TGU-ECON Discussion Paper Series
#2024-2

Media-Created Economic Uncertainty

Yoshito Funashima
Faculty of Economics, Tohoku Gakuin University

December 2024

Media-Created Economic Uncertainty*

Yoshito Funashima†

Faculty of Economics, Tohoku Gakuin University

February 27, 2023. This version: December 1, 2024.

Abstract

This study proposes a simple structural vector autoregressive analysis to identify economic uncertainty shocks originating from social and traditional media. Data availability limits the selection of representative media to newspapers for traditional media and X (formerly Twitter) for social media, with the analysis centered on the United States. Results reveal that heightened uncertainty spread via social media generates a persistent increase in equity market uncertainty. By contrast, uncertainty disseminated by journalists and experts through traditional media causes only a temporary increase in equity market uncertainty. These findings imply that volatility clustering in the equity market primarily stems from information diffusion through social media rather than traditional media.

Keywords: Economic uncertainty; Social media; Traditional media; Structural vector autoregressive analysis; Equity market

JEL classification: C32; D80

*This work was supported by JSPS KAKENHI Grant Number 21K01446.

†Faculty of Economics, Tohoku Gakuin University, 1-3-1 Tsuchitoi, Aoba-ku, Sendai, Miyagi 980-8511, Japan. E-mail: funashima@mail.tohoku-gakuin.ac.jp

1 Introduction

Economic uncertainty has been modeled through multiple approaches in macroeconomic and financial analyses, yet its temporal fluctuations remain poorly understood.[1] While no single uncertainty indicator exists, focusing on media-based uncertainty measures, such as counts of uncertainty-related words in media, offers key insights into this complex issue. A central factor in understanding uncertainty is the quality of the information being disseminated.[2] In modern times, economic uncertainty primarily stems from the flow of economic information which is largely transmitted through social and traditional media—two crucial sources of information. However, the economic uncertainty created by these media differs for one key reason: unlike traditional media, social media users include not only journalists and experts but also politicians and the general public, who can freely express their opinions through comments, blogs, posts, and articles, enabling the exchange of diverse opinions and animated discussions. To explain the fluctuations in economic uncertainty, in this study, we highlight the differences in the quality of information disseminated by social and traditional media.

We emphasize that the growing uncertainty generated by one medium can influence the uncertainty created by the other because social media discussions can spill over to traditional media and stimulate further debate, and vice versa. For example, Donald Trump, the 45th president of the United States (U.S.), frequently tweeted during his presidency, sometimes creating controversies on both social and traditional media platforms.[3] Newspaper articles can draw from social media content, and we hypothesize that such interactions between social and traditional media may amplify fluctuations in

[1]For example, Svensson and Williams (2008) and Williams (2012) assume Markov chains to represent uncertainty in theoretical models. Although this approach is useful for examining optimal policy under model uncertainty, it does not allow for the sources of uncertainty fluctuation.

[2]The literature lacks a general definition of uncertainty. As noted in Bloom (2014), multiple proxies for uncertainty exist. Widely used indicators of uncertainty include gross domestic product volatility and stock price fluctuations, although, in this study, uncertainty refers to the media-based measure introduced in Baker *et al.* (2016).

[3]Throughout this study, we use Twitter although it has officially been rebranded as X since July 2023.

economic uncertainty.

To investigate the distinct roles these media play in the dynamics of economic uncertainty, in this study, we introduce a novel approach for identifying exogenous uncertainty shocks driven by each medium. Specifically, we propose a bivariate structural vector autoregressive (VAR) model using daily indices of Newspaper-based Economic Uncertainty (NEU) and Twitter-based Economic Uncertainty (TEU).[4]

The model's key identifying assumptions are (i) TEU responds instantaneously to newspaper-specific uncertainty shocks, and (ii) NEU does not respond within the same day to Twitter-specific uncertainty shocks. These assumptions are justified in Section 2, where we explain that tweets can be posted instantly, whereas newspapers typically experience a delay between information acquisition and publication.

We apply an empirical approach to the U.S. owing to the availability of daily data. First, we demonstrate that the dynamic interaction between social and traditional media is a transmission mechanism through which economic uncertainty is created. A positive Twitter-specific uncertainty shock leads to a persistent increase in NEU. Notably, the response is stronger during the coronavirus disease 2019 (COVID-19) pandemic compared to the preceding period. We also find that a positive newspaper-specific uncertainty shock increases TEU, although this effect is less pronounced.

Furthermore, we trace the effects of the identified media shocks on daily equity market uncertainty (EMU). Our results demonstrate that social and traditional media have markedly different effects on the equity market. Positive shocks to Twitter-specific uncertainty result in a persistent increase in EMU, indicating that social media can be a source of volatility clustering in the equity market. By contrast, positive shocks to newspaper-specific uncertainty lead to a large but only temporary increase in EMU. Historical decomposition analysis suggests that Twitter-specific uncertainty shocks, especially during the Trump administration, played a significant role in explaining EMU. We argue that

[4]Newspaper and Twitter are respectively selected as representatives of each media due to data availability.

the differing effects of social and traditional media on the market stem from the accuracy and nature of the information they disseminate.

Related literature. The literature on economic uncertainty has burgeoned since the seminal works by Bloom (2009) and Baker *et al.* (2016). Many authors have highlighted the negative effects of increased economic uncertainty. For example, Colombo (2013) argues that an increase in the U.S. economic policy uncertainty (EPU) causes a decline in European industrial production, while Li and Wei (2022) find that when EPU is high, government spending is less effective.

In terms of media's influence on economic uncertainty, Duca and Saving (2018) contend that media fragmentation is linked to EPU. In addition, scholars have increasingly focused on social media's role in the field of economics.[5] However, despite extensive prior research, few studies have focused on how economic uncertainty is shaped by the dynamic interaction between social and traditional media.

Our work is closely related to that of Jiao *et al.* (2020), who find that the reaction of equity markets to social media differs from that of news media. However, we diverge from their approach in key ways. Jiao *et al.* (2020) employ monthly data and non-structural panel VAR models, implying that the shocks are not identified in economically meaningful terms. As noted by Jiao *et al.* (2020, p. 64), exogenous variations in social and news media have not been identified, leaving the mechanism unclear. Unlike their study, we use daily observations and present a structural VAR analysis to identify exogenous variations, thereby elucidating the dynamic interactions between these media and explaining the transmission mechanism through which economic uncertainty fluctuates. Moreover, we provide causal evidence on which media are important for volatility clustering in the equity market. Although volatility clustering is a well-known property in financial data and is modeled through various methods (e.g., Engle, 1982; Bollerslev, 1986; Hull and

[5]See, e.g., Chen *et al.* (2014), Desmarchelier and Fang (2016), Williams and Reade (2016), Lehrer and Xie (2017), Affuso and Lahtinen (2019), Allcott *et al.* (2020), Pettenuzzo *et al.* (2020), Levy (2021), and Braghieri *et al.* (2022). For a detailed survey, see Tumasjan (2024).

