A New Supply Bottlenecks Index Based on Newspaper Data*

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We develop a new monthly indicator of supply bottlenecks using newspaper articles. The supply bottlenecks index (SBI) provides a consistent narrative of supply issues related to wars, natural disasters, strikes, and, most recently, the COVID-19 pandemic. Innovations in the SBI have important macroeconomic implications: an increase in the SBI works as a cost-push shock, decreasing industrial production and employment and pushing prices up, making monetary policy face important trade-offs.

JEL Codes: F40, E23, E31.

1. Introduction

Since the beginning of the COVID-19 pandemic, supply bottlenecks have been one of the key determinants of the global outlook. The global lockdown adopted to fight the health crisis produced severe supply chain disruptions, which hampered the trade of goods within and across borders. The subsequent reopening led to a strong rebound in the global demand for manufacturing goods, unmatched by supply, which worsened disruptions further. In addition, several sectors, such as the semiconductor industry, could not accommodate the increase in demand for electronic products. On top of that, maritime transport, especially in the case of containers, also suffered from supply bottlenecks, due to port congestion caused

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by local lockdowns. Finally, in 2022, when the disruptions produced by the COVID were subsiding, the invasion of Ukraine heightened those risks—in particular, in the case of energy supplies and derived products, like fertilizers, and food.

From an economic point of view, the globalization of supply disruptions can severely affect inflation, as supply problems transmit through the production chain, creating upward price pressures. In the words of the European Central Bank president, Christine Lagarde, when explaining the 50 basis point interest rate increase implemented in July 2022: "Persistent supply bottlenecks for industrial goods and recovering demand, especially in the services sector, are also contributing to the current high rates of inflation."[1] At the same time, supply disruptions can also strongly depress economic activity, since their impact can have long-lasting and sizable effects on production processes. A survey of supply chain experts by the McKinsey Global Institute (2020) found that supply disruptions may reduce firms' annual profits by more than 40 percent over a period of 10 years. In this sense, these linkages have been thoroughly studied by the theoretical literature on the importance of input-output networks (Acemoglu and Tahbaz-Salehi 2020, Bonadio et al. 2021, Baqaee and Farhi 2022).

Supply (or, alternatively, supply chain) disruptions, however, are not new. They occurred before the COVID-19 pandemic, although they were of a more local nature, and were usually caused by wars, strikes, or natural disasters. An example of this is the Great Tôhoku Earthquake of 2011 in Japan, which created supply chain problems that spilled over the whole Japanese economy (Carvalho et al. 2021). Other examples are Hurricane Katrina, which affected port infrastructures, diverting all freight transport to alternative ports (Friedt 2021), or the supply chain uncertainty created by Brexit (Chung, Dai, and Elliott 2022).

However, the empirical evidence on the macroeconomic impact of supply bottlenecks is very limited. In this paper, we contribute to closing this gap by developing a high-frequency measure of supply disruptions and studying its impact on inflation and output through a vector autoregression (VAR). In particular, we construct a supply

[1]ECB press conference, July 21, 2022. Available at https://www.ecb.europa.eu/press/pressconf/2022/html/ecb.is220721~51ef267c68.en.html.

bottlenecks index (SBI), based on newspaper data, for the United States (starting in 1990), United Kingdom, Germany, France, Italy, Spain, and China.

We define supply disruption as a negative event related to supply provision or the functioning of supply chains. We follow the methodology developed by Baker, Bloom, and Davis (2016) to construct text indices of economic policy uncertainty for different countries and other topics such as geopolitical risk (Caldara and Iacoviello 2022) or trade policy uncertainty (Caldara et al. 2020). Our strategy relies on counting the relative frequency of the number of articles that contain some chosen words, belonging to two semantic groups. In English, the first group contains words related to the topic of supply chains, such as "supply chain, supply chains, supply, supplies." The second group of words includes terms reflecting a negative tone or the existence of problems or disruptions, such as "bottleneck, bottlenecks, shortage, shortages, woe, woes, disruption, disruptions, problem, problems, scarcity, scarcities, lack, delay, delays, backlog, backlogs." For the article to be identified as reflecting supply concerns, a word from each one of the two groups must be present within a range of 10 words. In the case of the euro-area economies, we rely on natives to translate the words to national languages, while the Chinese index is based on news from international and domestic sources in English.

