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Media-Created Economic Uncertainty

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Abstract

Employing different features between social media and traditional media, this paper proposes a simple structural vector autoregressive analysis to identify economic uncertainty shocks that originate from each of these media. Owing to data availability, newspaper and Twitter are respectively selected as a representative of each, and the analysis is applied to the United States. Our results reveal that the dynamic interaction between these media can be a transmission mechanism by which economic uncertainty fluctuates. In addition, we demonstrate that Twitter-specific uncertainty shocks have a stronger effect for newspaper-based economic uncertainty during the coronavirus disease 2019 pandemic.

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

JEL classification: C32; D80

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1 Introduction

Economic uncertainty arises as varying economic information is received, mainly via social media and traditional media—crucial sources of information. Social media users include journalists and experts as well as politicians and the general public, who can freely express their own opinions in comments, blogs, posts and articles, enabling the exchange of diverse opinions and animated discussions.

More importantly, the growing uncertainty indicated by one medium can influence the uncertainty created by other media. This is because discussions on social media can spill over onto traditional media and stimulate further debate, and vice versa. For example, Donald Trump, the 45th president of the United States, frequently tweeted as president on Twitter and sometimes created controversy on both social and traditional media. The fodder for newspaper articles can be gleaned from information on social media, and we surmised that such an interaction between social and traditional media may amplify fluctuations in economic uncertainty.

To investigate this interaction, this study proposed a simple approach to identify the exogenous uncertainty shocks driven by each medium. This is based on a bivariate structural vector autoregressive (VAR) model with daily indices of Newspaper-based Economic Uncertainty (NEU) and Twitter-based Economic Uncertainty (TEU).[1] The key identifying assumptions are (i) that TEU responds instantaneously to newspaper-specific uncertainty shocks, and (ii) that NEU does not respond within the same day to Twitter-specific uncertainty shocks. As detailed in Section 2, the assumptions are rationalized because one can tweet instantaneously on Twitter, whereas there is usually a delay when publishing in a newspaper after journalists obtain information.

[1]Newspaper and Twitter are respectively selected as a representative of each media due to data availability.

We applied the empirical approach to the United States owing to daily data availability. We demonstrate that a positive Twitter-specific uncertainty shock leads to a persistent increase in NEU. Interestingly, positive responses increased during the coronavirus disease 2019 (COVID-19) pandemic compared to the preceding period. We also found that a positive newspaper-specific uncertainty shock increases TEU, while the effect is less-pronounced. We conclude that the dynamic interaction between social and traditional media is a transmission mechanism through which economic uncertainty is created.

The literature on economic uncertainty has been burgeoning since seminal works such as Bloom (2009) and Baker, Bloom, and Davis (2016). Many authors have highlighted the negative effects of increased economic uncertainty. For example, Colombo (2013) argues that an increase in US EPU causes a decline in European industrial production. Moreover, Li and Wei (2022) claim that when economic policy uncertainty is high, government spending is less effective. Despite the many studies of our predecessors, to the best of our knowledge, the literature has not discussed how economic uncertainty is created by focusing on the dynamic interaction between social and traditional media.[2]

The remainder of the paper is organized as follows. In Section 2, we present a structural VAR model that allows us to identify newspaper-specific uncertainty shocks and Twitter-specific uncertainty shocks. In Section 3, we assess how responsive NEU and TEU are to these shocks and examine how they are explained by each structural shock. Section 4 concludes the paper.

[2]Duca and Saving (2018) argue that media fragmentation is linked to economic policy uncertainty. In economics literature there has been growing interest in social media (e.g., Desmarchelier and Fang, 2016; Williams and Reade, 2016; Lehrer and Xie, 2017; Affuso and Lahtinen, 2019; Allcott *et al.*, 2020; Levy, 2021; Braghieri, Levy, and Makarin, 2022), but its role in the creation of economic uncertainty is still poorly understood.

2 Data and empirical approach

We exploited the availability of daily data from the United States. U.S. daily NEU and TEU were obtained from Baker, Bloom, and Davis (2016) and Baker *et al.* (2021), respectively.[3] Figure 1 shows the series used in the empirical analysis. The study period is from January 20, 2017, to November 29, 2022. The start of the sample is the date when Donald Trump became president of the United States.