White, 1987; Scott, 1987; Wiggins, 1987; Nelson, 1991), its underlying sources have not been thoroughly explored.

This study also builds on that of Milas *et al.* (2021), who examine the Eurozone sovereign bond market's response to Twitter and traditional news, demonstrating that both can predict the sovereign bond market and maintain a mutually dependent relationship. Consistent with our results, they find that Twitter's influence on traditional news is more pronounced. While Milas *et al.* (2021) focus specifically on "Grexit" news, our study considers a broader spectrum of news interactions.

The remainder of this paper is organized as follows. In Section 2, we propose a novel approach to identifying newspaper-specific and Twitter-specific uncertainty shocks through a structural VAR analysis. Using this approach, we assess the responsiveness of NEU and TEU to these shocks and examine how each is explained by structural shocks. In Section 3, we extend our structural VAR analysis to investigate the effects of these media shocks on EMU. Finally, Section 4 concludes the paper.

2 Media-specific uncertainty shocks

2.1 Identification

We utilize the availability of daily data from the U.S., obtaining NEU and TEU from Baker *et al.* (2016) and Baker *et al.* (2021), respectively.[6] The data were transformed into natural logarithmic form, and Figure 1 shows the series used in the empirical analysis. The sample period spans January 20, 2017, to November 29, 2022, beginning on Donald Trump's first day as U.S. president.

[Insert Figure 1]

[6] These data can be retrieved from the website of EPU (`https://www.policyuncertainty.com/index.html`). We employ the "TEU-USA" index of Baker *et al.* (2021), which is constructed on the tweets of users in the U.S., as U.S. daily TEU series.

We denote NEU and TEU at time t as n_t and τ_t, respectively. Defining the vector of variables as $\boldsymbol{y}_t = (n_t,\ \tau_t)'$ we specify a daily bivariate VAR model:

$$\boldsymbol{A}_0\boldsymbol{y}_t = \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \boldsymbol{A}_2\boldsymbol{y}_{t-2} + \cdots + \boldsymbol{A}_s\boldsymbol{y}_{t-s} + \boldsymbol{\varepsilon}_t,$$

where $\boldsymbol{\varepsilon}_t = (\varepsilon_t^n,\ \varepsilon_t^\tau)'$ represents structural shocks, with ε_t^n denoting newspaper-specific uncertainty shocks and ε_t^τ Twitter-specific uncertainty shocks. Our strategy for identifying mutually uncorrelated structural disturbances relies on delay restrictions, under the following two assumptions:

Assumption 1. *ε_t^n simultaneously affects τ_t.*

Assumption 1 leverages Twitter's real-time capabilities, where users can immediately post responses to newspaper articles they read. Twitter's short-message format enables rapid information sharing, with features such as retweeting allowing wide dissemination within a day.

Assumption 2. *n_t does not respond within the same day to ε_t^τ.*

Assumption 2, a distinctive viewpoint of this study, reflects the delay typically associated with newspaper publishing, implying little or no response of newspaper reports to unexpected simultaneous movements in Twitter messages. The rationale for this assumption is based on three reasons. First, in contrast to Twitter, where individuals can make quick decisions regarding tweets, print newspapers are published only once or twice daily, and even online newspapers require fact-checking, making an immediate response to Twitter posts unlikely. Second, Schmierbach and Oeldorf-Hirsch (2012) contend that journalists treat information from Twitter as less credible, often necessitating verification. Third, unlike Twitter, writing news articles after obtaining information is time-consuming for journalists because they need to coordinate internally within the company.

Assumptions 1 and 2 form a recursive identification, and $\boldsymbol{A}_0$ is assumed to be lower triangular.[7] Our identification strategy relies on daily media data, following a similar approach to Blanchard and Perotti (2002) in analyzing fiscal multipliers. Unlike previous studies, such as Kuttner and Posen (2001), which use annual data and suffer from the simultaneity problem in measuring fiscal multipliers, Blanchard and Perotti (2002) address this problem by using higher frequency (i.e., quarterly) data to capture the specific characteristics of fiscal policy. Our study adopts a parallel approach by differentiating between Twitter and newspaper characteristics, allowing us to identify media-specific uncertainty shocks by using recently available daily data for the U.S., rather than the more common monthly data that would risk simultaneity issues between newspaper reports and Twitter activity.[8] The use of monthly data presents a simultaneity issue between newspaper reports and Twitter activity, making it difficult to identify the structural shocks specific to each medium.

Additionally, as a robustness check, we estimate a time-varying parameter VAR model with stochastic volatility, used widely in empirical macroeconomics since the pioneering work by Primiceri (2005).[9] This approach is particularly relevant because dynamic interactions may evolve. Moreover, as Figure 1 illustrates, the volatility seems to change over time.

2.2 Dynamic interaction of media-specific uncertainty shocks

Figure 2 shows the impulse responses of the variables over a 120-day horizon. The left (right)-hand side of Figure 2 presents responses to a positive newspaper-specific (Twitter-specific) uncertainty shock. Solid lines represent point estimates, while dashed lines indicate two-standard-error bands. The lower-left chart reveals that TEU increases persistently to newspaper-specific uncertainty shocks. The upper-right chart indicates that

[7] The lag length was set to seven, based on the Schwarz criterion.

[8] Our identification would also be related to the use of information delay (e.g., Inoue *et al.*, 2009). See Kilian and Lütkepohl (2017) for additional identification strategies.

[9] For details on the time-varying parameter VAR framework, see Nakajima (2011). The code used in our analysis is available online (`https://sites.google.com/site/jnakajimaweb/program`).

an exogenous increase in TEU induces a more sustained increase in NEU. These results suggest that the exchange of information between newspapers and Twitter amplifies economic uncertainty. As expected, the simultaneous impact of newspaper-specific (Twitter-specific) uncertainty shock on NEU (TEU) is substantial.