This paper improves the existing measures of bottlenecks available on several dimensions. First, our text-based procedure guarantees the selection of only supply-side events. We confirm this through two exercises. On the one hand, we check that the news generating the main spikes of the index are related to supply-side news. Before the COVID pandemic, we find several spikes that correspond closely to identified supply disruptions, such as strikes, Hurricane Katrina, or the Gulf War. After the COVID pandemic, although our index explodes, the spikes are related to the lack of global supplies such as semiconductors, raw materials, medical equipment, and COVID vaccines. On the other hand, we use word embedding, an unsupervised machine learning technique, to show that our word selection only identifies supply chain pressures in the case of the *New York Times* for the United States. On the contrary, the widely used monthly Purchasing Managers' Index (PMI) surveys on delivery times, backlogs, or purchased stocks react to both demand and supply issues, as shown by Benigno et al. (2022). Finally, we show that the index does not wrongly identify as bottlenecks an increase in newspaper news due to a reduction in disruptions.

Second, the high-frequency nature of the indicator, which can be retrieved daily, allows for a real-time analysis of bottlenecks and helps to better identify shocks to macro variables.[2] Survey-based indicators tend to be more lagging, like the monthly PMIs or the quarterly survey on restrictions of production by the European Commission. Moreover, we show that our index for the United States leads the monthly one developed by Benigno et al. (2022).

Third, our index spans a longer sample and covers the whole economy. In the U.S. case, the index is based on daily article searches from 11 nationwide newspapers since 1990, while the European indices start in the early or mid-2000s. Other supply bottlenecks indices based on text, such as Young et al. (2021), using the quarterly Standard & Poor's (S&P) earnings calls as a source of information, are available for a more limited period.

In addition, we provide VAR evidence showing that the news-based index has a relevant impact on production, unemployment, and prices, in the United States and in a panel of six economies (United States, United Kingdom, Germany, France, Italy, and Spain). We use a recursive identification, which relies on the interpretation of the index as a proxy (or an instrument, in the sense of Plagborg-Møller and Wolf 2021) for supply problems. Our results suggest that a shock of one standard deviation in the index raises both unemployment and prices, and decreases industrial production. This evidence confirms the macroeconomic importance of supply chain disruptions for inflation using the PMI-based indices, as in di Giovanni et al. (2022), Blanchard and Bernanke (2023), Hall, Tavlas, and Wang (2023), or Kabaca and Tuzcuoglu (2023). In contrast, we provide evidence that our index captures this behavior both before and during the pandemic period and that it behaves as a true supply shock, affecting activity and inflation in an opposite way.

The paper is organized as follows. In the first section, we start by defining and measuring supply disruptions. Section 2 shows a

[2] Other high-frequency indicators, such as the Baltic Dry Index or the Harpex Index for maritime transport, only cover particular sectors and thus are more related to trade dynamics.

variety of checks that verify the plausibility of the SBI and compare it with existing supply chain indicators. Section 3 presents VAR evidence on the macro impact of supply bottlenecks. Finally, Section 4 concludes.