[Insert Figure 1]

We denote the NEU and TEU at time t as n_t and τ_t, respectively. Let the vector of variables be $\boldsymbol{y}_t = (n_t,\ \tau_t)'$ and consider the 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 $\boldsymbol{\varepsilon}_t = (\varepsilon_t^n,\ \varepsilon_t^\tau)'$ is the structural shocks, such that ε_t^n is newspaper-specific uncertainty shocks and ε_t^τ is Twitter-specific uncertainty shocks. Our strategy for identifying mutually uncorrelated structural disturbances involves the use of information delays.[4] Specifically, we impose two assumptions, as stated in the introduction.

The first assumption is that ε_t^n simultaneously affects τ_t. The rationale is that one can send messages on Twitter without delay soon after reading a newspaper, owing to the capability of Twitter to tweet at any time and moment.

The second assumption is that n_t does not respond within the same day to ε_t^τ. This is because it seems difficult to publish a newspaper article on the same day as seeing Twitter

[3] These data can be retrieved from the website of Economic Policy Uncertainty (`https://www.policyuncertainty.com/index.html`). As U.S. daily TEU series, we used "TEU-USA" index of Baker *et al.* (2021), which is constructed on the tweets of users in the United States.

[4] A similar strategy can be found in Inoue, Kilian, and Kiraz (2009), among others.

messages. Unlike Twitter, where individuals can make quick decisions about tweets, print newspapers publish on one or two occasions, at best, per day. According to experiments by Schmierbach and Oeldorf-Hirsch (2012), stories on Twitter are less credible than those of online newspapers. Thus, although online newspapers are posting articles through the day, journalists must validate information on Twitter unlike an individual who usually does not bother. Writing news articles after journalists obtain the information takes time because of internal coordination within the company.

These two assumptions amount to recursive identification and $\boldsymbol{A}_0$ is assumed to be lower triangular. The lag length was set to seven, based on the Schwarz criterion.

In addition, as a robustness check, we estimate a time-varying parameter VAR model with stochastic volatility, which has been widely used in empirical macroeconomics since the pioneering work by Primiceri (2005).[5] This is relevant, because dynamic interactions may vary over time. Moreover, as can be seen in Figure 1, the volatility seems to change over time.

3 Results

Figure 2 shows the impulse responses of the variables for up to 120 days. The left (right) column of Figure 2 presents the impulse responses to a positive newspaper-specific (Twitter-specific) uncertainty shock. The solid and dashed lines in each graph represent the point estimates and two-standard-error bands, respectively. We observe from the left lower chart that TEU increases persistently to the newspaper-specific uncertainty shock. The upper right chart indicates that an exogenous increase in TEU caused a more per-

[5] See Nakajima (2011) for the details of the present time varying parameter VAR framework. In our analysis, we used code downloaded from the website (`https://sites.google.com/site/jnakajimaweb/program`).

sistent increase in NEU. These results suggest that the information exchange between newspapers and Twitter amplifies economic uncertainty. As expected, the initial impact of newspaper-specific (Twitter-specific) uncertainty shock on NEU (TEU) seems large.

[Insert Figure 2]

Figure 3 summarizes the time-varying responses calculated by estimating a time-varying parameter VAR model with stochastic volatility. While similar results are confirmed overall, the most striking result to emerge from the time-varying modeling can be found in Panel (b). At the five- to seven-day horizon, the impulse responses of the NEU to a Twitter-specific uncertainty shock increased rapidly at the beginning of 2020 and remained high thereafter. This observation suggests that newspaper stories were more strongly affected by Twitter messages during the COVID-19 pandemic than previously.

[Insert Figure 3]

Finally, we present the results of the historical decompositions. We use the constant VAR model because the procedure for historical decompositions of the time-varying parameter VAR model is unclear, as stated by Kilian and Lütkepohl (2017). Figures 4 and 5 decompose NEU and TEU respectively into two components explained by each structural shock. From Panel (b) of Figure 4, we note that Twitter-specific uncertainty shocks are able to explain much of the steep rise in NEU at the beginning of 2020. Moreover, Twitter-specific uncertainty shocks seem to have accounted 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 seen in Panel (a) of Figure 5, there are no historical episodes that variation of TEU can be attributed mainly to newspaper-specific uncertainty shocks.