[Insert Figure 2]

To check robustness, Figure 3 summarizes the time-varying responses calculated by estimating a time-varying parameter VAR model with stochastic volatility. While overall results remain consistent, the most striking result appears in Panel (b). At the five- to seven-day horizon, the impulse responses of NEU to a Twitter-specific uncertainty shock surged sharply in early 2020 and remained high thereafter. This finding indicates that during the COVID-19 pandemic, Twitter messages had a heightened influence on newspaper stories.

[Insert Figure 3]

We also present historical decomposition results. Figures 4 and 5 decompose NEU and TEU into two components explained by each structural shock, respectively. Panel (b) of Figure 4 illustrates that Twitter-specific uncertainty shocks can explain much of the sharp surge in NEU at the beginning of 2020. Moreover, Twitter-specific uncertainty shocks seem to account for the bulk of the decline in NEU from the first half of 2020 to the middle of 2021. Thus, we conclude that Twitter-specific uncertainty shocks played an important role in triggering fluctuations in NEU during the COVID-19 pandemic. By contrast, as evident in Panel (a) of Figure 5, newspaper-specific uncertainty shocks had little influence on TEU across historical episodes.

[Insert Figures 4 and 5]

In summary, Twitter-specific uncertainty shocks had a more pronounced impact on NEU, especially during the COVID-19 pandemic. This highlights the value of Twitter as a source of real-time information for journalists during unprecedented crises, such as a novel viral outbreak. Although our findings differ in context from those of Milas *et al.* (2021), who examine "Grexit" news, they align in suggesting that social media becomes more influential than traditional media during extraordinary events.

3 Media-created equity market uncertainty

A substantial body of literature examines the factors driving equity market volatility. Previous research emphasizes the critical role of information in driving EMU (e.g., French and Roll, 1986; Shleifer, 2000; Hirshleifer, 2001; Boudoukh *et al.*, 2019). In this section, we explore how equity market participants interpret information from diverse media sources, particularly Twitter and newspapers. Specifically, we extend our analysis by incorporating equity market volatility into a trivariate VAR model to investigate differences in how equity markets respond to newspaper reports and Twitter activity.

3.1 Methodology

To examine the effects of social and traditional media on U.S. EMU, we utilize the daily newspaper-based equity market volatility index developed by Baker *et al.* (2019).[10] Similar to the transformations for NEU and TEU, the EMU series is transformed by taking the natural logarithm.

Let m_t denote EMU at time t. We extend the bivariate VAR model to a trivariate one, where $\boldsymbol{y}_t = (n_t,\ \tau_t,\ m_t)'$ and $\boldsymbol{\varepsilon}_t = (\varepsilon_t^n,\ \varepsilon_t^\tau,\ \varepsilon_t^m)'$. The identification is recursive, implying that the structural shocks ε_t^n and ε_t^τ are economically identified similarly as the bivariate model above; that is, ε_t^n and ε_t^τ indicate newspaper-specific and Twitter-specific

[10]The daily series is publicly available on the EPU website (`https://www.policyuncertainty.com/`).

uncertainty shocks, respectively. Our recursive identification assumes that EMU responds to ε_t^n and ε_t^τ on the same day.

Assumption 3. *ε_t^n and ε_t^τ simultaneously affects m_t.*

Assumption 3 aligns with the efficient market hypothesis, which, in the present context, implies that the equity market responds instantaneously to the information transmitted via newspaper and Twitter. Such instantaneous equity market responses are commonly considered in the literature (e.g., Kang *et al.*, 2015).

Given that our primary objective is to investigate how the U.S. EMU is affected by these two shocks, identifying only newspaper-specific and Twitter-specific uncertainty shocks suffices. Thus, we do not focus on the residual shock ε_t^m, and the trivariate model is semistructural as ε_t^m is not identified as having a unique economic meaning. Specifically, ε_t^m are shocks unexplained by ε_t^n and ε_t^τ and include all shocks affecting EMU.

3.2 Effects of media-created uncertainty on equity market uncertainty

Figure 6 illustrates the impulse responses of EMU to newspaper-specific and Twitter-specific uncertainty shocks. As evident from the right-hand side panel, Twitter-specific uncertainty shocks generate a persistent increase in EMU, whereas a newspaper-specific shock causes a temporary increase in EMU, as shown in the left-hand side panel. These results are consistent with those of Jiao *et al.* (2020), who use monthly panel data to show that social media coverage predicts an increase in equity market volatility. However, their results do not imply causality, as acknowledged in Jiao *et al.* (2020, p.64). By contrast, our results provide a causal interpretation that the well-documented volatility clustering in equity markets stems from information dissemination through social media rather than traditional media.

[Insert Figure 6]

Note that the variance in the EMU series changes over time.[11] Hence, this raises the question of how sensitive the results are to an alternative specification, specifically, a time-varying parameter VAR model with stochastic volatility. To confirm this and check the robustness of the results, we estimate the alternative model. The estimated time-varying responses of EMU (m) to newspaper-specific uncertainty shocks (ε^n) and Twitter-specific uncertainty shocks (ε^τ) are illustrated in Figure 7. Overall, the responses are similar to those in Figure 6, reinforcing the above findings. Additionally, we find evidence of time-varying responses. Panel (a) of Figure 7 shows that the simultaneous effects of newspaper-specific uncertainty shock tend to increase gradually over time. Similarly, Panel (b) of Figure 7 shows that the four- to six-day horizon responses of EMU to a Twitter-specific uncertainty shock appear to increase gradually over time. These increasing patterns indicate that media influence on the equity market has intensified over the years.

[Insert Figure 7]

What is the reason for the differing impact of newspapers and Twitter on the market? The key factor is likely the difference in the nature of the two media. Unlike journalists and experts, a significant number of Twitter users tend to express subjective opinions without any objective evidence resulting in a high volume of inaccurate information on Twitter. This implies that Twitter-specific uncertainty shocks include more noise than newspaper-specific uncertainty shocks. Given that Twitter information is noisy, several models explain why EMU persistently increases in response to Twitter-specific uncertainty shocks.