2. The Supply Bottlenecks Index

2.1 Definition of Supply Disruptions

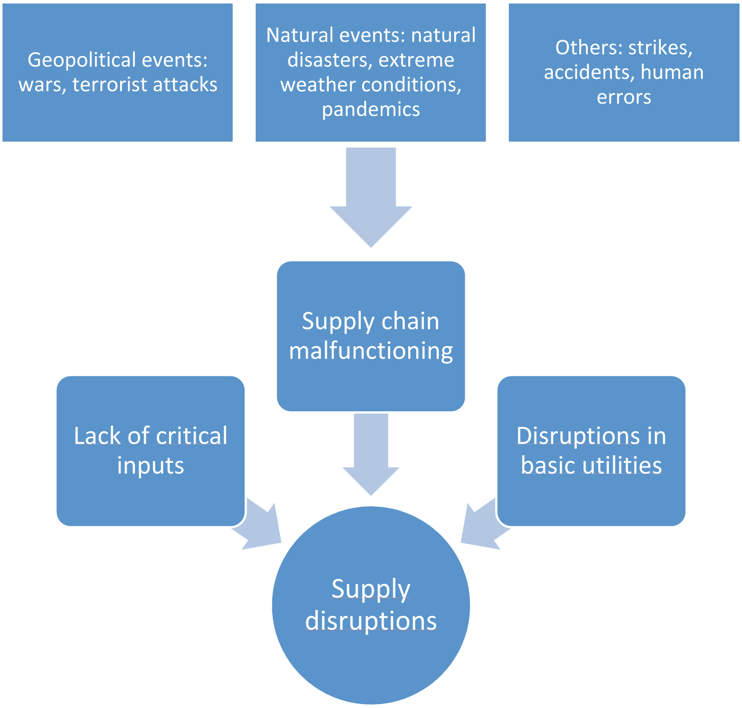
In line with the literature, we define a supply disruption as a negative event related to supply provision or the functioning of supply chains (see also Young et al. 2021). These events might be anticipatory (for example, the possibility of a supply shortage due to port congestion at the source of imports) or realized (such as energy shortages after a blackout). Figure 1 shows the main sources of supply disruptions we are considering. They include geopolitical events, such as wars and terrorist attacks; natural phenomena, like natural disasters, extreme weather conditions, or pandemics; and a variety of other human-related events, such as strikes, accidents, or human errors, which can give rise, for instance, to transportation issues or power outages. These events may lead to supply chain disruptions or lack of critical inputs when happening in foreign economies (such as the ones reported during the COVID crisis or the invasion of Ukraine) and to the destruction of capital and lack of provision of basic utilities in the directly affected country.

2.2 Constructing a Newspaper Supply Bottlenecks Index

The methodology followed in this article to construct the supply bottlenecks index using newspaper articles from Factiva is the following. First, in line with Baker, Bloom, and Davis (2016) or Young et al. (2021), we set two groups of words, one with the terms "supply" and "supply chain," that aim to capture the nature of the article, and then we search if within 10 words,[3] before or after each of the terms of the first group, there appears a word of the second group, which is related to negative sentiment words such as "bottleneck," "shortage," etc. In particular, the words in English used for the United

[3]We present robustness exercises around this window in Appendix D.

Figure 1. Diagram of Main Sources of Supply Disruptions



States and the United Kingdom to compute our supply bottlenecks index are

1. supply chain, supply chains, supply, supplies;
2. bottleneck, bottlenecks, shortage, shortages, woe, woes, disruption, disruptions, problem, problems, scarcity, scarcities, lack, delay, delays, backlog, backlogs.

Second, we follow the approach of Baker, Bloom, and Davis (2016) to construct the index from the selected articles (see Appendix A for a detailed description of the procedure).[4] For each newspaper, we divide the number of articles that comply with our

[4]See also Ghirelli et al. (2021) for the case of Spain.

search by the total number of articles published. This ratio is then standardized by dividing it by the standard deviation of the subsample of that newspaper previous to 2022. The supply bottlenecks index (SBI) is calculated as the average value for all newspapers in each country. To make the indices comparable across countries, the SBI of each country is divided by the mean of its subsample previous to 2022 and multiplied by 100.[5] Finally, to avoid the impact of outliers at each date, only the newspapers with a significant number of articles for that month are included in the index.

Using this methodology, supply bottlenecks indices for seven different countries are constructed: United States, United Kingdom, Germany, France, Italy, China, and Spain. The list of words chosen is translated into the languages of the non-English-speaking countries by native speakers and adapted when necessary. For example, in the case of Germany, a new third group of words was added to account for the fact that the German language has words that by themselves mean "supply bottleneck," such as "Versorgungsengpass." Thus, in the German search, we count the article as 1 if we find the same search as for the other languages (groups 1 and 2) or any word of group 3.

