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CORPORATE EARNINGS ANNOUNCEMENTS AND ECONOMIC ACTIVITY*

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Are corporate earnings (CE) announcements important for economic activity? We address this question using a novel identification method that combines the valuable information from 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 similar to traditional financial disruptions. We establish that CE announcements' shocks can be classified as financial shocks, highlighting their critical role in the financial system.

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 (2023) have highlighted the heightened significance of CE, revealing that they serve as collateral for approximately 80% of nonfinancial 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 United States. In order 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

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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 nonevent 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% 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% 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 United States. In order to further investigate the interpretation of the shock derived from CE announcements, we conduct a formal analysis. First, we compare our shock series with the four financial disturbances identified by Brunnermeier et al. (2021, hereafter BPSS). We discover a high correlation between the CE announcements shock and an exogenous increase in corporate spreads. Second, 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. In order 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 data set developed by Baker et al. (2021), 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 the Baker et al. (2021) data set corresponding to asset price jumps that have been triggered by nonfinancial firms' CE announcements.[1] Therefore, our selected event days encompass the corporate profit releases of significant and strategically important nonfinancial 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. In order to address concerns that our identification strategy might capture broader uncertainty, we performed a placebo exercise, randomly selecting days with significant stock price movements for

[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.

baseline analysis. As anticipated, this experiment yielded high noise levels due to the convolution of different shocks. In order to reinforce the financial nature of our CE announcement 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.

1.1. *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, 2021; Gu et al., 2020) have explored this relationship in depth. In our investigation, we focus on a specific category of economic news, namely, CE announcements, and establish their connection to the broader concept of financial disturbances.

This is not the first article to look at CE 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; 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. (2023), Cesa-Bianchi and Sokol (2022), Furlanetto et al. (2019) and Caggiano et al. (2021). Exceptions to this strand are Gilchrist and Zakrajšek (2012), Walentin (2014) and Barnichon et al. (2022) 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 article 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). In order to refine the identification, this approach is usually employed in high-frequency models (daily or intradaily). 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 article is organized as follows. In Section 2, we introduce the identification strategy providing details on the selection of the event 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. In Section 4, we provide a structural interpretation of the CE announcements shock as a financial shock. Section 5 concludes.

[2] This aspect has been widely assessed both domestically (see Gilchrist et al., 2009; Nolan and Thoenissen, 2009; Del Negro et al., 2017; Jermann and Quadrini, 2012; Christiano et al., 2014; Ajello, 2016) and internationally (see Dedola and Lombardo, 2012; Perri and Quadrini, 2018).

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 CE news using the data set produced by Baker et al. (2021). In this data set, 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 contain 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 17 preestablished categories, which include, among others, news about policy (monetary and fiscal), macroeconomic and outlook, CE, elections, commodities, and terrorist attacks and wars. They classify the primary reason for each jump into one of the 17 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 the Baker et al. (2021) data set 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 nonfinancial firms, as described in Table 1.

Baker et al. (2021) data set 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] Third, Baker et al. (2021) data set precludes the use of intradaily data, which are 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

[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

NOTE: The table reports the stock market jumps due to corporate earning news as reported by Baker et al. (2021). 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.

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 a $1 \times N$ 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 an $(NP+1) \times N$ 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

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

2.2.1. *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 macrodynamics 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.