The first model pertains to sticky information or inattentiveness (e.g., Mankiw and Reis, 2002; Reis, 2006a, b). This model suggests that the diffusion of accurate information on Twitter is slow and market responses to Twitter shocks become sticky. The second is the rational inattention model (Sims, 2003), which assumes that individuals must pay a

[11] The demeaned EMU series is represented as a dashed line in Figure 8.

cost to obtain accurate information. This assumption can cause individual decisions to adjust slowly. These models suggest that imperfect information is a key factor for the differences in the impact of newspapers and Twitter on the equity market.[12]

[Insert Figure 8]

Finally, Figure 8 presents the historical decomposition of EMU. The solid line denotes the decomposed components that are explained by shocks from (a) newspaper-specific uncertainty shocks, (b) Twitter-specific uncertainty, and (c) EMU. The dashed line, which is common across all panels, represents the demeaned EMU. As evident from Panel (b), Twitter shocks explain much of the trends in EMU and sharp positive spikes around 2019 and early 2020. Notably, a significant portion of the volatility during Donald Trump's presidency, particularly before January 20, 2021, can be attributed to the effects of Twitter shocks. In contrast to the crucial role of Twitter shocks, newspaper shocks cannot explain any episodes, as shown in Panel (a). In summary, the historical decomposition suggests that social media, rather than newspapers, plays a dominant role in creating market turmoil. This finding reinforces the disruptive impact of noisy information from Twitter on the equity market.

4 Conclusion

In the era of social media, social and traditional media increasingly complement each other in disseminating information. The structural VAR model proposed in this study allowed us to distinguish between uncertainty shocks generated from each medium. Evidence from U.S. data indicated that economic uncertainty is created not only by each medium's own behavior but also by the dynamic interaction between them. Our analyses revealed the substantial effects of Twitter-specific uncertainty shocks on NEU, especially during the COVID-19 pandemic.

[12]For more details on imperfect information models, see Baley and Veldkamp (2023).

We also characterized the dynamic effects of these identified shocks on equity market volatility in the U.S. The results consistently show that social media can drive volatility clustering in equity markets. While volatility clustering is common in the equity market, little is known about its mechanisms. Thus, our findings expand our knowledge of the sources of volatility clustering.

This study attempted to enhance the understanding of how economic uncertainty fluctuates through modern media and serves as a foundation for future research in several directions. First, we relate our empirical results to imperfect information models, such as sticky information and rational inattention; however, a more rigorous discussion of theoretical models and behavioral finance is warranted. Second, although newspapers and Twitter were selected as representatives because of data availability, further studies should consider other media platforms to provide a more comprehensive analysis. Finally, although this study focuses on equity market volatility, uncertainty in other financial markets is worth examining.

References

Affuso, E., Lahtinen, K.D. (2019). Social media sentiment and market behavior. *Empirical Economics*, 57, 105–127.

Allcott, H., Braghieri, L., Eichmeyer, S., Gentzkow, M. (2020). The Welfare Effects of Social Media. *American Economic Review*, 110(3), 629–676.

Baker, S.R., Bloom, N., Davis, S.J. (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, 131(4), 1593–1636.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K.J. (2019). Policy News and Stock Market Volatility. NBER Working Paper, No. 25720.

Baker, S.R., Bloom, N., Davis, S.J., Renault, T. (2021). Twitter-Derived Measures of

Economic Uncertainty. Available online: https://www.policyuncertainty.com/twitter_uncert.html

Baley, I., Veldkamp, L. (2023). Bayesian learning. In Handbook of economic expectations, 717–748, Academic Press.

Blanchard, O., Perotti, R. (2002). An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output. *Quarterly Journal of Economics*, 117(4), 1329–1368.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, 77(3), 623–685.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of economic Perspectives*, 28(2), 153–176.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327.

Boudoukh, J., Feldman, R., Kogan, S., Richardson, M. (2019). Information, Trading, and Volatility: Evidence from Firm-Specific News. *Review of Financial Studies*, 32(3), 992–1033.

Braghieri, L., Levy, R., Makarin, A. (2022). Social Media and Mental Health. *American Economic Review*, 112(11), 3660–3693.

Chen, H., De, P., Hu, Y., Hwang, B.H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies*, 27(5), 1367–1403.

Colombo, V. (2013). Economic policy uncertainty in the US: Does it matter for the Euro area? *Economics Letters*, 121, 39–42.

Desmarchelier, B., Fang, E.S. (2016). Social Media and the Diffusion of Information: A Computational Experiment on the Emergence of Food Scares. *Kyklos*, 69(4), 559–583.

Duca, J.V., Saving, J.L. (2018). What drives economic policy uncertainty in the long and short runs: European and U.S. evidence over several decades. *Journal of Macroeconomics*, 55, 128–145.

Engle, R.F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4) , 987–1007.

French, K.R., Roll, R. (1986). Stock return variances: The arrival of information and reaction of traders. *Journal of Financial Economics*, 17, 5–26.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance*, 56, 1533–1597.

Hull, J., White, A. (1987). The Pricing of Options on Assets with Stochastic Volatilities. *Journal of Finance*, 42(2), 281–300

Inoue, A., Kilian, L. Kiraz, F.B. (2009). Do Actions Speak Louder Than Words? Household Expectations of Inflation Based on Micro Consumption Data. *Journal of Money, Credit and Banking*, 41(7), 1331–1363.

Jiao, P., Veiga, A., Walther, A. (2020). Social media, news media and the stock market. *Journal of Economic Behavior & Organization*, 176, 63–90.

Kang, W., Ratti, R.A., Yoon, K.H. (2015). The impact of oil price shocks on the stock market return and volatility relationship. *Journal of International Financial Markets, Institutions and Money*, 34, 41–54.

Kilian, L., Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press.

Kuttner, K.N., Posen, A.S. (2001). The Great Recession: Lessons for Macroeconomic Policy from Japan. Brookings Papers on Economic Activity, 2001(2), 93–160.

Lehrer, S., Xie, T. (2017). Box Office Buzz: Does Social Media Data Steal the Show from Model Uncertainty When Forecasting for Hollywood? *Review of Economics and Statistics*, 99(5), 749–755.

Levy, R. (2021). Social Media, News Consumption, and Polarization: Evidence from a Field Experiment. *American Economic Review*, 111(3), 831–870.

Li, R., Wei, N. (2022). Economic policy uncertainty and government spending multipliers. *Economics Letters*, 217, 110693.

Mankiw, N.G., Reis, R. (2002). Sticky information versus sticky prices: A proposal to replace the new Keynesian Phillips curve. *Quartaly Journal of Economics*, 117(4), 1295–1328.

Milas, C., Panagiotidis, T., Dergiades, T. (2021). Does it matter where you search? Twitter versus traditional news media. *Journal of Money, Credit and Banking*, 53(7), 1757–1795.

Nakajima, J. (2011). Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications. *Monetary and Economic Studies*, 29, 107–142.

Nelson, D.B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2), 347–370.

Primiceri, G.E. (2005). Time Varying Structural Vector Autoregressions and Monetary Policy. *Review of Economic Studies*, 72(3), 821–852.