In addition, we ensure that the newspaper articles refer to supply bottlenecks developments in a specific country by using a Factiva option that restricts the search to the articles related to that country.[6]

The list of newspapers and words used in the respective language to build each country index is described in Appendix A. For the case of the United States, these are the following: *USA Today*, the *Miami Herald*, the *Chicago Tribune*, the *Washington Post*, the *Los Angeles Times*, the *Boston Globe*, the *San Francisco Chronicle*, the *Dallas Morning News*, the *Houston Chronicle*, the *Wall Street Journal*, and the *New York Times*; and the time period goes from January 1, 1990 until today.[7]

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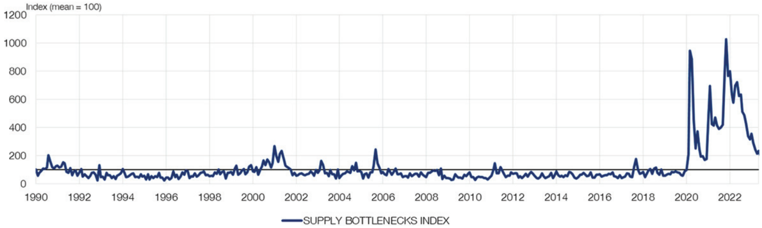
[5]This standardization is done to avoid the problem that raw counts vary substantially across newspapers and time.

[6]Factiva allows to select the region that an article is about.

[7]For instance, for the United States there is only available data for all the sample for four newspapers: the *Los Angeles Times*, the *San Francisco Chronicle*, the *Houston Chronicle*, and the *New York Times*. The rest of the newspapers join the index when their data become available in Factiva (in parentheses is the

Figure 2. U.S. Supply Bottlenecks Index (full sample)



Note: U.S. SBI from 1990 until June 2023. U.S. SBI is normalized to 100 throughout the 1990–2021 period.

2.3 Results and Validation of the Index

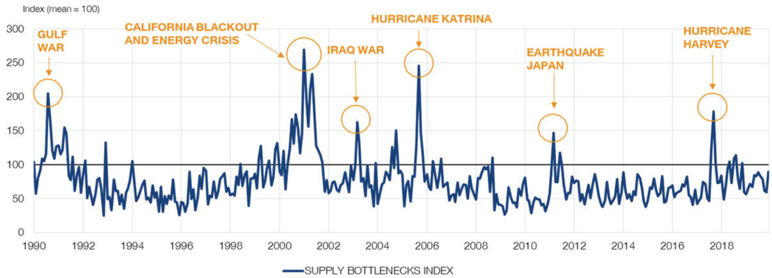
The evolution of the monthly SBI for the United States is shown in Figure 2. The index increased dramatically in 2020, as a result of the COVID-19-related supply disruptions, and has remained at this higher level until today. In Figures 3 and 4 we show the evolution of the SBI over, respectively, the pre-COVID and post-COVID subsamples. Similar dynamics are observed for all the countries considered, but for brevity's sake we concentrate in the main text on the results relative to the United States and provide the analysis for the other countries in Appendix B.

2.3.1 Checking the Historical Events Driving the Index

To understand the evolution of the index and ensure that it is correctly capturing supply disruptions, we report in the charts the main events behind the spikes. This is achieved by reading the articles that comply with our search criteria on each date. In particular, we consider as spikes all the observations that are one standard deviation above the mean, using sample-specific mean and standard deviation for the pre-COVID and the post-COVID sample. We highlight in

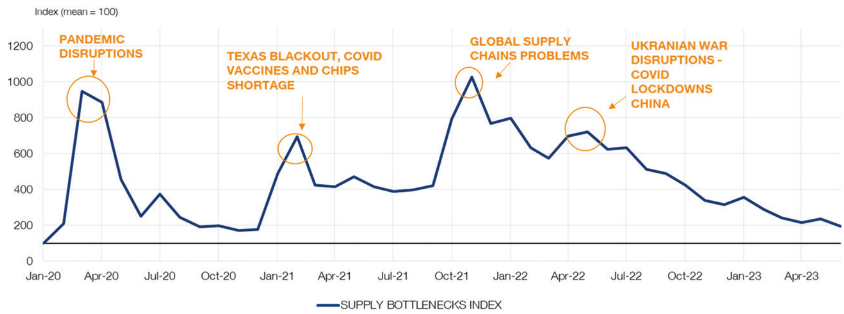
time they joined the index): the *Washington Post* (December 1997), the *Chicago Tribune* (January 2000), the *Wall Street Journal* (April 2001), the *Miami Herald* (June 2001), the *Boston Globe* (September 2001), *USA Today* (February 2002), and the *Dallas Morning News* (May 2003).

