement shocks. These include an assessment of the magnitude effects of CE shocks, variance decomposition, historical decomposition, and the examination of the international transmission of these shocks. Detailed results are available in Appendix E.

4 CE announcements shocks are financial shocks

Having analyzed the transmission mechanism of CE announcements on aggregate indicators, the results highlight substantial economic effects. However, a limitation of our analysis is the lack of a clear structural interpretation for the identified shock. To address this, we demonstrate in this section that the shock derived from CE announcements can be interpreted as a conventional financial disturbance. Three key pieces of evidence support domestic BVAR.pdf

Figure 3 – IRFs of domestic US variables to a CE shock raising S&P 500 by 1 percent in the monthly BVAR model. Solid black line, median. The 68 and 90 credibility sets are shaded areas and dotted lines, respectively.

this interpretation: firstly, the dynamics generated by CE announcements closely resemble those of a traditional financial disturbance; secondly, variance decomposition analysis reveals that CE announcements explain the largest share of variation in financial variables; and thirdly, as earnings significantly impact firms' access to credit in the US, CE announcements align with the characteristics of a traditional financial shock (*e.g.* Gilchrist and Zakrajšek, 2012; Christiano et al., 2014; Ajello, 2016; and Brunnermeier et al., 2019).

To validate our conjecture and offer a formal interpretation for our shock, we conduct two experiments. Initially, we compare the CE announcements shock series with financial disturbances documented by BPSS, revealing a high correlation with a shock to corporate spreads. Subsequently, employing the theoretical framework of Ajello (2016), we demonstrate that the CE announcements shock yields results highly analogous to a model-based financial disturbance.

4.1 CE announcements and the BPSS framework

BPSS utilize a VAR model identified by heteroscedasticity to examine the relationship between credit expansion and economic activity in the US, using monthly data from January 1973 to June 2015 (listed in Table C.2). All variables are in log levels, except for the spread and interest rate which enter the model unchanged. While heteroscedasticity identification typically yields variable-by-variable innovations lacking clear economic interpretation, BPSS map these innovations to economic shocks through impulse responses. Their model, isolating various financial disturbances, serves as a suitable foundation for our analysis. Taking the heteroscedasticity identification further, we integrate it with the event study approach to identify the unpredictable component of CE announcements. We estimate the BPSS VAR model, identifying CE announcement shocks within it using our baseline CE instrument. Comparing the resulting structural shock series with four financial disturbances from the BPSS model, we find that our CE shock series is highly correlated (around 80%) with the GZ Spread shock, interpreted as a non-bank financial disturbance capturing tightness in business financing. The strong resemblance supports the interpretation of CE announcement shocks as financial shocks, aligning with the composition of our events involving CE news of non-financial firms. This also explains the lack of correlation with banking and household credit shocks.

Table 3 – Correlation of the CE shock with financial shocks in BPSS

BPSS shocks	Shocked variable	Correlation with the CE shock	p-value
Non-bank financial shock	GZ Spread	0.79	0.00
Banking credit shock	TED Inter-bank Spread	0.08	0.16
Household credit shock	Consumer loans	-0.01	0.84
Firm credit shock	Business loans	0.05	0.38

Notes. The table reports the correlation coefficient of the CE shock extracted from the monthly BVAR model defined as in BPSS and identified with our baseline CE instrument. The correlation coefficient is computed for the overlapping sample 1990m1 to 2015m1.

4.2 CE announcements and the Ajello (2016) framework

In this section we rely on a more formal framework to show that CE announcements can be interpreted as financial shocks. Specifically, we build on Ajello (2016) who develops a New Keynesian DGSE model featuring financial frictions and financial disturbances.

The Ajello (2016) framework is appealing for our exercise for two main reasons. First, the financial shock in this model is defined as an innovation to the financial intermediation spread which is similar in spirit to a shock to corporate spread, as shown in the previous section. [11] Second, the model is estimated on US quarterly data on a sample going from 1989Q1 to 2008Q2.

[11] The financial intermediation spread in the Ajello (2016) framework represents the cost that financial intermediaries bear for each unit of financial claims that they transfer from

This allows us to extract the structural financial shock series and use it as an instrumental variable to identify a financial shock in a quarterly BVAR model.[12] We then compare these results with the ones obtained by using our baseline CE instrument in the same VAR model.

The structure of the quarterly BVAR follows Ajello (2016) and includes GDP, consumption, investment, prices, real wage, hours worked, short-term rates, and the GZ corporate bond spread measure. All variables are in log levels except for the interest rate and the bond spread which are not transformed. The sample goes from 1980Q1 to 2019Q2 and the estimation strategy is consistent with the monthly BVAR analysis. As customary for quarterly models, we include four lags for each endogenous variable. The instrument is linked to the GZSPREAD residuals on the overlapping period (*i.e.* 1989Q1 to 2008Q2). More details on the data construction are available in Appendix C.

In Figure 4 we report the impulse responses to a financial shock that increases the GZ Spread by 1% point. The shock is identified using the transitory financial shock series from Ajello (2016) as an instrumental variable (black solid line) in the quarterly BVAR model. [13] For comparison, the figure also reproduces the impulse responses to the CE shock (green solid line) obtained by performing the same exercise with the CE instrument instead (available from 1990Q1 to 2019Q2).

The similarity in results is striking. The financial tightening leads to a large drop in quarterly investment of around 7% in both scenarios. Prices fall by around 0.5% and remain persistently below the long-run trend while

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sellers to buyers. The intermediation cost evolves exogenously in response to two kinds of shocks, called permanent and transitory financial shocks, depending on their different degree of persistence. Specifically, the persistent shock fluctuates around its steady-state level following an AR(1) process, while the transitory shock evolves according to an autoregressive process.

[12] Model-based shock series have been previously employed as instrumental variables in VAR models by Stock and Watson (2012) and Mumtaz et al. (2018).

[13] The Ajello (2016) model features two types of financial disturbances, a transitory shock and a permanent shock. We explored both, but only the transitory shock achieves identification, which is also the most conceptually aligned with our CE shock.

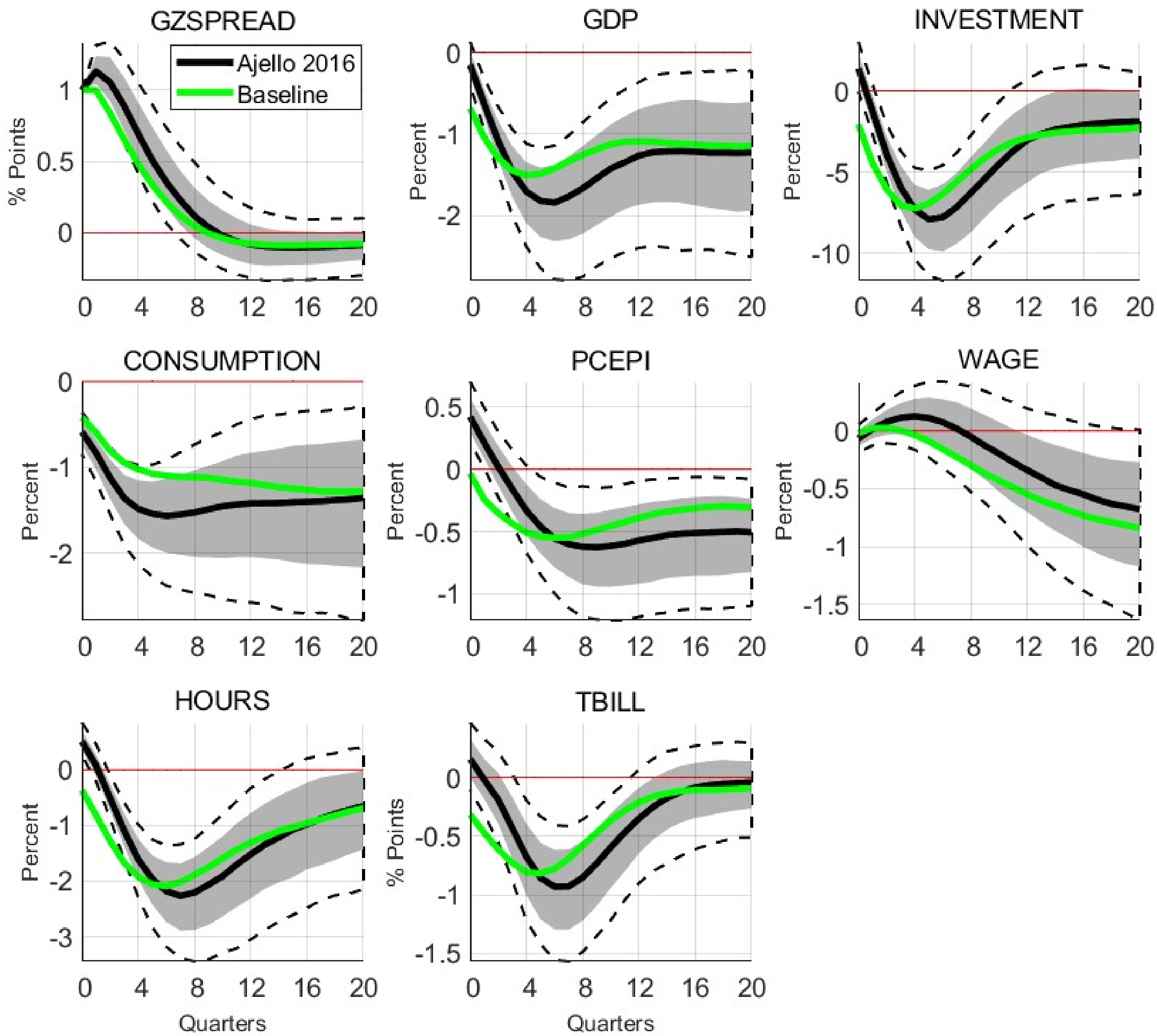

Figure 4 – IRFs of US variables to a financial shock identified with the Ajello (2016) transitory financial instrument vs. the baseline CE instrument. The shock is scaled to raise GZ Spread by 1 percent in the quarterly BVAR model. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively. Green line is the median obtained with the baseline CE identification.

the central bank lowers the short-term rate by almost 1% point and keeps accommodating for around 3 years. The financial disruption triggers a fall in GDP and consumption of comparable magnitude (1.5% at its peak). The drop in real wage is more modest, in line with the nominal rigidity assumption from the theoretical framework. With the limited downward adjustment in real wages, hours worked drop substantially by around 2 in response to lower aggregate demand. Not only the two shocks produce similar dynamics, but they are also aligned with the theoretical predictions of Ajello (2016) framework for financial shocks, which brings additional support to the validity of our exercise.