Reis, R. (2006a). Inattentive consumers. *Journal of Monetary Economics*, 53 (8), 1761–1800.

Reis, R. (2006b). Inattentive producers. *Review of Economic Studies*, 73 (3), 793–821.

Schmierbach, M., Oeldorf-Hirsch, A. (2012). A Little Bird Told Me, So I Didn't Believe It: Twitter, Credibility, and Issue Perceptions. *Communication Quarterly*, 60(3), 317–337.

Scott, L.O. (1987). Option pricing when the variance changes randomly: Theory, estimation, and an application. *Journal of Financial and Quantitative Analysis*, 22(4), 419–438.

Shleifer, A. (2000). *Inefficient markets: An introduction to behavioral finance.* Oxford: Oxford University Press.

Sims, C.A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3), 665–690.

Svensson, L.E.O., Williams, N. (2008). Optimal Monetary Policy Under Uncertainty: A Markov Jump-Linear-Quadratic Approach. Federal Reserve Bank of St. Louis *Review*, 90(4), 275–293.

Pettenuzzo, D., Sabbatucci, R., Timmermann, A. (2020). Cash Flow News and Stock Price Dynamics. *Journal of Finance*, 75(4), 2221–2270.

Tumasjan, A. (2024). The many faces of social media in business and economics research: Taking stock of the literature and looking into the future. *Journal of Economic Surveys*, 38(2), 389–426.

Wiggins, J.B. (1987). Option values under stochastic volatility: Theory and empirical estimates *Journal of Financial Economics*, 19(2), 351–372.

Williams, N. (2012). Monetary policy under financial uncertainty. *Journal of Monetary Economics*, 59(5), 449–465.

Williams, L.V., Reade, J.J. (2016). Prediction Markets, Social Media and Information Efficiency. *Kyklos*, 69(3), 518–556.

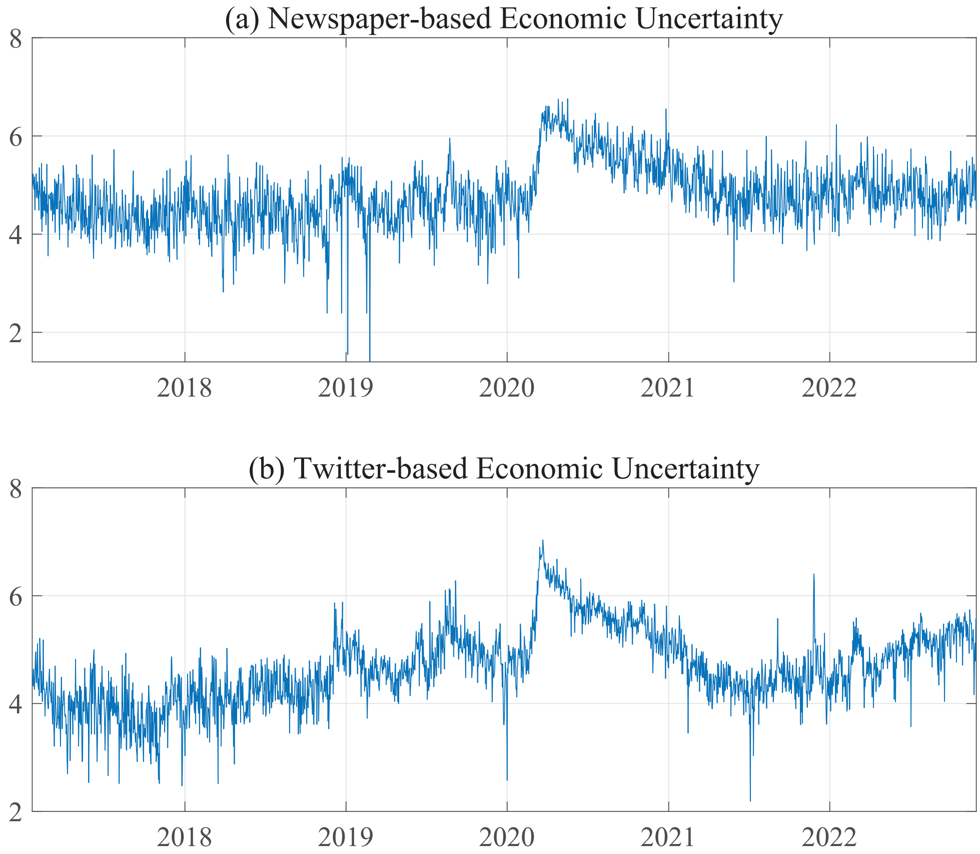

Figure 1: The U.S. daily NEU and TEU index (log level)