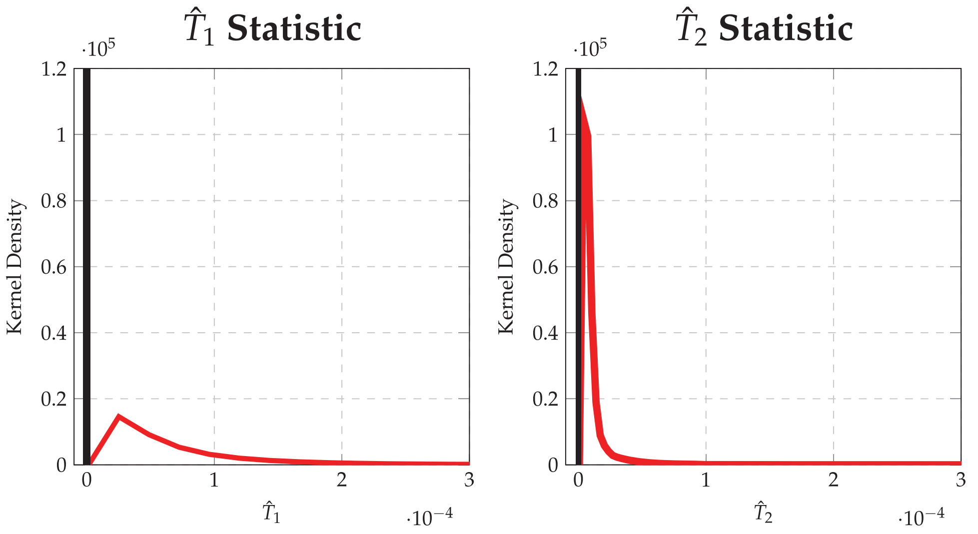


FIGURE 1

KERNEL DENSITY FUNCTIONS CALCULATED ON 5,000 POSTERIOR DRAWS OF THE STATISTICS $\hat{T}_1$ AND $\hat{T}_2$

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:

$$\begin{aligned} A_{(1)} = \underset{A_{(1)}}{argmin}&\Big[vech(\hat{\Sigma}_1 - \hat{\Sigma}_0) - vech\Big(A_{(1)}A'_{(1)}\Big)\Big]'\Big[\hat{V}_0 + \hat{V}_1\Big]^{-1} \\ &\times \Big[vech(\hat{\Sigma}_1 - \hat{\Sigma}_0) - vech\Big(A_{(1)}A'_{(1)}\Big)\Big], \end{aligned} \tag{4}$$

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.

2.2.2. *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 nonevent days, that is, $\Sigma_1 \neq \Sigma_0$. This is necessary to achieve identification as it signals heteroscedasticity on event days. In order to verify this requirement, we compute for each saved draw in the Gibbs-sampler, the following statistical distance:

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

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, $\Gamma_1\Gamma_1^{'}$, that is, $\Sigma_1 - \Sigma_0 = \Gamma_1\Gamma_1^{'}$. This would indicate that the difference in the variance–covariance matrices between event and nonevent 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

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

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).

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. First, 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. In order to maintain consistency, we chose to begin the sample in 1990.

The baseline model contains five variables,

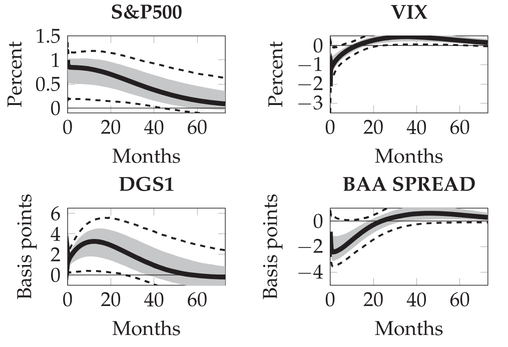
$$X_t = [ln(VIX_t),\ ln(S\&P500_t),\ DGS1_t,\ BAA_t,\ Sentiment_t], \tag{7}$$

$ln\,(S\&P500_t)$ is the (log of) the S&P 500 Index, the main U.S. 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, for example, Bloom (2009).$DGS1_t$ is the One-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, whereas $Sentiment_t$ 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.

2.3.1. *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%. 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, captured by the fall in BAA credit spread (−2 bp). 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.

[4] We follow Baker et al. (2016) and use the VIX index in logs to have a clear interpretation in percent terms of the impulse response function (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)



NOTES: Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

FIGURE 2

IRFS TO A CE ANNOUNCEMENTS SHOCK INCREASING S&P 500 BY 1% IN THE DAILY BVAR SETTING

2.3.2. *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. In order to reassure the reader that the identification strategy is picking up CE news, we perform a placebo exercise in which we randomly select 17 events from all days in Baker et al. (2021) data set 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 Bayesian Vector Autoregressive (BVAR) analysis as in the baseline case across 1,000 iterations. As expected, the results produced by this experiment (see Appendix D) are very noisy since they reflect a convolution of different shocks instead of 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. In order 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 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 Appendix D.

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.

[5] Alessandri et al. (2023) utilize monthly averages of daily shocks instead of sum. However, we show in Figure D9 that using averages instead of sums has a negligible impact on our results.

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 noninvertibility 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 a $1 \times N$ 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 an $(NP+1) \times N$ 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:

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

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

Without loss of generality, let us assume that $\epsilon_{1,t}$ is the CE announcements shock whereas $\epsilon_{2:n,t}$ is the $(n-1) \times 1$ vector of the remaining shocks in the model. 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, that is, $\mathbf{a_1}$, is identified up to scale as follows:

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

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 (see Table C1). 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 Global Financial Factor (GFF), which is in original units; interest rates are expressed in bp. The VAR model includes measures of real activity (GDP and Industrial Production), prices (Personal Consumption Expenditure (PCE) Deflator), consumer and business credit based on the Federal Reserve's weekly surveys of U.S.