Finally, to confirm that our results are not a statistical artifact, in Table C.3 we report the correlation between the CE shock series extracted from the quarterly BVAR model with the original structural shocks as reported in Ajello (2016). Apart from the transitory financial shock, none of the remaining shocks (including supply, demand and policy shocks) are correlated with the CE shock. Moreover, this result provides further robustness of our CE shock to potential demand and supply confounding factors. We conclude that the CE shock can be interpreted as a financial shock.

5 Conclusion

We provide novel evidence on the macroeconomic effects of CE announcements using an identification design that exploits the valuable information around days with important CE releases and the higher variance of shocks on these days. We find that CE announcements have significant effects on the macroeconomy. We then provide a structural interpretation for our shocks as financial shocks. We first show that the CE announcement shock is highly correlated with a financial shock defined as an exogenous innovation in corporate spreads. We then contrast the CE announcement shock with a model-based financial shock. The striking similarity in the dynamics triggered by the two shocks leads us to conclude that the shocks derived from CE announcements are financial shocks.

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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:

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

where μ_i denotes the sample means of the endogenous variables calculated using AR(1) preliminary regressions. As standard 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

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

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

where $R_t = \Sigma_1$ over periods characterized by the CE 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 periods 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:

$$Y_t = X_tB + u_t \quad \text{(A.6)}$$

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 that 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 – 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.

C Description of the quarterly BVAR data

- GDP is the quarterly Real Gross Domestic Product from FRED-QD data, transformed in logs, mnemonic GDPC1;
- INVESTMENT is the quarterly Real Gross Private Domestic Investment, from FRED-QD data, transformed in logs, mnemonic GDPIC1;
- CONSUMPTION is the quarterly Real Personal Consumption Expenditures, from FRED-QD data, transformed in logs, mnemonic PCECC96;
- PCEPI is the quarterly Personal Consumption Expenditures: Chain-type Price Index, from FRED-QD data, transformed in logs, mnemonic PCECTPI;
- WAGE is the Real Average Hourly Earnings of Production and Non-supervisory Employees deflated by Core PCE, from FRED-QD data, transformed in logs, mnemonic AHETPIx;

- HOURS is the Nonfarm Business Sector: Hours of All Persons, from FRED-QD data, transformed in logs, mnemonic HOANBS;
- TBILL is the 3-Month Treasury Bill: Secondary Market Rate (Percent), from FRED-QD data, mnemonic TB3MS;
- GZSPREAD is the corporate bond spread from Gilchrist and Zakrajšek (2012);

Table C.2 – Data series in BPSS

Variable	Description
IP	Industrial production
Prices	Personal consumption expenditure price index
Household loans	Sum of commercial bank real estate and consumer loans
Business loans	Commercial bank commercial and industrial loans
M1	M1 money supply
R	Federal fund rate
PCM	BLS spot commodity price index
Term spread	Term spread of 10 year over 3 month Treasuries
GZ spread	Gilchrist and Zakrajšek (2012) bond spread
Bank lending spread	TED spread of 3 month Eurodollars over 3 month Treasuries

D Robustness checks

In this section, we show the robustness of our results across several dimensions. In Tables D.1, C.3 and D.3, we report the correlation of our instrument with other proxies available in the literature as well as with the remaining

Table C.3 – Correlation of the CE shock series with the structural shocks in Ajello (2016) model

Structural Shock from Ajello (2016) model	Frequency	Correlation coefficient	p-value
Financial Transitory	Quarterly	0.29	0.01
Financial Persistent	Quarterly	-0.04	0.75
TFP	Quarterly	-0.01	0.92
Preference	Quarterly	0.05	0.70
Price markup	Quarterly	0.18	0.12
Wage markup	Quarterly	-0.02	0.86
Government Spending	Quarterly	-0.13	0.93
Monetary policy	Quarterly	0.01	0.25

Notes. The table reports the correlation coefficient of the CE shock extracted from the quarterly BVAR model with the structural shock series from Ajello (2016) framework, as reported in the original paper. The correlation coefficient is computed for the overlapping sample 1990Q1 to 2008Q2.

shocks from the Ajello (2016) model and BPSS model. In Figures D.1 and D.4 we show that our results in the daily VAR framework are robust if we increase the number of lags to 21 and if we increase the number of events to 34. We extend the number of events by including all events in which at least one coder assessed that the primary cause of the jump is a non-financial CE announcement. The extended list of events is described in Table D.2.

In Figure D.2 we perform a placebo exercise in which the 17 events are randomly selected from the whole Baker et al. (2019)dataset, excluding any events that involve Corporate Earnings announcements, either as a primary or secondary cause. We then conducted the following steps:

1. Estimation of the Daily VAR model using the 17 randomly selected events.

2. Computation of the structural shock series.

3. Estimation of the Large BVAR model, utilizing the structural shock series obtained in the previous step as an instrumental variable.

4. Saving the median Impulse Response Functions in the Large BVAR model.

These steps were repeated 1000 times as part of a Monte Carlo experiment. Subsequently, we present the outcomes obtained from this Monte Carlo experiment for both the Daily (Figure D.2) and Monthly VAR (Figure D.3) models, in addition to the baseline results. This comprehensive analysis offers a more robust perspective on the data. This exercise shows that if the events are not specifically related to CE, the shock is not identified.

We show as well in Figures D.6 and D.5 that our findings hold if we jointly identify the CE announcement shock with uncertainty or sentiment shocks.

In Figure D.10 we show that the sluggish response of business loans to shocks is verified when we look at monetary policy shocks as well. To this end, we conduct an analysis estimating the impact of Monetary Policy shocks on a small VAR model incorporating four variables (One-year rates, Industrial production, CPI, and Excess bond premium), augmented with consumer and business loans. The VAR model is identified using the instrumental variable provided by Gertler and Karadi (2015) and the sample follows the baseline specification (January 1980- May 2019).

Finally, in Figure D.8 our results are shown to be robust to using the same sample in the estimation of the impact matrix and the VAR dynamics.

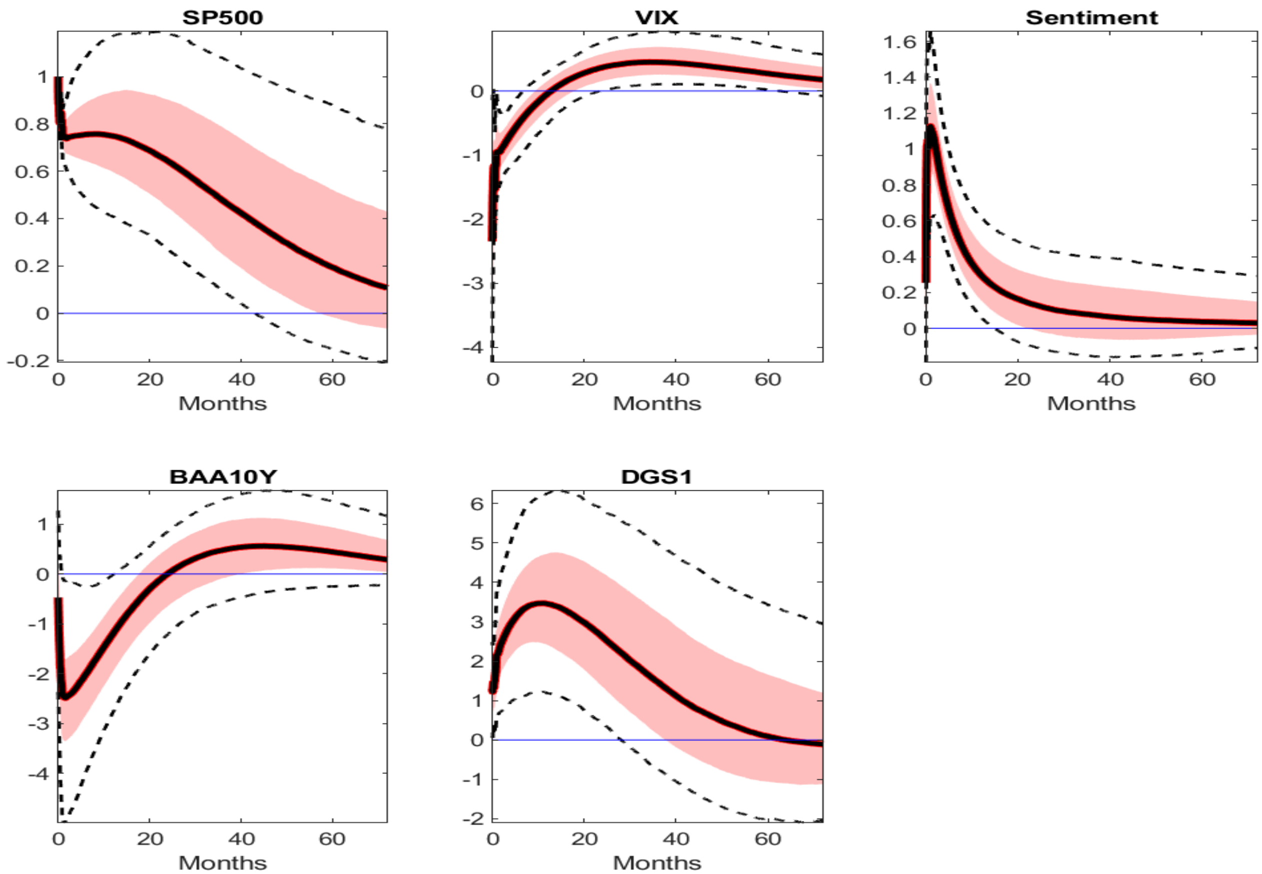

Figure D.1 – IRFs to a CE shock increasing S&P 500 by 1 percent in the daily BVAR setting with 21 lags. Solid black line, shaded areas and dotted lines are the median, 68 and 90 credibility sets.