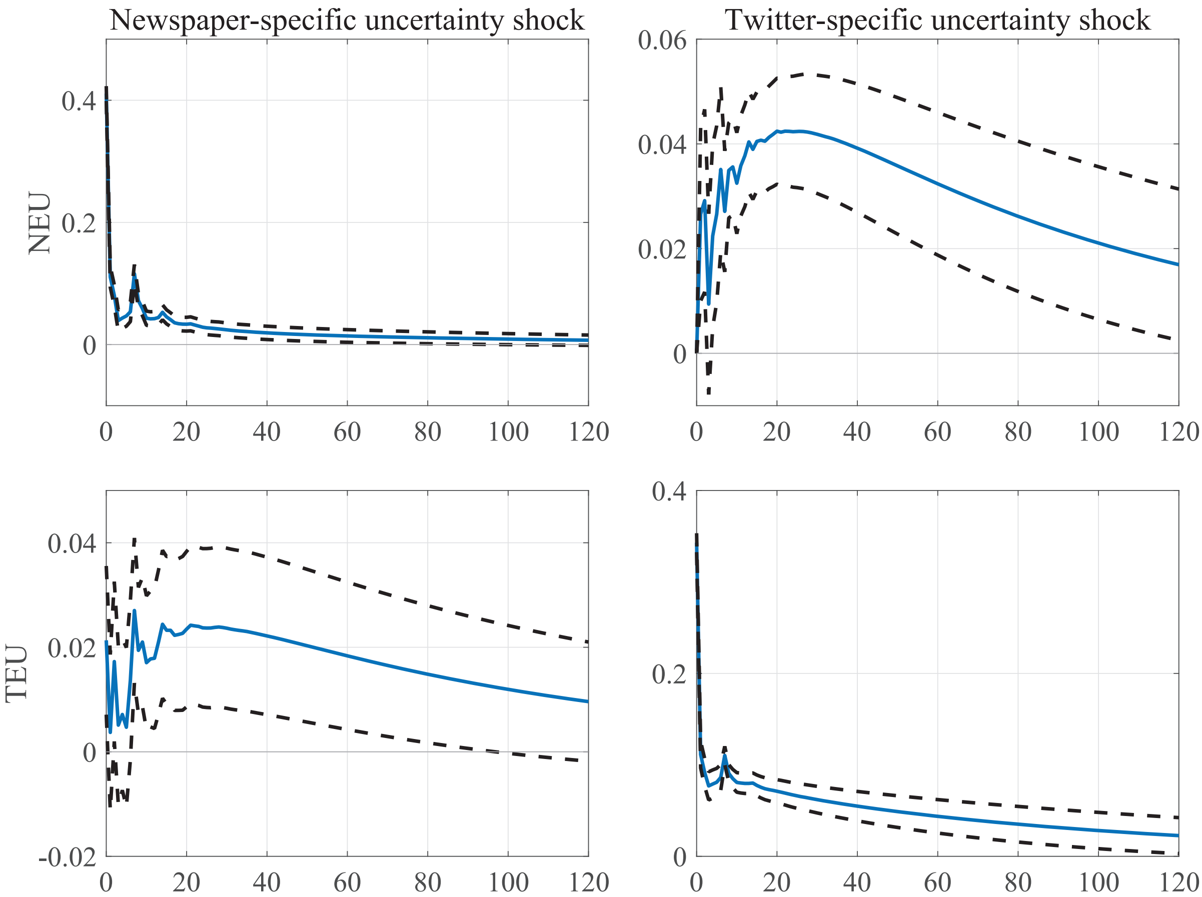

Figure 2: Impulse responses

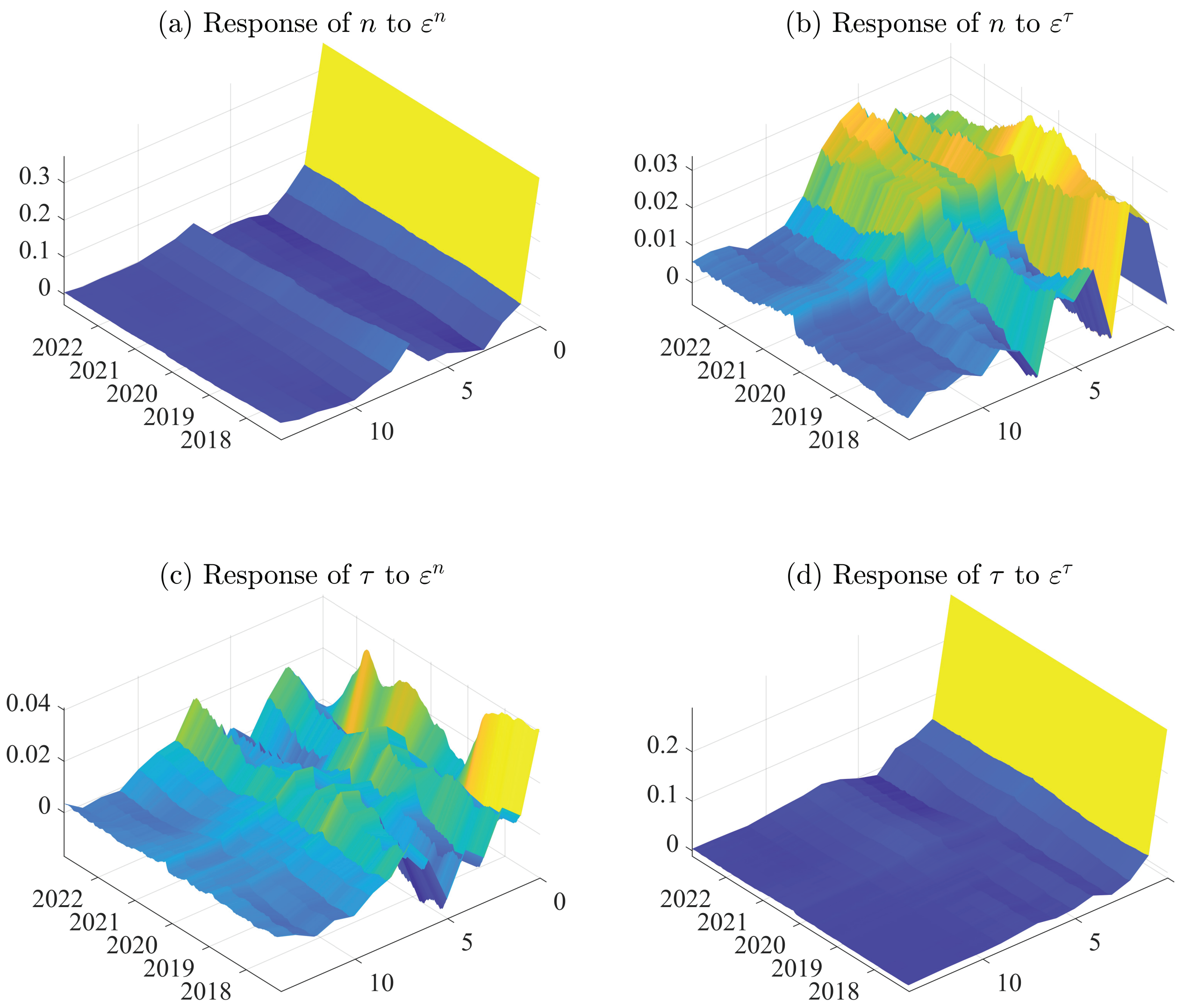

Figure 3: Impulse responses in the time-varying parameter VAR model

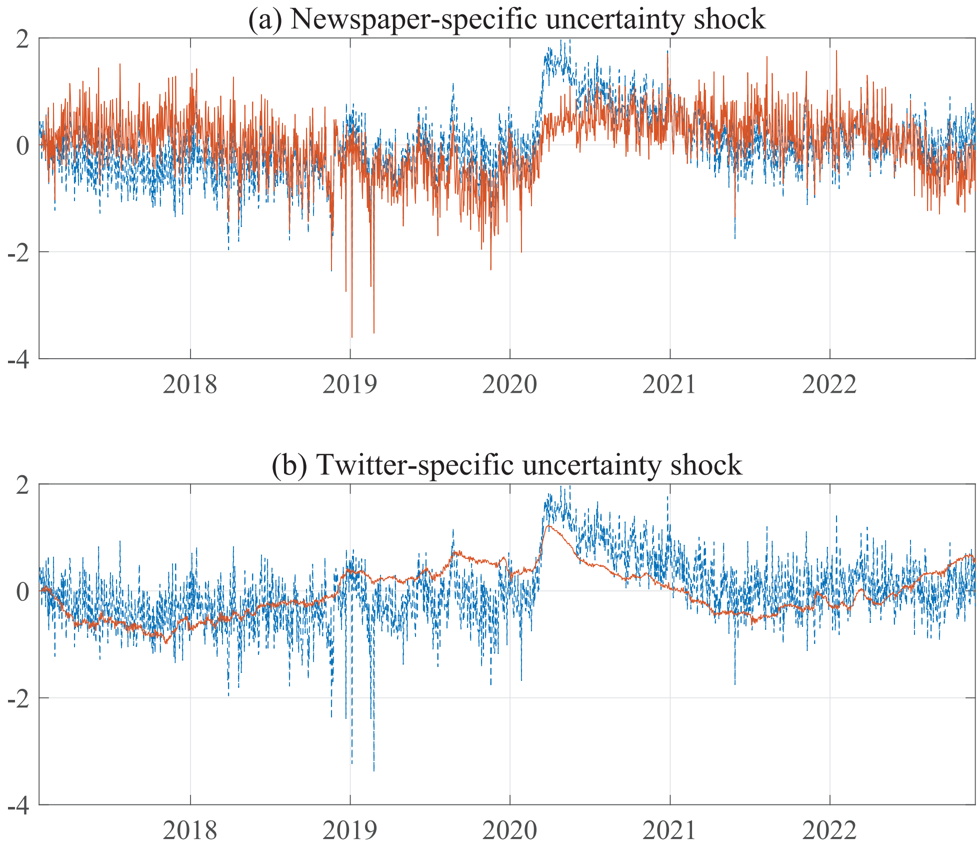

Figure 4: Historical decomposition of NEU