[6] The noninvertibility 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.

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

TABLE 2
TESTS FOR INSTRUMENT RELEVANCE

Model	*F*-Stat	90 HPDI	Reliability	90 HPDI
Monthly BVAR	174	[130 185]	47	[43 52]

NOTE: The table reports first-stage *F*-statistics, statistical reliability, and 90% high probability density intervals (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.

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 BV AR 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) whereas 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 D8 in the Appendix, 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.

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%.[9] We report the median over the saved draws, together with the 68 and 90 coverage set.

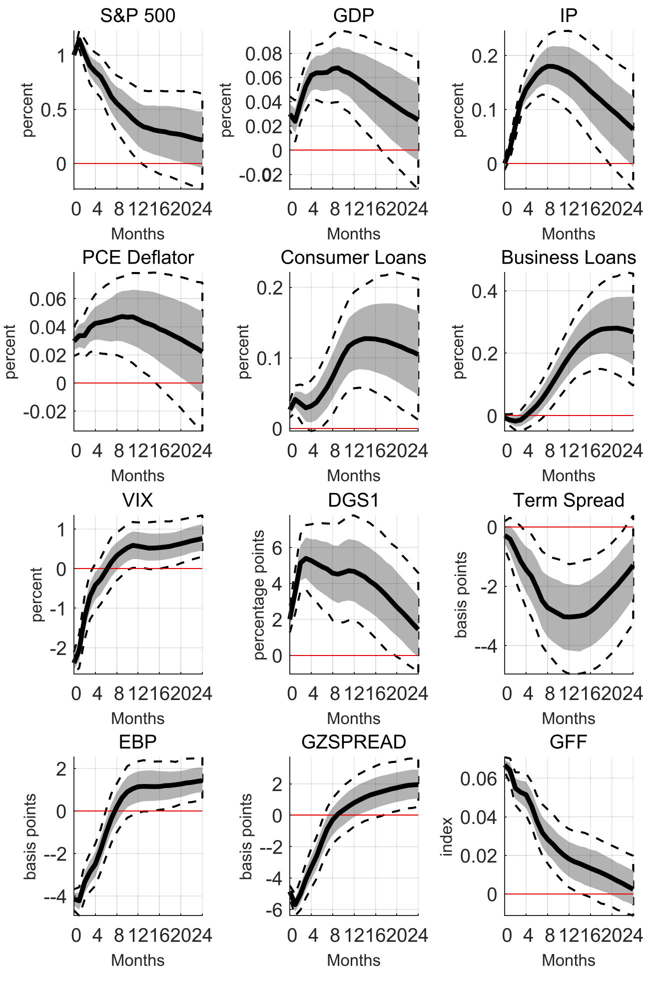
Expansionary CE announcements trigger a sharp and significant increase in stock prices accompanied by a contemporaneous raise in the GDP with effects that persist for almost two years. Industrial production starts increasing shortly after the shock reinforcing the expansionary features of the disturbance. 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 index, GZ spread, and EBP

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

[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 been observed in previous studies as well, notably in response to shocks to the GZ Spread (see Brunnermeier et al., 2021) and to lending stan-



NOTES: Solid black line, median. The 68 and 90 credibility sets are shaded areas and dotted lines, respectively

FIGURE 3

IRFS OF DOMESTIC U.S. VARIABLES TO A CE SHOCK RAISING S&P 500 BY 1% IN THE MONTHLY BVAR MODEL

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 United States 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.,

dards shocks (Lown and Morgan, 2006). Figure D9 in the Online Appendix illustrates that similar dynamics are evident in the case of monetary policy shocks.

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 comovement 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 earnings.

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

Robustness checks and additional results In order 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 (see Appendix D).

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 ANNOUNCEMENT 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. In order 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 this interpretation: First, the dynamics generated by CE announcements closely resemble those of a traditional financial disturbance; second, variance decomposition analysis reveals that CE announcements explain the largest share of variation in financial variables; and third, as earnings significantly impact firms' access to credit in the United States, 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., 2021).