[Insert Figures 4 and 5]

In summary, Twitter-specific uncertainty shocks have a stronger effect for NEU during the COVID-19 pandemic. This implies that in the face of a perceived unprecedented crisis such as unknown viral outbreak, it is useful for journalists to glean information from an individual on Twitter.

4 Conclusion

In the social media era, social and traditional media would mutually supplement information. The structural vector autoregressive model proposed in this study allowed us to distinguish between the 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 social and traditional media. Further, additional analyses showed that the effects of Twitter-specific uncertainty shocks became stronger for NEU during the COVID-19 pandemic.

This study is the first step towards enhancing our understanding of how economic uncertainty is created through modern media. Although we selected newspaper and Twitter as a representative owing to data availability, further studies, which take other media into account, will need to be undertaken.

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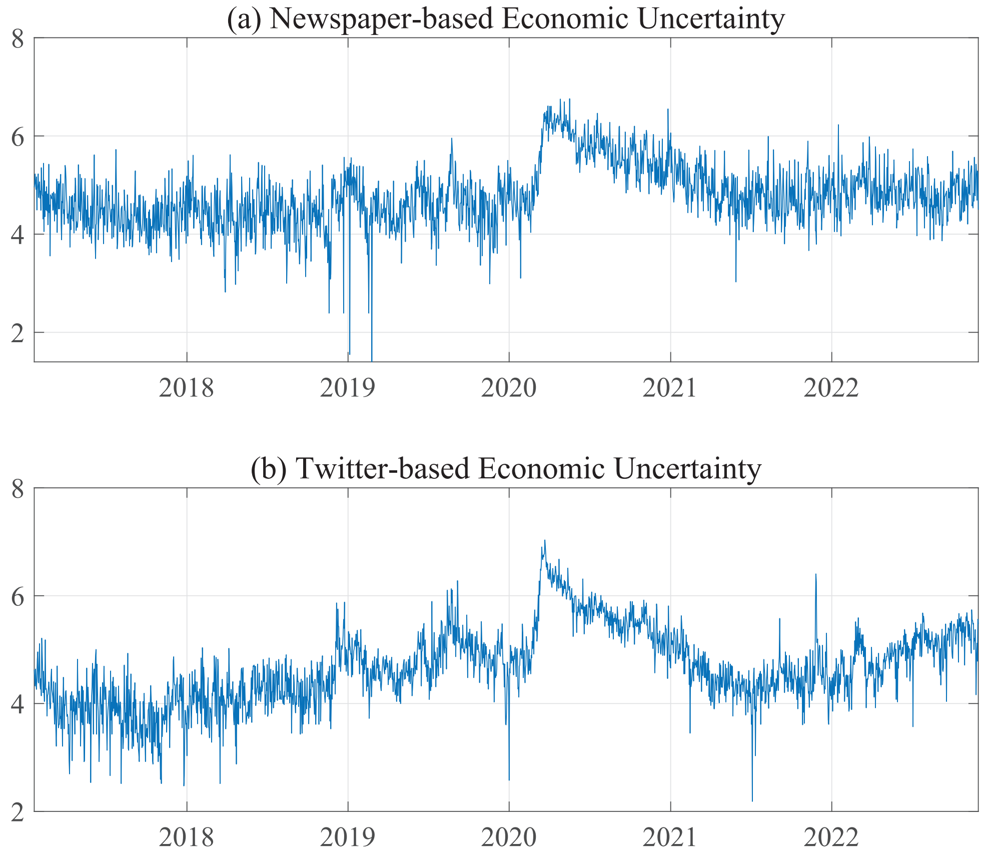

Figure 1: The U.S. daily NEU and TEU index (log level)