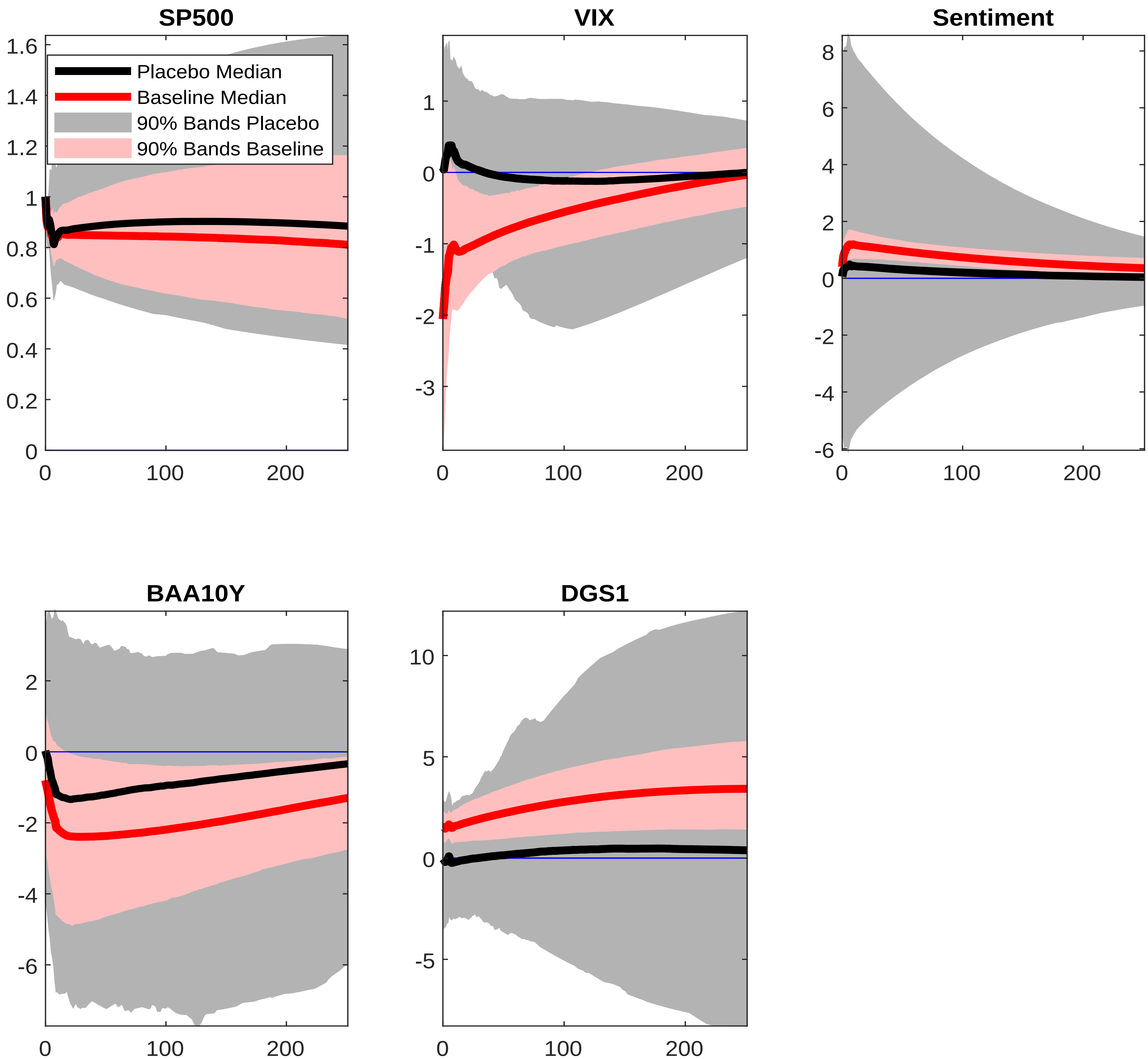

Figure D.2 – IRFs to a CE announcements shock increasing S&P 500 by 1 percent in the daily BVAR setting in the placebo exercises and in the baseline case. Medians are reported for the placebo exercise (solid black) as well as for the baseline case (solid red). Shaded areas 90 credibility sets, respectively.

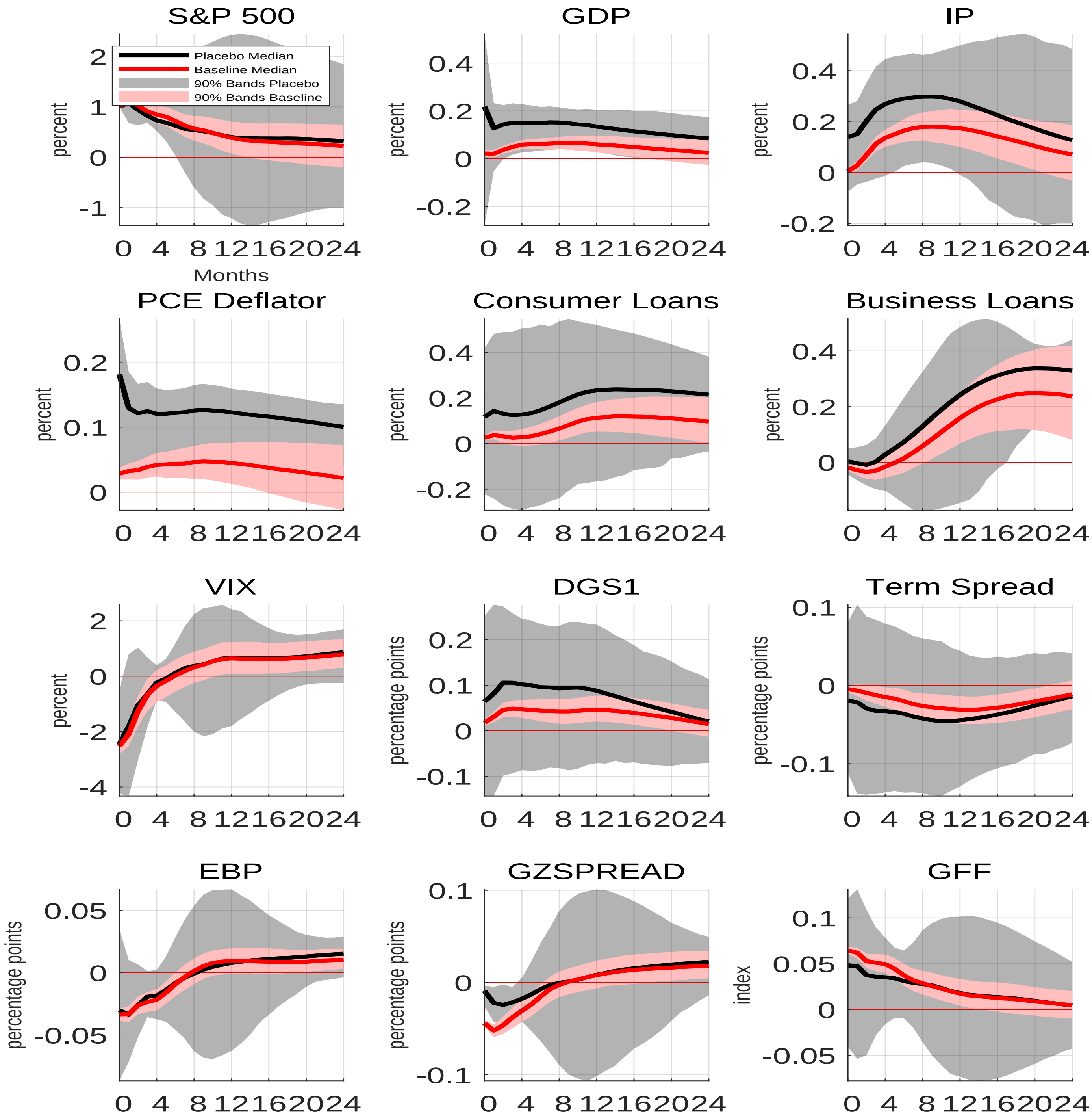

Figure D.3 – IRFs to a CE announcements shock increasing S&P 500 by 1 percent in the monthly BVAR setting for placebo exercises and the baseline scenario. The medians are presented for both the placebo exercise (solid black) and the baseline case (solid red), while the shaded areas represent the 90 percent credibility intervals in both instances.

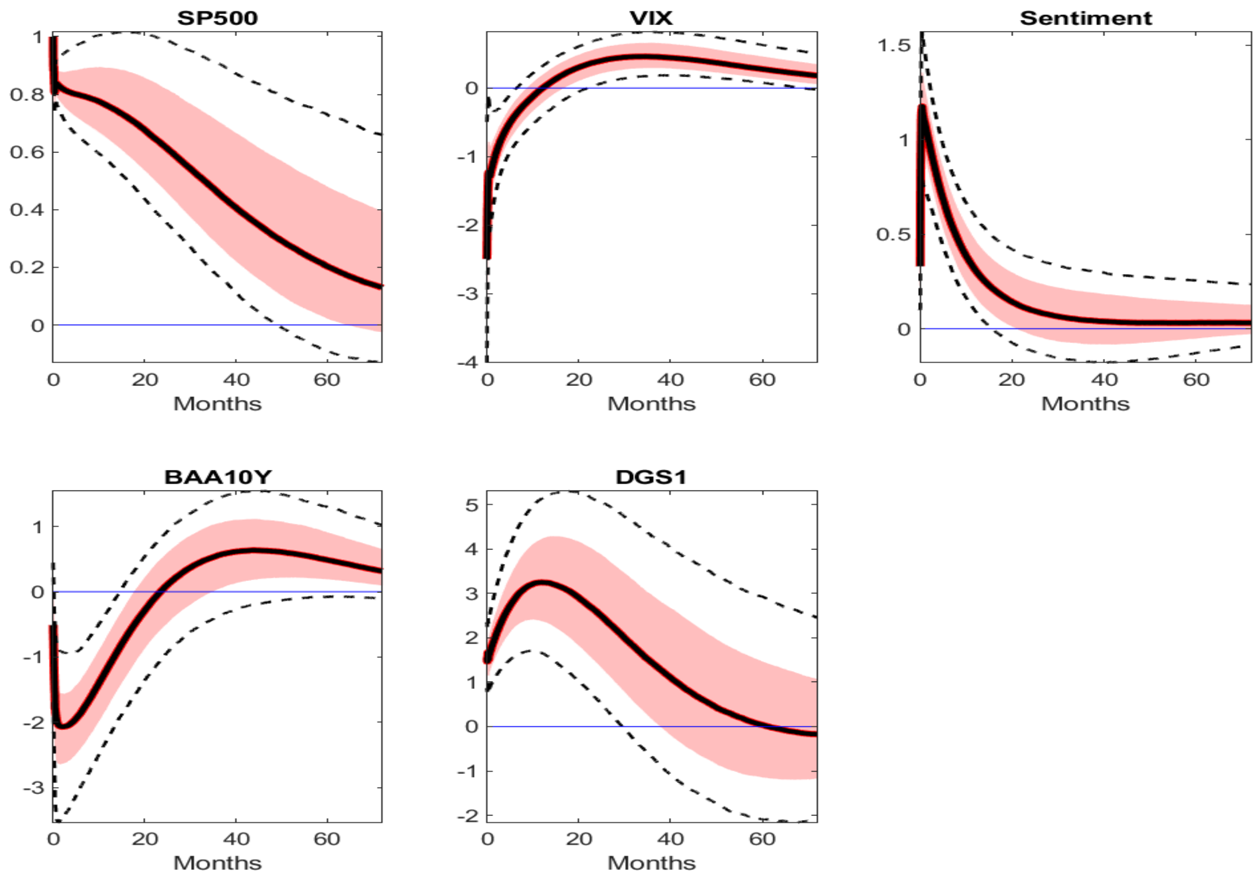

Figure D.4 – IRFs to a CE announcements shock increasing S&P 500 by 1 percent in the daily BVAR setting with an extended number of events for a total of 34. Solid black like are the medians, while shaded and dashed areas are the 68 and 90 % credibility sets, respectively.