Figure 3. U.S. Supply Bottlenecks Index (before COVID)



Note: U.S. SBI from 1990 until the end of 2019. U.S. SBI is normalized to 100 throughout the 1990–2021 period. We describe in yellow the main events behind the spikes of the U.S. SBI.

Figure 4. U.S. Supply Bottlenecks Index (after COVID)



Note: U.S. SBI from 2020 until June 2023. U.S. SBI is normalized to 100 throughout the 1990–2021 period. We describe in yellow the main events behind the spikes of the U.S. SBI.

yellow in the charts below the main events behind the local maxima of the U.S. SBI. A similar graphical analysis is performed in Appendix B for the other countries.[8]

Figure 3 shows that the main spikes in the pre-COVID period are related to three kinds of events: wars, natural disasters, and energy crises. For instance, the U.S. SBI captures the impact on

[8]For the rest of countries in the post-COVID period, we include in the charts some additional peaks that would be left out following the restrictive one-standard-deviation criterion.

supply chains of the Gulf and Iraq Wars, Hurricanes Katrina and Harvey, the Japan Earthquake of 2011, and the energy crisis in California. Instead, after 2019 (see Figure 4) spikes are related to the disruptions caused by the COVID-19 pandemic and the invasion of Ukraine, the global supply chain problems in health and energy products, semiconductors, and raw materials, as well as logjams in maritime transport.

The list in Appendix E reports a more detailed description of the events behind the SBI's spikes, for the United States and for all the other countries. The results of this audit exercise let us conclude that the SBI's spikes capture correctly both local and global events leading to supply bottlenecks.

2.3.2 Supply Bottlenecks Narratives

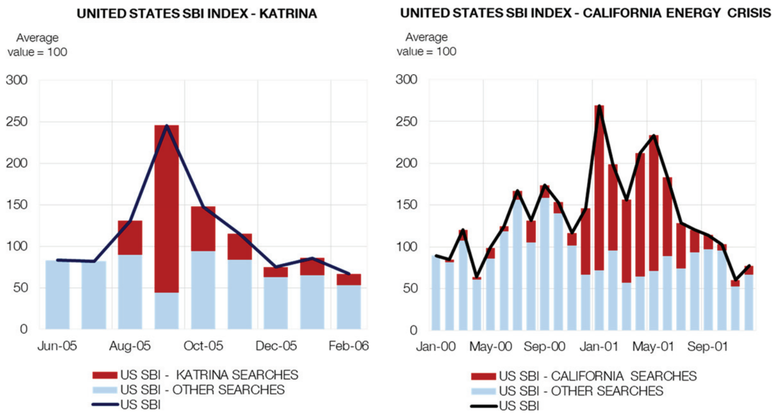
The text-based nature of our index also allows for a detailed narrative analysis of the contribution of specific events to aggregate bottlenecks. For example, Hurricane Katrina hit the United States in summer 2005, causing supply disruptions and fears of oil supply shortages due to damages at the Gulf Coast refineries. In Figure 5 (left-hand panel), we show that Hurricane Katrina contributed significantly to the increase in the U.S. SBI over August and September 2022. In particular, we count any article that includes our standard search plus the term "Katrina" in any place of the article. Similarly, in the right-hand panel of Figure 5, we show that the increase in the U.S. index observed at the beginning of 2001 was mainly due to the energy crisis in California. To wit, we relate to the energy crisis any article that includes our standard search plus a second search in any place of the article encompassing two additional groups of words, one related to the cities and the region of "California,"[9] and a second one related to "electricity" and "fuels,"[10] which have to appear within 10 words before or after each of the terms of the first group.

In a similar way, we can analyze the risk of supply disruptions due to the Brexit process by decomposing the SBI for the United

[9] Namely, "California," "San Jose," "San Francisco," "San Diego," "Los Angeles."

[10] "Electricity," "blackout," "blackouts," "power," "energy," and "fuel."