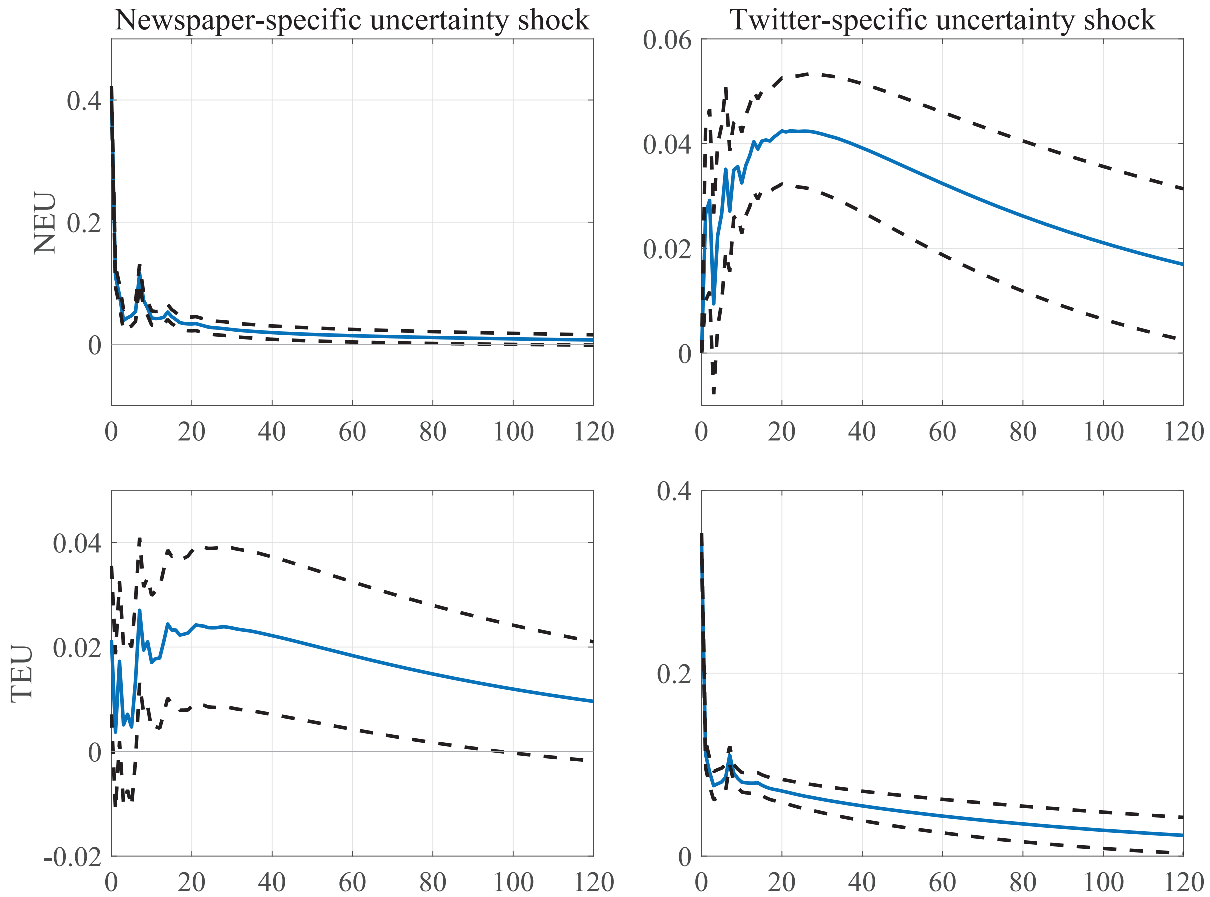

Figure 2: Impulse responses

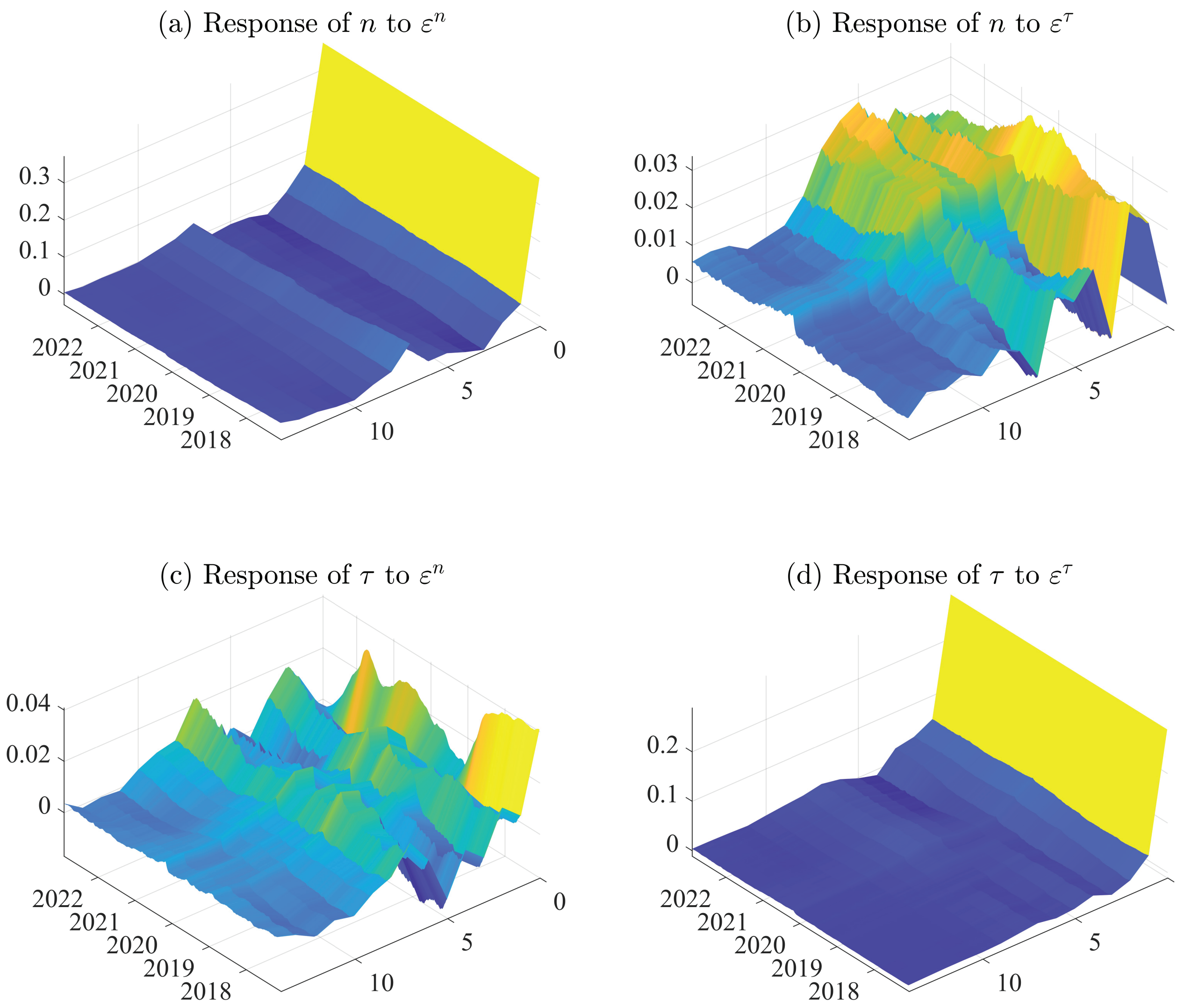

Figure 3: Impulse responses of TVP-VAR