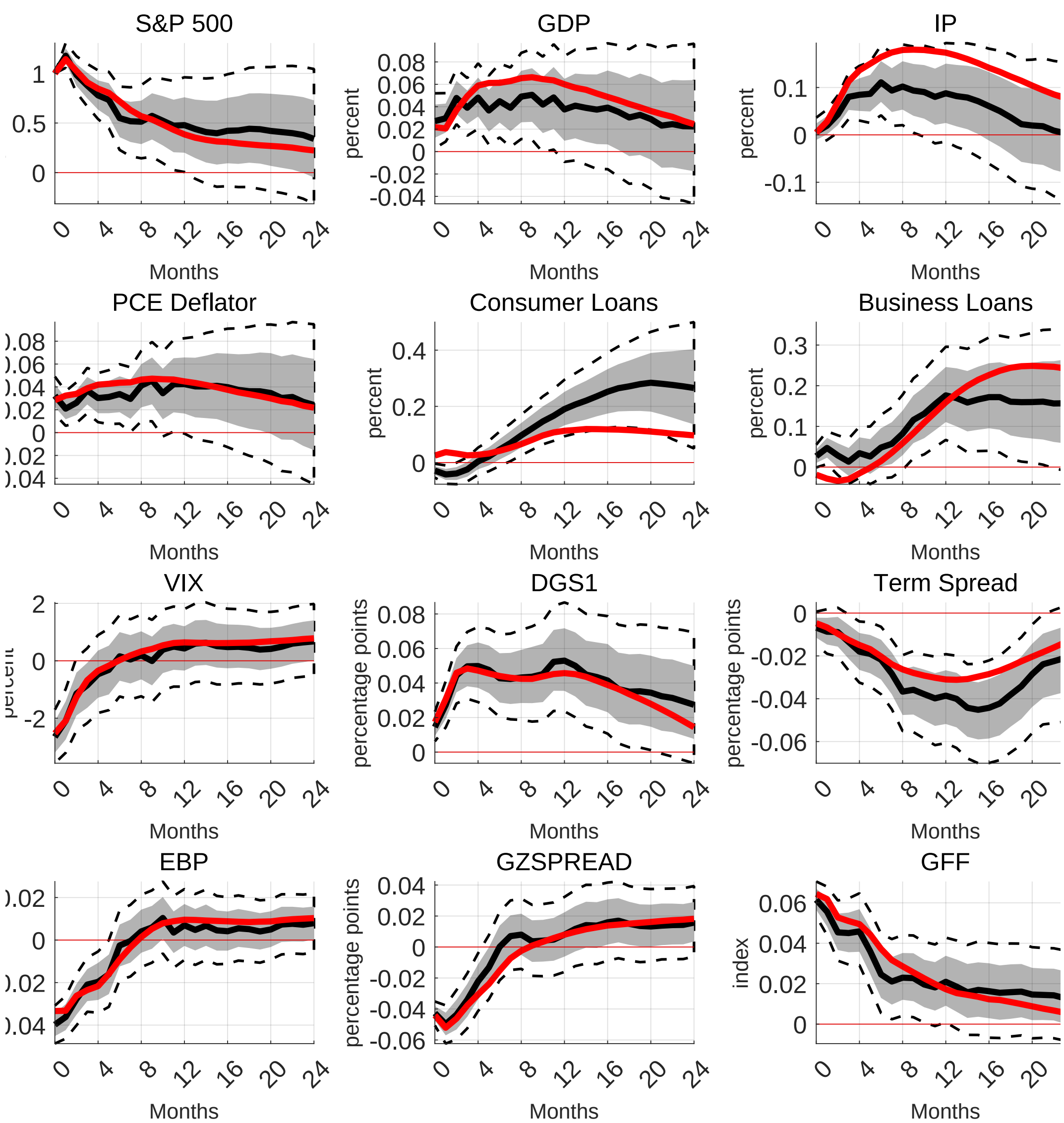

Figure D.5 – IRFs to a CE annoucements shock raising S&P 500 by 1 percent in a model in which both CE shocks and uncertainty shocks are identified. Solid black lines, shaded areas, and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.

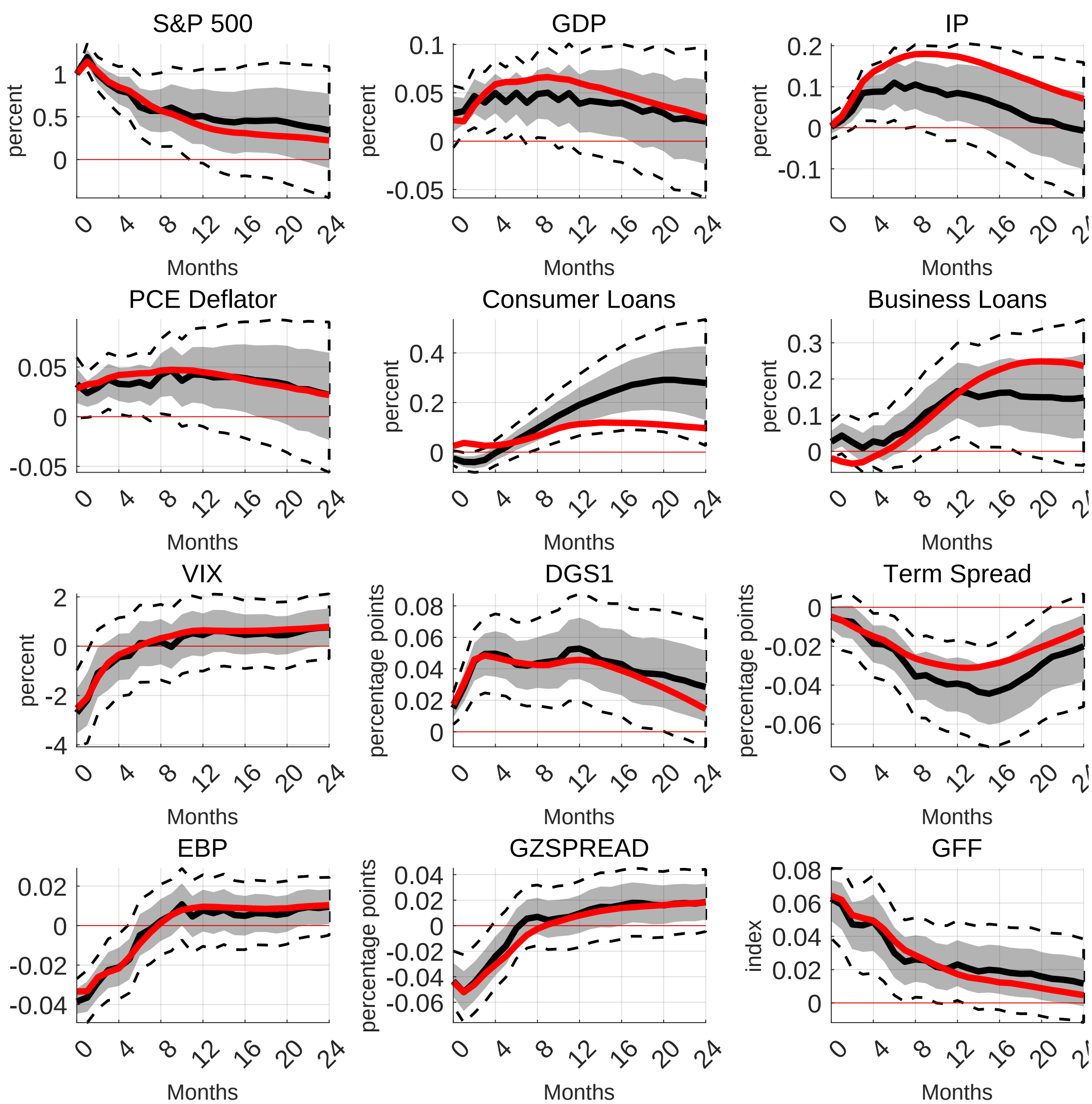

Figure D.6 – IRFs to a CE announcements shock raising S&P 500 by 1 percent in a model in which both CE announcements shocks and sentiment shocks are identified. Solid black line, shaded areas, and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.

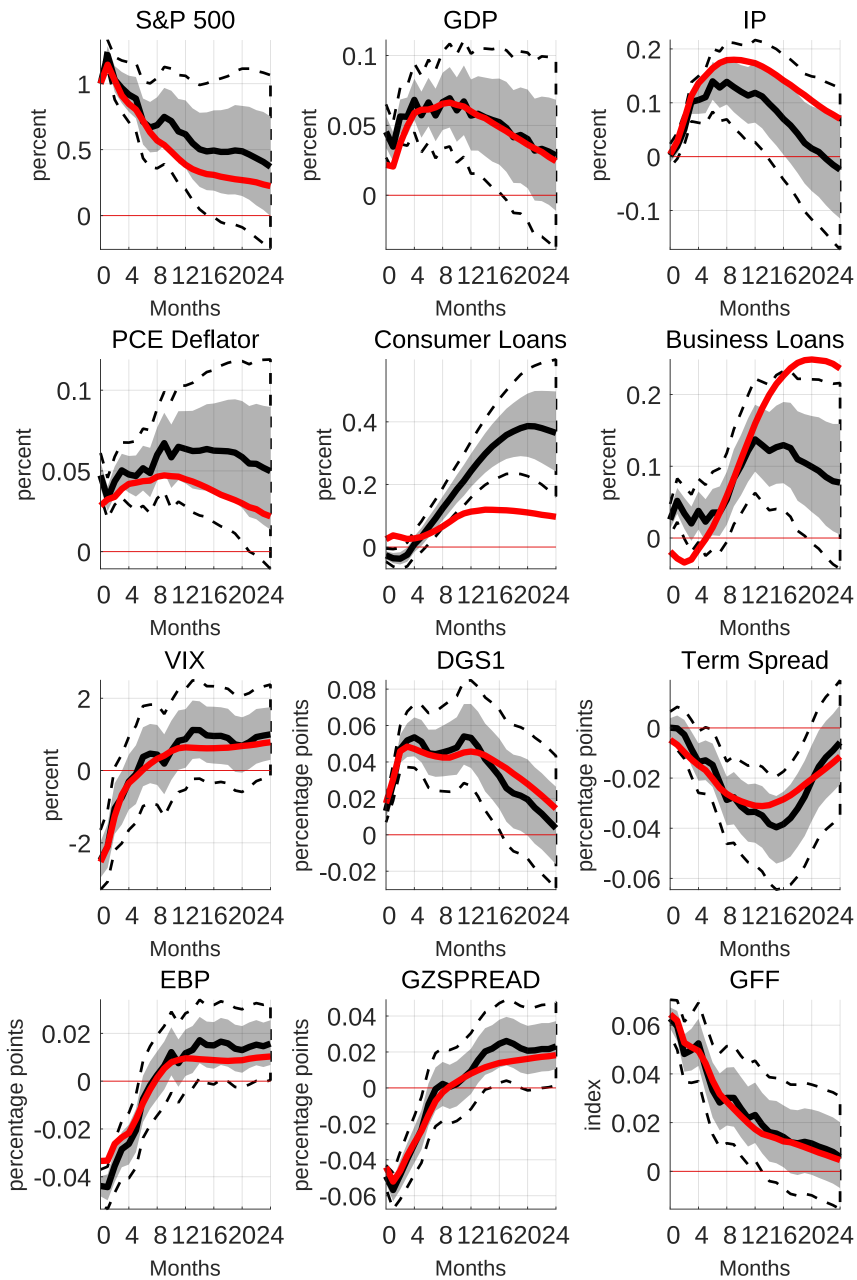

Figure D.7 – IRFs to a CE announcements shock raising S&P 500 by 1 percent in a model in which both CE announcements shocks and demand shocks are identified. Solid black line, shaded areas, and dotted lines are the median, the 68 and 90 credibility set. The solid, red line is the median in the baseline model.