Notes: The solid line is the decomposed series, while the dashed line is the demeaned NEU.

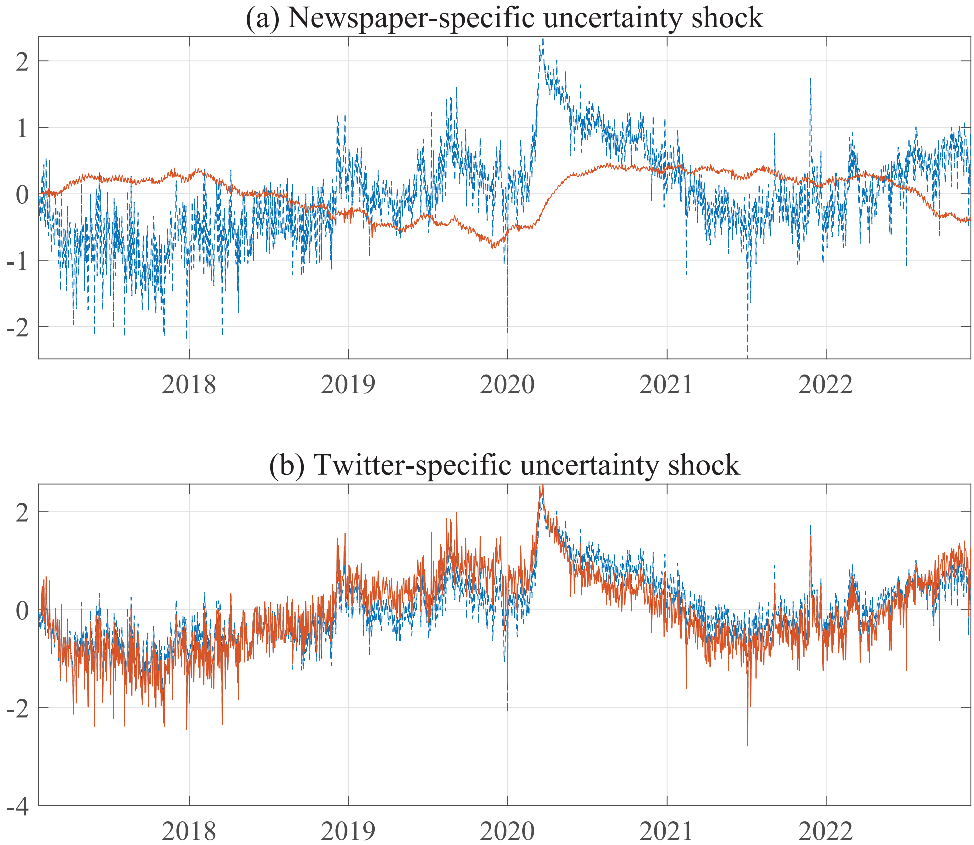

Figure 5: Historical decomposition of TEU

Notes: The solid line is the decomposed series, while the dashed line is the demeaned TEU.