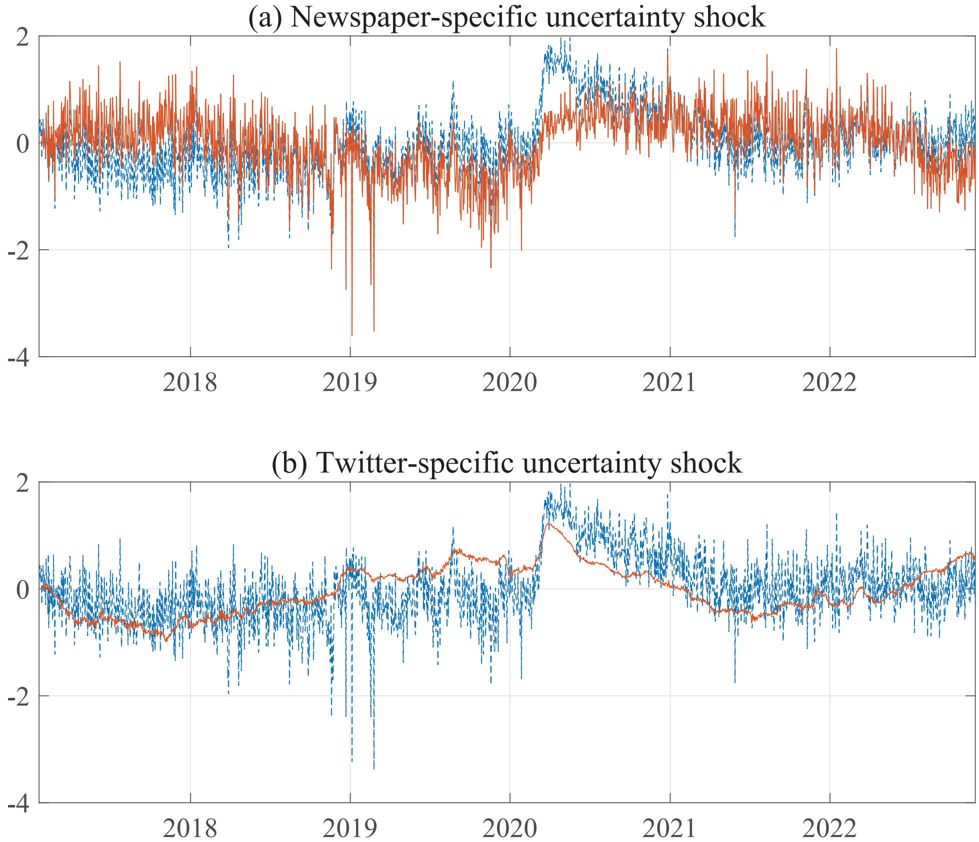

Figure 4: Historical decomposition of NEU

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