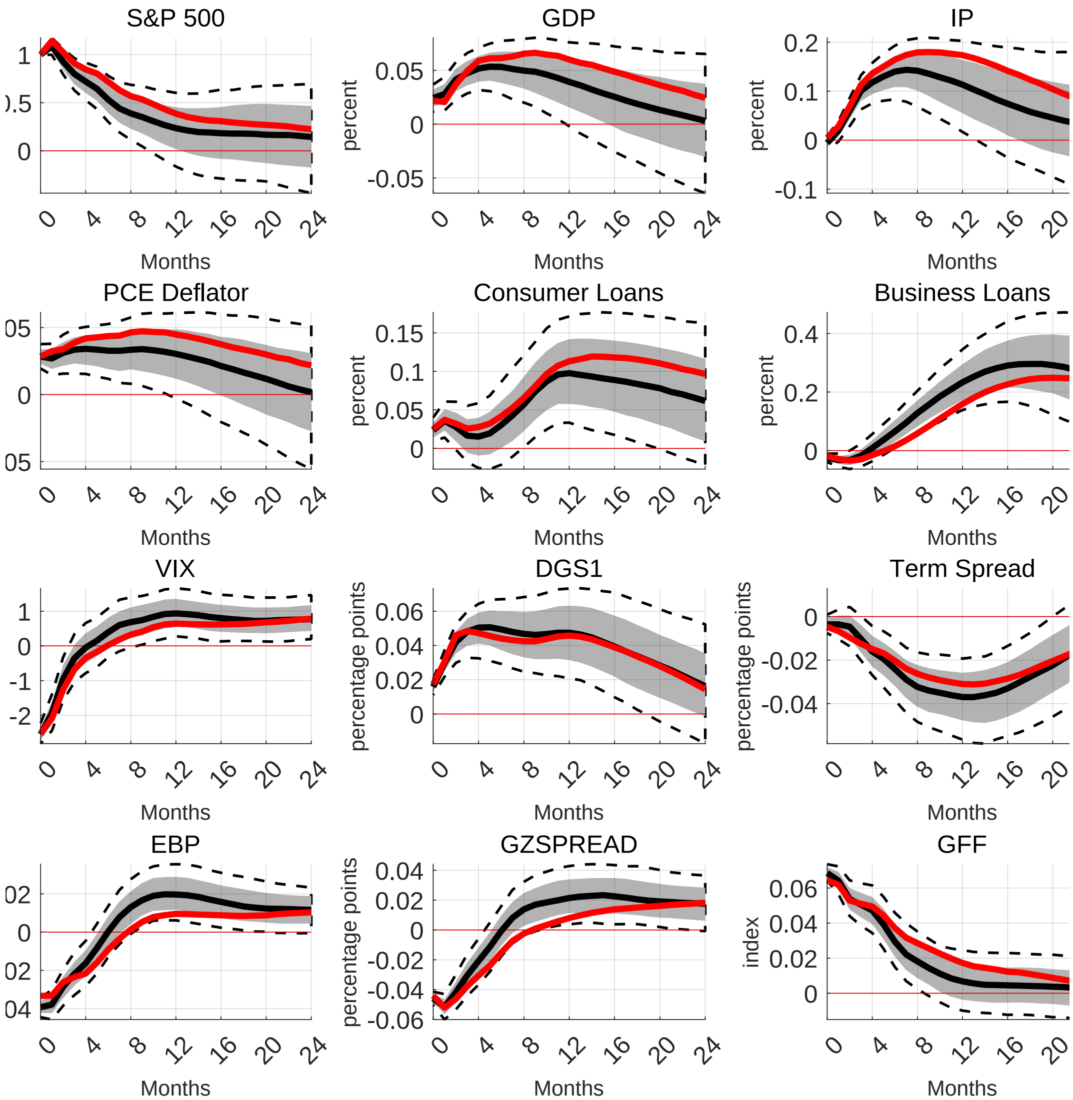

Figure D.8 – IRFs to a CE shock raising S&P 500 by 1 percent with estimation sample 1990:2-2019:4. Solid black line, shaded areas, and dotted lines are the median, the 68 and 90 credibility set. Solid, red line is the median in the baseline model.

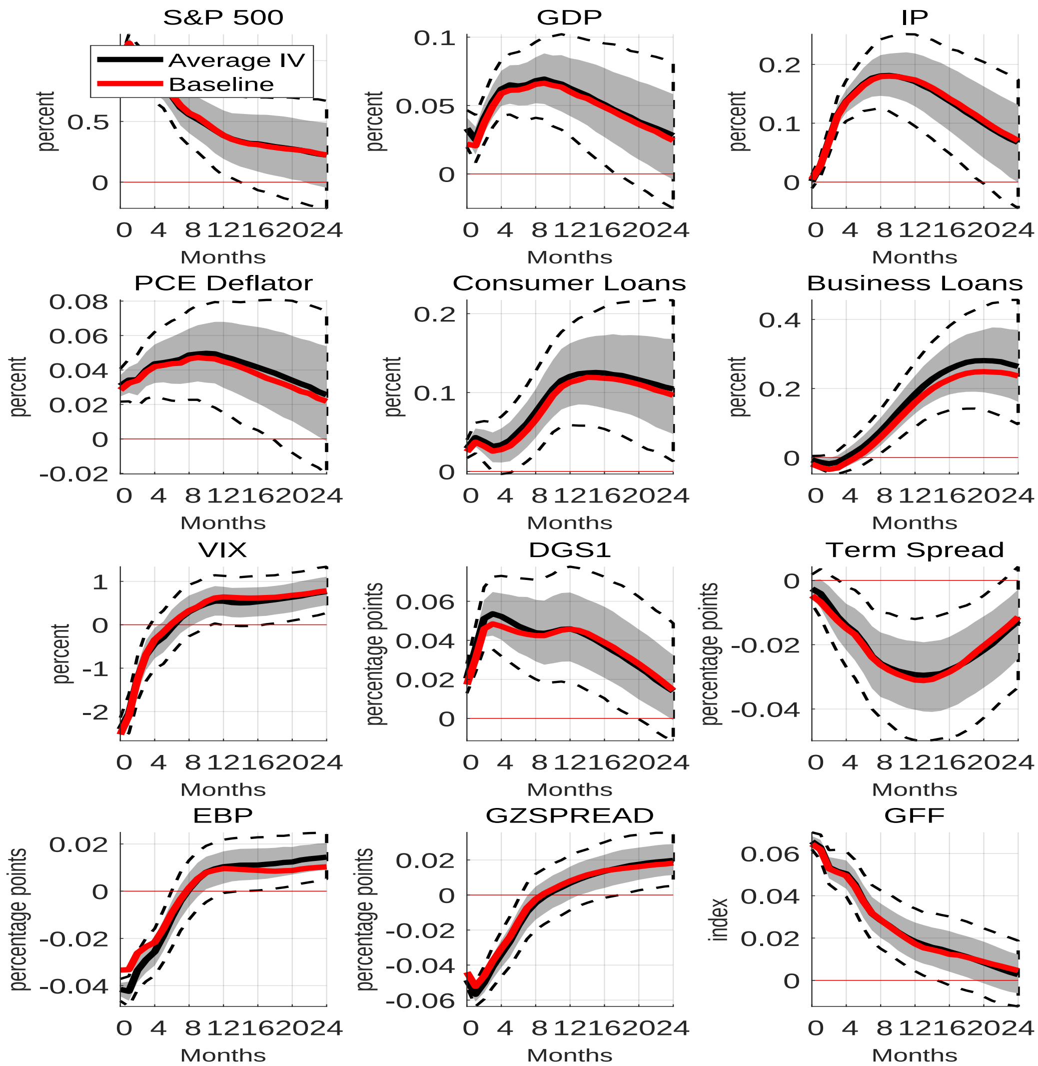

Figure D.9 – IRFs of US variables to a CE shock in which the instrument is computed as the monthly averages of the daily shocks, and to our baseline CE shock. Medians are reported for the alternative temporal aggregation model (solid black) as well as for the baseline case (solid red). Shaded areas represent the 68 and 90 percent bands in the sensitivity check.

Table D.1 – Correlation of the daily CE series with other instruments

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

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

E Additional results

In this section we show the results of additional analysis, such as the findings related to the magnitude effects of CE shocks on real activity, the variance decomposition and historical decomposition, as well as the international transmission of CE announcement shocks to the Euro Area.

E.1 Assessing the magnitude effects on real activity: the role of international feedback

Given the high resemblance between the CE announcements and financial shocks, we compare the magnitude of our baseline estimates for GDP and IP with those of the literature for financial shocks. For ease of exposition, we scale the shock to increase EBP by 1% point, as in Barnichon et al.