In order 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 United States, using monthly data from January 1973 to June 2015 (listed in Table C2). All variables are in log levels, except for the spread and interest rate, which enter the model unchanged. Although 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

TABLE 3
CORRELATION OF THE CE SHOCK WITH FINANCIAL SHOCKS IN BPSS

BPSS Shocks	Shocked Variable	Correlation with the CE Shock	p-Value
Nonbank financial shock	GZ spread	0.82	0.00
Banking credit shock	TED Interbank spread	0.07	0.21
Household credit shock	Consumer loans	0.01	0.9
Firm credit shock	Business loans	0.07	0.23

NOTE: 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.

component of CE announcements. We estimate the BPSS VAR model, identifying CE announcement shocks within it using our baseline CE instrument. In Table 3, we compare the resulting structural shock series with the four financial disturbances from the BPSS model. We find that our CE shock series is highly correlated (around 82%) with the GZ Spread shock, interpreted as a nonbank 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 nonfinancial firms. This also explains the lack of correlation with firm and household credit shocks.

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 U.S. quarterly data on a sample going from 1989Q1 to 2008Q2. 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.

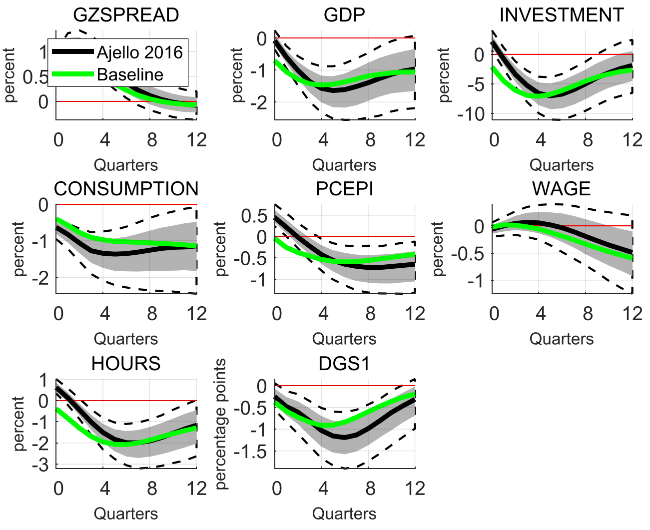
The structure of the quarterly BVAR follows Ajello (2016) and includes GDP, consumption, investment, prices, real wage, hours worked, short-term rates, and the GZ corporate bond spread measure. All variables are in log levels except for the interest rate and the bond spread, which are not transformed. 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]

[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 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, whereas 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.



NOTES: The shock is scaled to raise GZ Spread by 1% in the quarterly BVAR model. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively. The green line is the median obtained with the baseline CE identification.

FIGURE 4

IRFS OF U.S. VARIABLES TO A FINANCIAL SHOCK IDENTIFIED WITH THE AJELLO (2016) TRANSITORY FINANCIAL INSTRUMENT VS. THE BASELINE CE INSTRUMENT

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 the central bank lowers the short-term rate by almost 1% point and keeps accommodating for around three 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, 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) (see Table C3). 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.

DATA AVAILABILITY STATEMENT The data that support the findings of this study are openly available in OPENICPSR at https://www.openicpsr.org/openicpsr/workspace?goToPath=/openicpsr/198565&goToLevel=project

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table C.1 - Data series used in the model estimation
Table C.2 - Data series in BPSS
Table C.3 - Correlation of the CE shock series with the structural shocks in Ajello (2016) model
Table D.1 - Correlation of the daily CE series with other instruments
Figure D.1 - IRFs to a CE shock increasing S&P 500 by 1 percent in the daily BVAR setting with 21 lags.
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.
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.
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.
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.
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.
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.
Figure D.8 - IRFs to a CE shock raising S&P 500 by 1 percent with estimation sample 1990:2-2019:4.
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
Figure D.10 - IRFs of US variables to a monetary policy shock in a small monthly VAR model.
Table D.2 - Corporate earnings extended events list
Table D.3 - Correlation of the CE shock with financial shocks in BPSS
Figure D.11 - The figure illustrates a comparison between the IRFs of US variables in response to a CE shock.
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).
Figure E.2 - IRFs of EA variables to a CE shock raising S&P 500 by 1 percent in the monthly international BVAR model.
Figure E.3 - IRFs of UK variables to a financial shock, as defined in CBS, and to our baseline CE shock.
Table E.1 - Forecast error variance decomposition
Figure E.4 - Historical decomposition of US GDP growth (left) and US IP growth (right).
Figure E.5 - This figure shows the monthly CE announcements shock series constructed as the sum of the daily surprises.

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