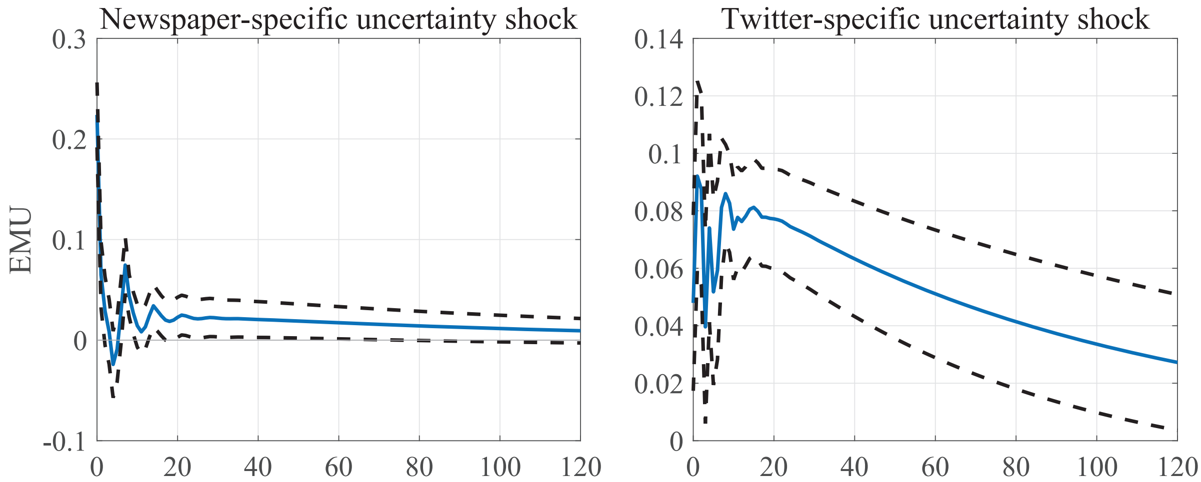

Figure 6: Impulse responses of EMU

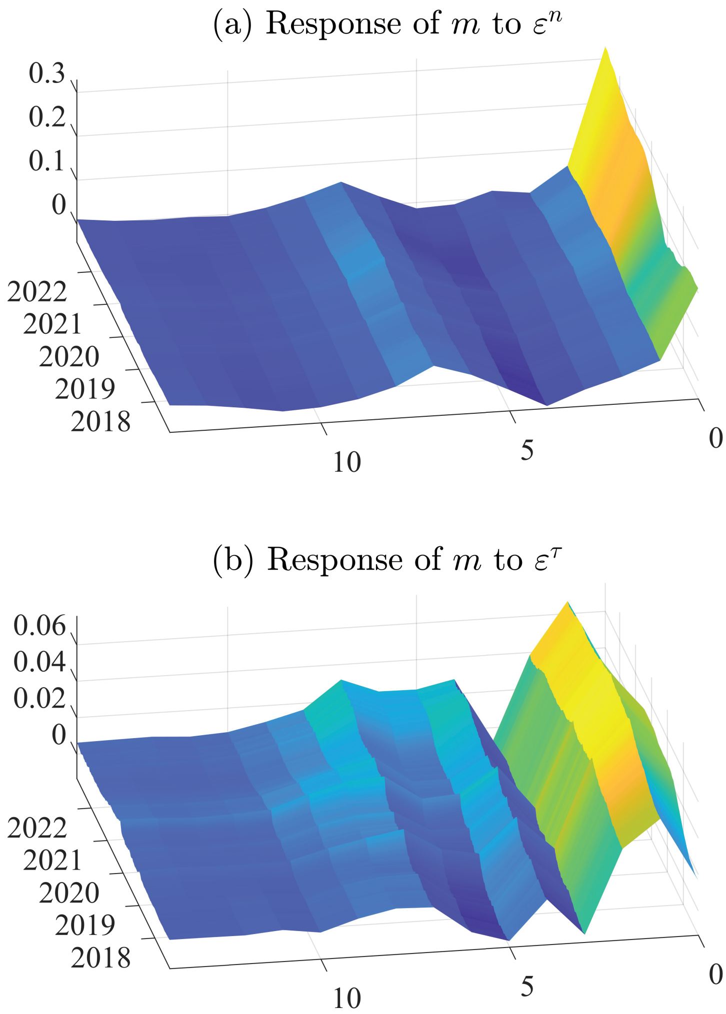

Figure 7: Impulse responses of EMU in the time-varying parameter VAR model

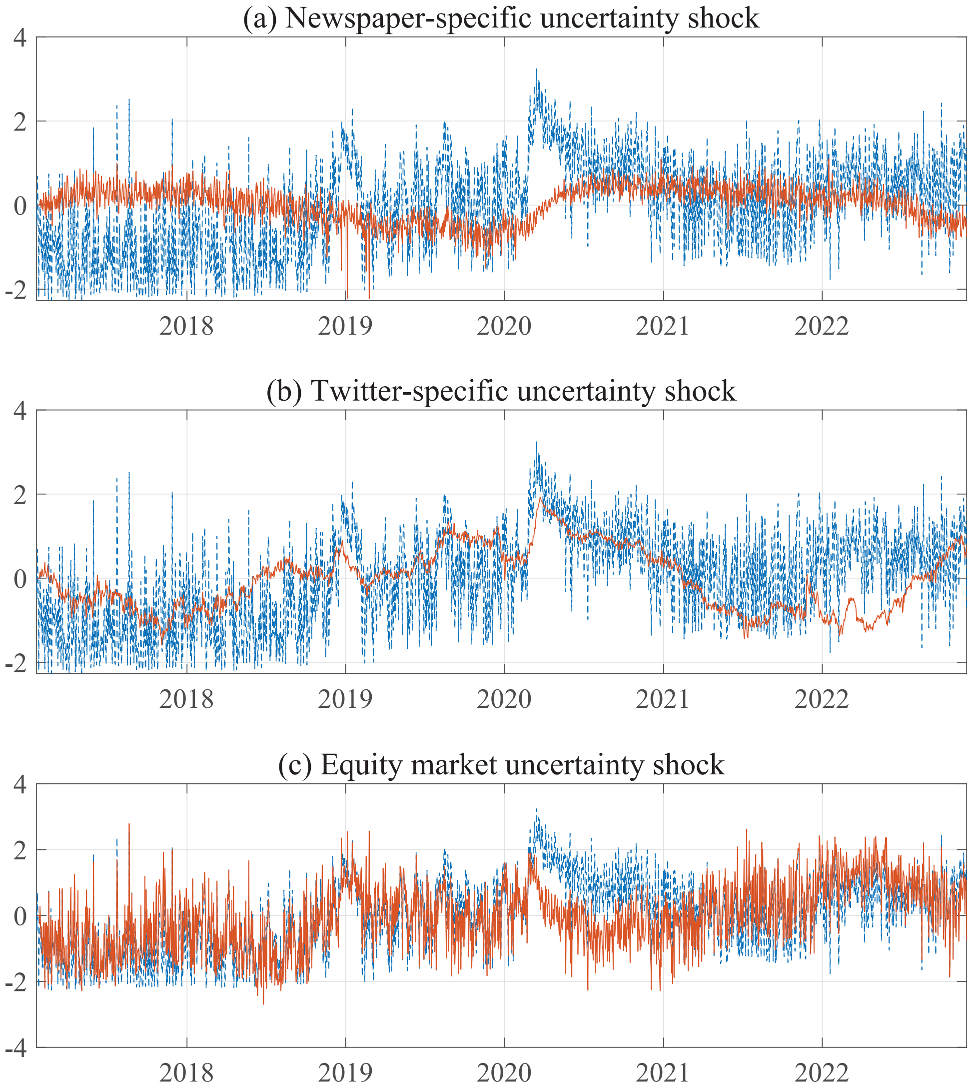

Figure 8: Historical decomposition of EMU

Notes: The solid line is the decomposed components that are explained by shocks from (a) newspaper-specific uncertainty, (b) Twitter-specific uncertainty, and (c) EMU. The dashed line is the demeaned EMU.