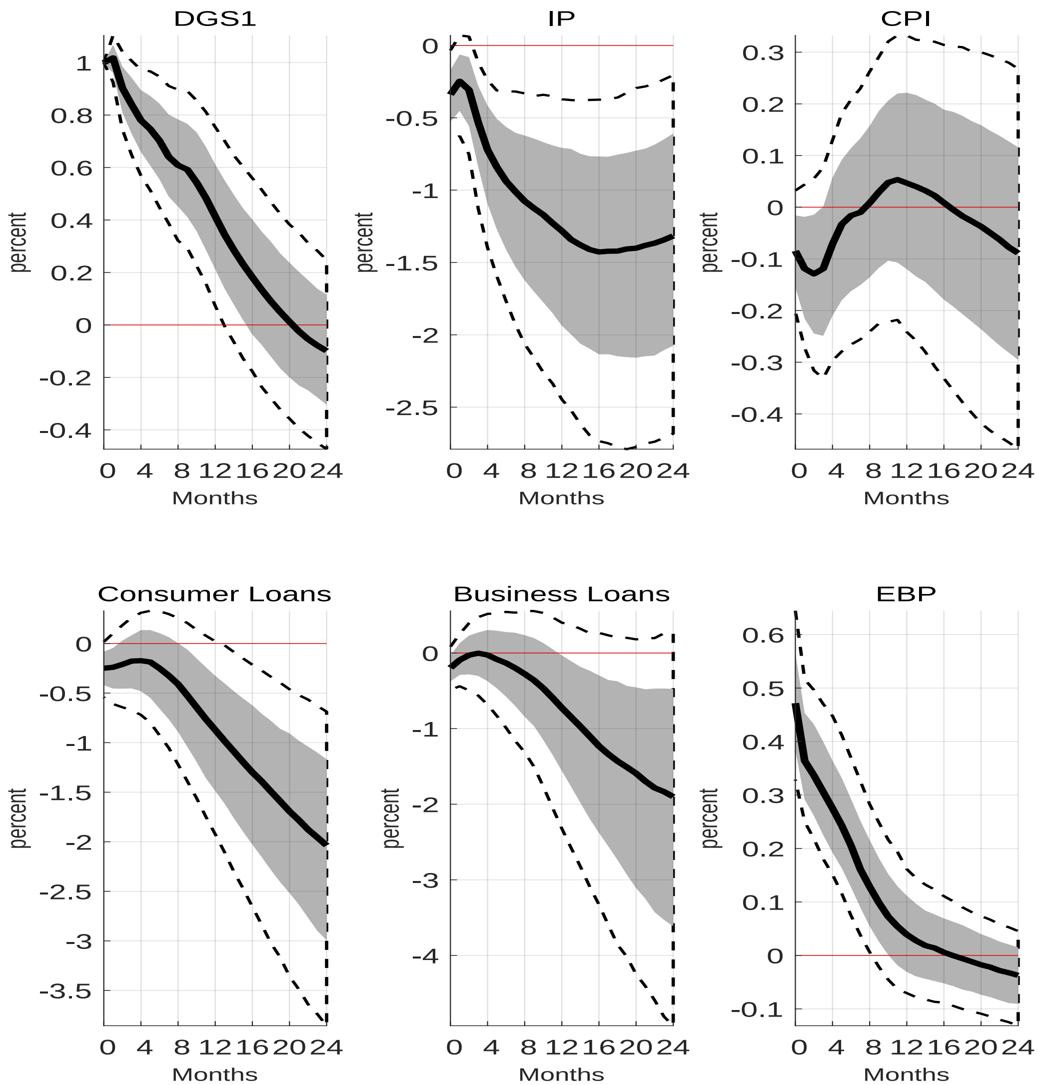

Figure D.10 – IRFs of US variables to a monetary policy shock in a small monthly VAR model. Medians are reported in solid black. Shaded areas represent the 68 and 90 percent bands.

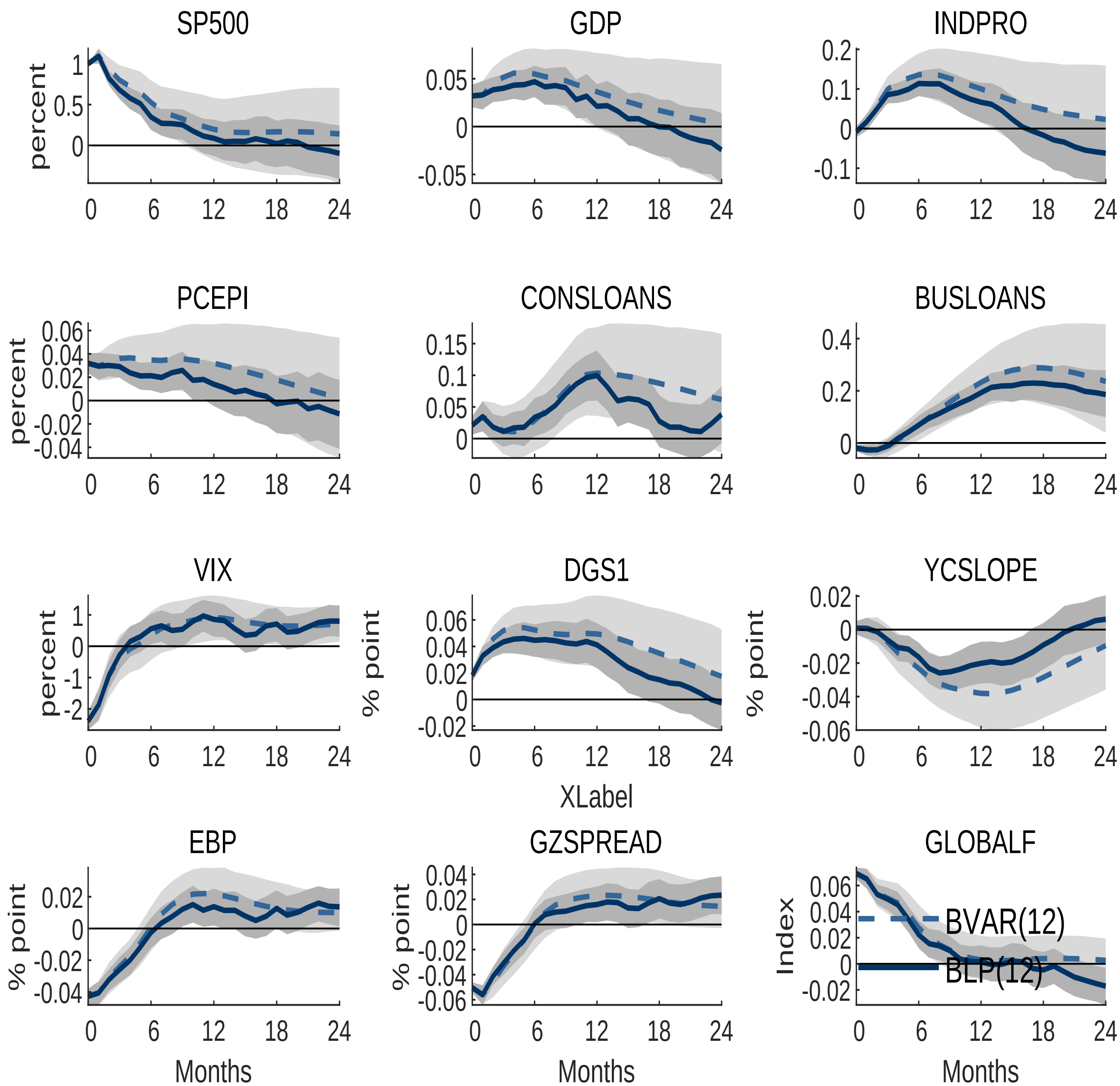

Figure D.11 – The figure illustrates a comparison between the IRFs of US variables in response to a CE shock. The estimation is conducted using two different approaches: local projections (solid line) and the baseline BVAR model (dashed line). The shaded areas in both models represent the 90 percent confidence intervals. The estimation sample is 1990:1 -2019:4 for both models.

Table D.2 – Corporate earnings extended events list

Date	S&P500 % jump	Brief Explanation
15/07/1996	-2.5	Weak earnings reports of high-flying tech firms
11/09/1998	2.9	Good News from Brazil
01/10/1998	-3.1	Profit fears
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 everywhere, from chemicals to technology
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
18/07/2002	-2.7	Dissapointing second quarter profit forecasts
19/07/2002	-3.8	Poor profits and stocks sow mutual misery
14/08/2002	4	More confidence in financial statements after Enron scandal
25/09/2002	2.5	Earnings in a recovery
01/10/2002	4	Good earnings news
09/10/2002	-2.7	Expectations that earnings won't be picking up soon
10/10/2002	3.5	Strong earnings announced
11/10/2002	3.9	On-target earnings report from GE
15/10/2002	4.7	Citigroup, GM show good earnings
19/10/2007	-2.6	Fears of falloff in profits
17/01/2008	-2.9	Default fears
29/02/2008	-2.7	Woes about Dell and Aig
21/10/2008	-3.1	Tech companies reported weak quarterly results
22/10/2008	-5.9	Weak corporate earnings
06/11/2008	-5	Corporate losses for Retailers, Auto sector, and banks
12/03/2009	4.1	Good news for Bank of America, GM and GE
18/05/2009	3	Better than expected earnings at house sector and good news from BoA
15/07/2009	3	Intel reports strong sales
02/06/2010	2.6	Few favorable corporate announcements and strong economic dta
07/07/2010	3.1	Jobless claims declined, and mixed sales numbers
24/10/2018	-3	double-digit declines of tech companies

Notes. The table reports the extended list of 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.

Table D.3 – Correlation of the CE shock with financial shocks in BPSS

BPSS shocks	Shocked variable	Correlation with the CE shock	p-value
Non-bank financial shock	GZ Spread	0.79	0.00
Banking credit shock	TED inter-bank spread	0.08	0.16
Household credit shock	Consumer loans	-0.01	0.84
Firm credit shock	Business loans	0.05	0.38
Term spread shock	Term spread	0.16	0.01
Industrial production shock	Industrial production	-0.04	0.43
Prices shock	PCE deflator	0.26	0.00
Monetary aggregate shock	M1	0.12	0.03
Monetary policy shock	Federal fund rates	0.04	0.44
Commodity price index shock	Commodity price index	0.03	0.65

Notes. The table reports the correlation coefficient of the CE shock extracted from the monthly BVAR model defined as in BPSS and identified with our baseline CE instrument. The correlation coefficient is computed for the overlapping sample 1990m1 to 2015m1.

(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 E.1, 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 to a CE announcements shock (-2%) is in line with what reported by Gilchrist and Zakrajšek (2012) and Ajello (2016) for spread shocks, while the peak reaction of IP of -5% is somewhat higher than the estimates of BPSS for the GZ stress shock.

In a recent contribution, Barnichon et al. (2018) show that the presence of asymmetry in the effects of financial disturbances 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 —, 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 E.1, 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 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 announcements is in line with findings pertaining to corporate spread shocks; and that (ii) the output response to such 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.

E.2 International transmission of US CE announcements 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 (Eickmeier and Ng, 2015, Abbate et al., 2016, Cesa-Bianchi and Sokol, 2017).