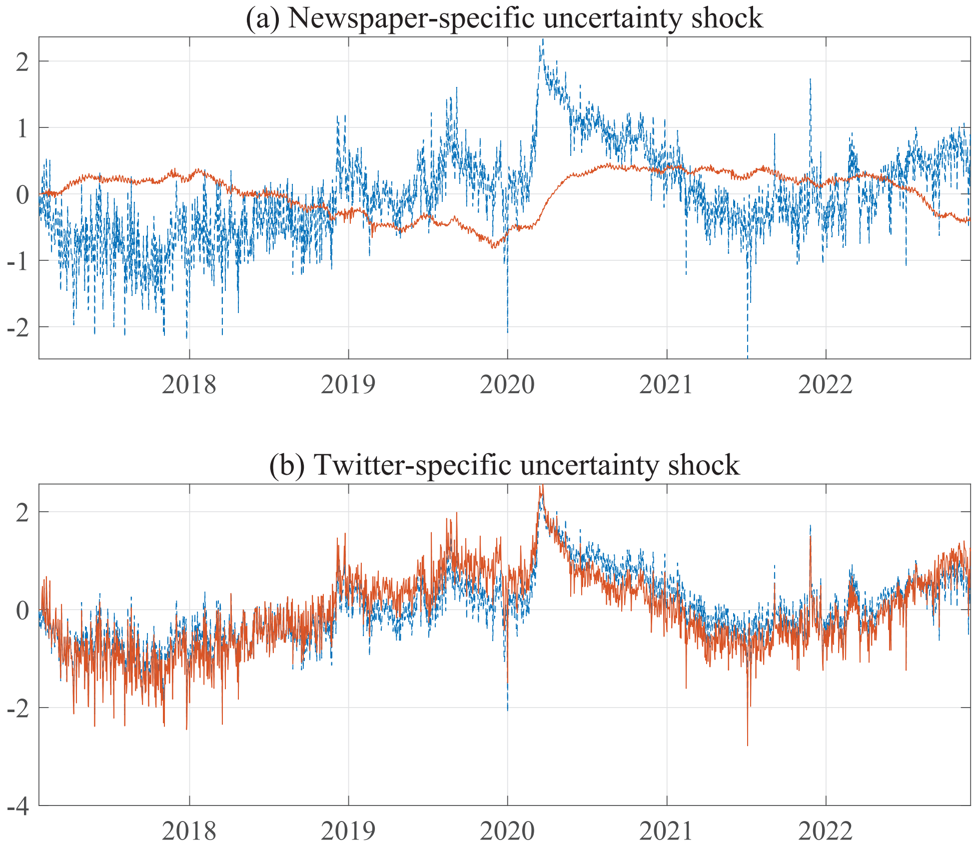

Figure 5: Historical decomposition of TEU

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