We contribute to this literature by examining the international transmission of the US CE annoncements. In this exercise we focus on EA, which is

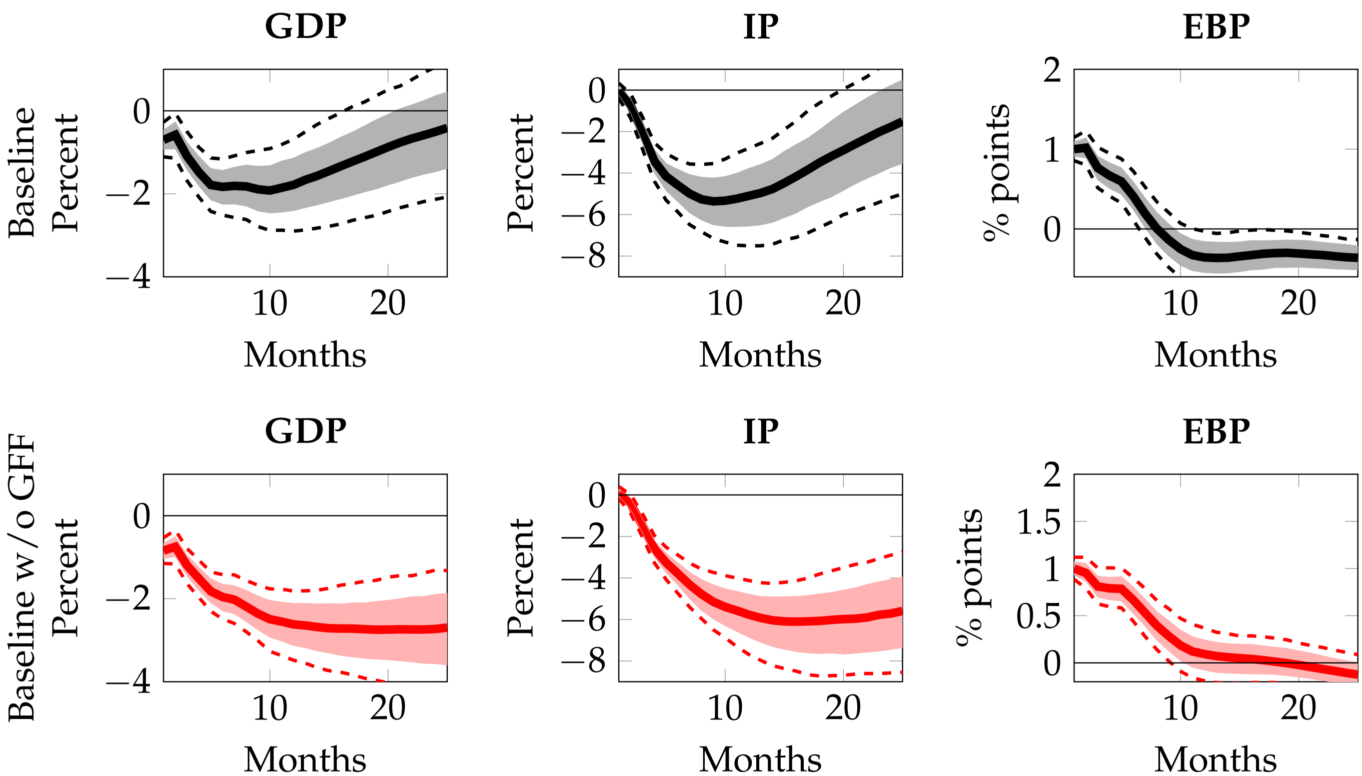

Figure E.1 – IRFs of EBP and real activity variables to a CE shock raising EBP by 1 % point in the baseline domestic model (first row) and the baseline without GFF (second row). Solid line, median. The 68 and 90 credibility sets are shaded areas and dotted lines, respectively.

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 E.2 we report the IRFs for the EA variables.

Expansionary US CE announcements trigger 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

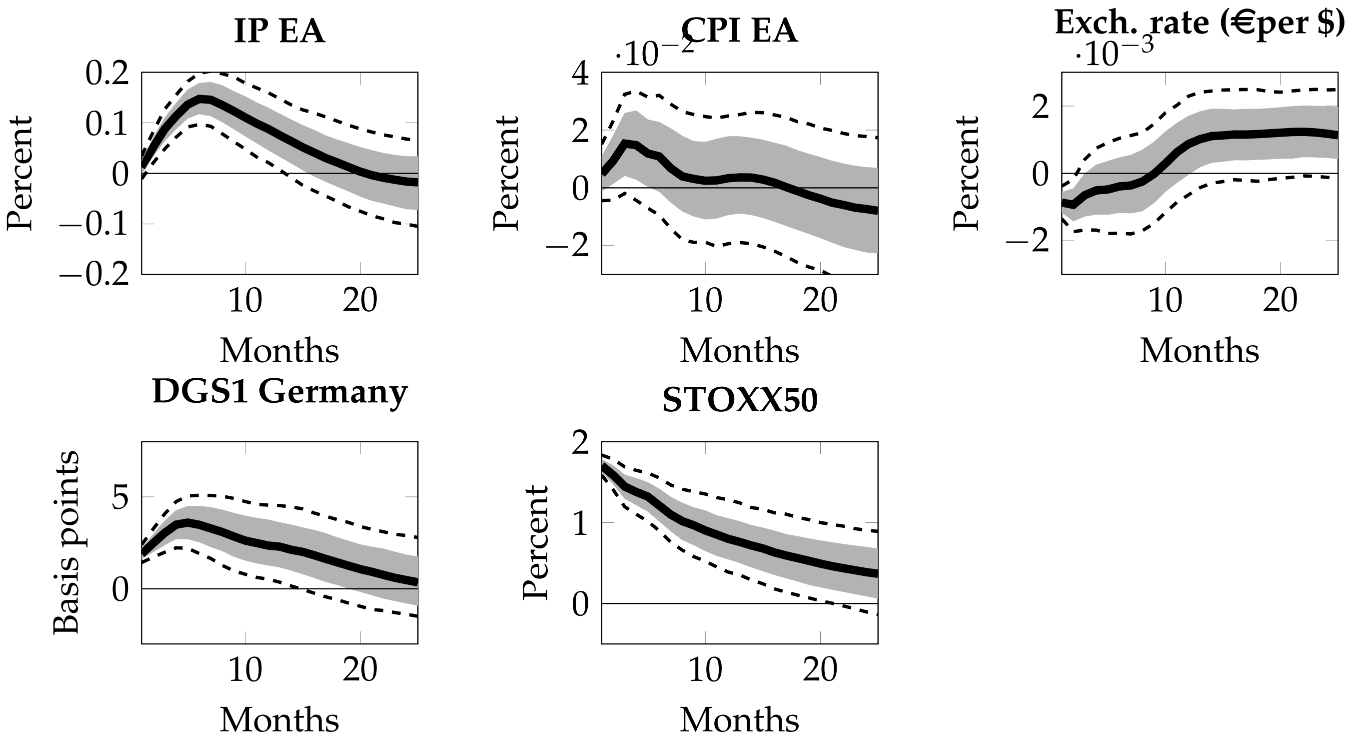

Figure E.2 – IRFs of EA variables to a CE shock raising S&P 500 by 1 percent in the monthly international BVAR model. Solid black line, median. The 68 and 90 credibility sets are shaded areas and dotted lines, respectively.

respect to the euro, but the effect is small and short-lived.

Discussion. The US CE announcements 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 CE announcements 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). 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 CE announcements shocks.

Finally, in line with the results for the US, we provide an external validation of our international results as well. To achieve this, we evaluate the impact of our CE shock on the UK variables and juxtapose the outcomes with those derived by Cesa-Bianchi and Sokol (2017) (CBS), who estimated the effects of financial shocks on the same set of UK variables. To ensure comparability, we adjust both shocks to increase the EBP in both models by 6 basis points.

The results presented in Figure E.3 reveal a remarkable degree of similarity, underscoring the notion that our CE shock aligns with the international transmission of financial shocks.

E.3 Variance decomposition analysis

A different way to asses the economic relevance of the CE announcements is by computing the share of forecast error variance explained by these shocks. The estimates from this exercise for selected variables are reported in Table E.1. [14]

The highest shares explained by the shock correspond to S&P500 and the GFF, with an impact estimate of 68 and 70%, respectively. Notice that the impact estimate for VIX (+ 19%) 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—brings evidence in favor of a first-moment shock rather than a second moment one. [15]

[14] The variance decomposition results for all variables are available in Figure E.1 in the Appendix.

[15] In a robustness exercise we also show that orthogonalizing the shock with respect to uncertainty leaves our results unchanged.

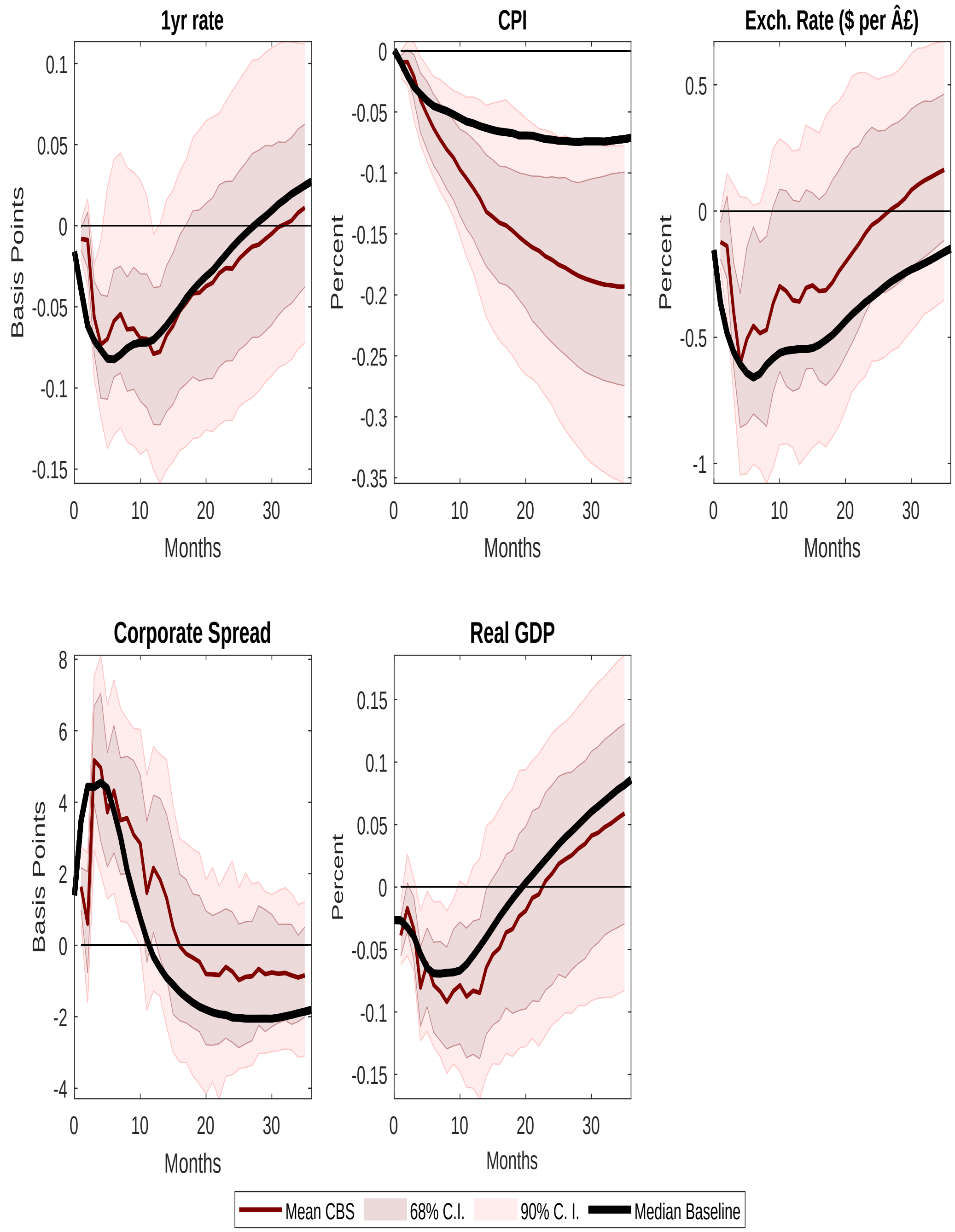

Figure E.3 – IRFs of UK variables to a financial shock, as defined in CBS, and to our baseline CE shock. Both shocks have been scaled to increase the EBP in the US by 6 basis points. Medians are reported for the CBS model (solid red) as well as for the baseline case (solid black). Shaded areas represent the 68 and 90 percent bands in the CBS model.

Table E.1 – Forecast error variance decomposition

Part A: US variables

	S&P500	GDP	IP	PCE deflator	DGS1	VIX	GFF
0	0.68	0.01	0	0.03	0.01	0.19	0.70
	(0.62 0.72)	(0 0.02)	(0 0)	(0.01 0.05)	(0 0.03)	(0.14 0.22)	(0.65 0.73)
6	0.54	0. 13	0.21	0.10	0.11	0.15	0.55
	(0.43 0.62)	(0.06 0.17)	(0.11 0.27)	(0.04 0.15)	(0.04 0.16)	(0.10 0.18)	(0.44 0.62)
12	0.33	0.15	0.24	0.10	0.13	0.14	0.42
	(0.21 0.41)	(0.06 0.21)	(0.12 0.33)	(0.04 0.17)	(0.04 0.20)	(0.10 0.17)	(0.30 0.49)
24	0.18	0.09	0.16	0.07	0.12	0.15	0.30
	(0.09 0.26)	(0.03 0.16)	(0.06 0.25)	(0.03 0.13)	(0.03 0.20)	(0.10 0.19)	(0.19 0.37)

Part B: EA variables

	Stoxx50	IP EA	CPI EA	Euro-dollar ex. rate	DGS1 Germany
0	0.65	0	0	0.01	0.06
	(0.58 0.69)	(0 0)	(0 0.01)	(0 0.01)	(0.03 0.08)
6	0.56	0.15	0.01	0.01	0.12
	(0.44 0.63)	(0.07 0.20)	(0 0.05)	(0.01 0.05)	(0.05 0.18)
12	0.44	0.14	0.01	0.02	0.11
	(0.30 0.54)	(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
	(0.16 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 announcements shocks at horizons 0,6, 12 and 24 months. The 90 credibility sets are displayed in brackets.

The CE announcements disturbance accounts for a share of 15 and 24% 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 and 13%, respectively. These results are comparable to previous analyses focusing on financial disturbances (see Gilchrist and Zakrajšek, 2012, Eickmeier and Ng, 2015, Ajello, 2016 and Furlanetto et al., 2019 among others).

In the second part of Table E.1 we report the values for the EA variables. The variance decomposition analysis delivers a similar message to the impulse responses. Specifically, the portion accounted for by the US CE announcements shock in the variance of stock prices, output, and interest rates in the EA are about the same as the US one. This result further supports the hypothesis of a strong international co-movement generated by the US CE 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 announcements shock is responsible for most of the impact variation of domestic and foreign stock prices and the GFF. This result reinforces the potential financial nature of the CE announcments shock and highlights its crucial role in shaping the global financial cycle.

E.4 Historical contribution of CE announcements shocks to real activity

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

Unlike structural impulse responses, historical decomposition is designed for stationary VAR models and should not be applied to integrated or cointegrated 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 E.4 shows the cumulative historical contribution of CE announcements 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).

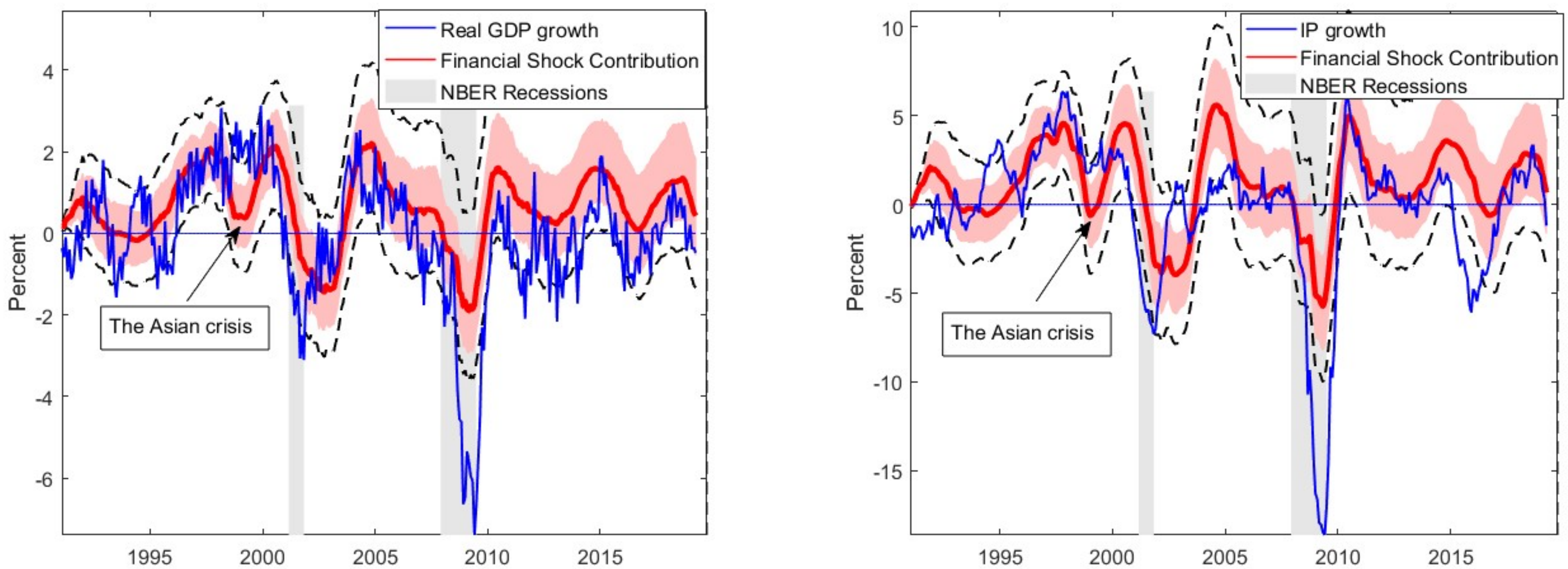

Figure E.4 – Historical decomposition of US GDP growth (left) and US IP growth (right). The figure shows the cumulative historical contribution of CE announcements shocks (red line) together with the actual variables (blue line) in percent deviations from the mean. The 68 and 90 credibility sets are shaded areas and dotted lines, respectively.

The shock is an important driver of the output drop on the occasion of the National Bureau 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 in financial markets (*i.e.* the speculation of internet-related companies and the subprime crisis respectively). We signal the negative contribution of the CE announcements shock during the Asian Crisis, even though it did not materialize in a recession. CE announcements shocks track closely the historical fluctuations in output outside recessions periods as well, highlighting the relevance of CE disturbances in shaping real activity.

When comparing our results to prior research on the historical contribution of financial shocks to the GFC, our findings do not deviate significantly. For instance, Caggiano et al. (2021) found that a financial shock contributed to 40% of the output decline during the GFC. Mumtaz et al. (2018) arrived at results similar to ours by examining the average effect of credit supply shocks using various identification strategies. Furlanetto et al. (2019) identified a slightly smaller share explained by financial shocks in the historical decomposition of output during the GFC. Additionally,Barnichon et al. (2018) detected a share of two-thirds explained by financial shocks in the recession triggered during the GFC. However, it's important to note that their counterfactual scenario differs slightly, as they halted the estimation sample in 2007 and conducted output forecasting without the influence of financial

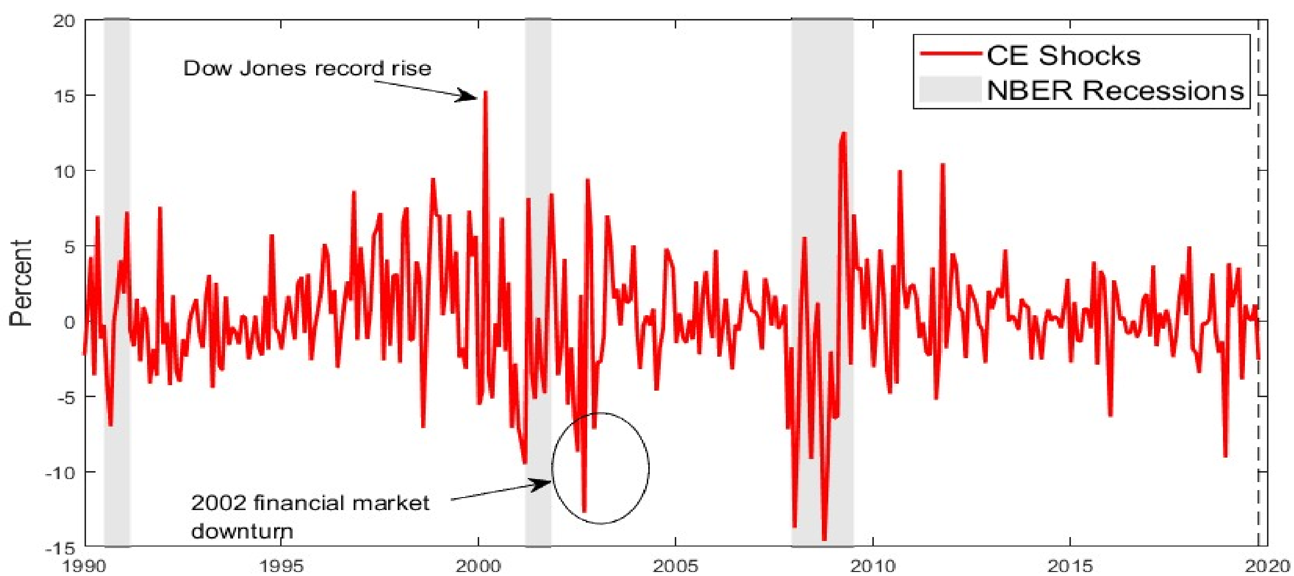

Figure E.5 – This figure shows the monthly CE announcements shock series constructed as the sum of the daily surprises. Shaded areas are NBER recession periods