Figure 5. Contributions of Specific News around the Date of Important Supply Chain Events



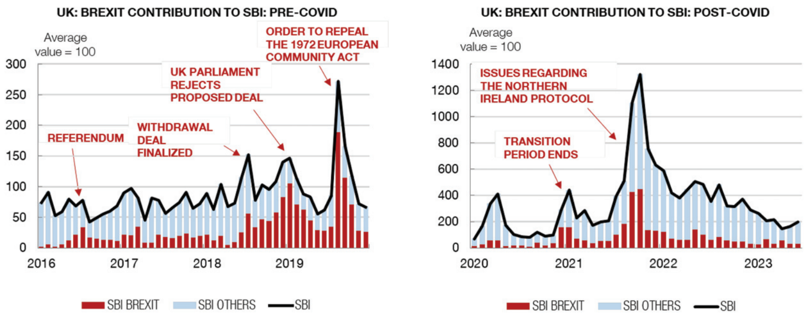
Note: U.S. SBI evolution around Hurricane Katrina (2005, left) and the California energy crisis (2000–01, right). The U.S. SBI is normalized to 100 throughout the 1990–2021 period. In blue, the contribution of the specific news about these topics to the index, calculated as described in Appendix A.

Kingdom into the contribution of Brexit-related news (identified by adding the word "Brexit" to our searches) and the contribution of all the other news (Figure 6). The Brexit-related risk of supply disruptions increased in correspondence to key policy events, such as the rejection by the U.K. parliament of the first proposed deal in January 2019; or the order, by the U.K. Brexit secretary, to repeal the 1972 European Community Act, in August of the same year; or the end of the transition period in January 2021. As shown in Appendix C, the Brexit component of our index is highly correlated with an alternative measure designed to reflect the same phenomenon, that is, the supply chain component of the Brexit Uncertainty Index of Chung, Dai, and Elliott (2022).

2.3.3 Using Machine Learning Techniques to Validate the Word Selection

In order to further validate the news searches, we apply the word embedding technique that was first introduced by Mikolov et al.

Figure 6. Risk of Supply Disruptions Due to Brexit



Note: U.K. SBI evolution in the pre- (left) and post-COVID period (right). Red bars show the contribution of Brexit-related news to the index, calculated as described in Appendix A. We describe in red the main events behind the peaks of the Brexit-related component of the U.K. SBI. The U.K. SBI is normalized to 100 throughout the 1990–2021 period. Left panel: January 2016–December 2019. Right panel: January 2020–June 2023.

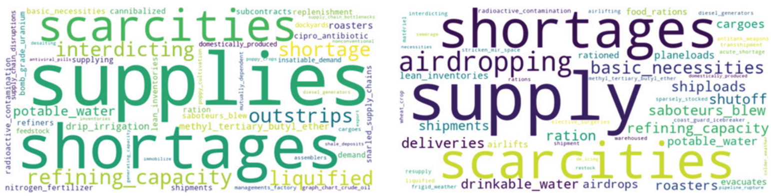
(2013). According to word embedding, the text of an article is a continuous vector representation of words in a suitable low-dimensional Euclidean space, and, therefore, syntactic and semantic similarities between words can be captured by associating words with a similar meaning with vectors that are closer to each other. The main idea is to obtain a substantial amount of the meaning of a word from its context words, that is, from the words surrounding it (Moreno Pérez and Minozzo 2022).

In particular, we use word embedding to validate the words that would be more useful to describe supply bottlenecks. In order to do this, we concentrate on the headlines, the snippets, and the first paragraph of the articles of the *New York Times* from January 1, 1990 until the end of June 2022.[11]

Figures 7–9 show word clouds with the 50 most similar words or combinations of words (tokens) to the vectors of words used to define the index: “supply,” “supplies,” “supply chain,” supply chains,”

[11] We compute the bigrams of the words with a frequency higher than 100 and the trigrams with a frequency higher than 150. We perform these computations using Word2Vec of the Gensim Python library. In particular, we consider the Skip-gram model with a hidden layer of H = 200 elements and a context window of size 10 on each side of the center word.

Figure 7. Word Clouds of the 50 Most Similar Words to the Tokens "Supply" (left) and "Supplies" (right)



Note: These word clouds show the 50 most similar tokens to the vectors of the tokens "supply" (left-hand side) and "supplies" (right-hand side) according to our results of word embedding. We excluded the words related to personal names, companies, countries, and regional names.

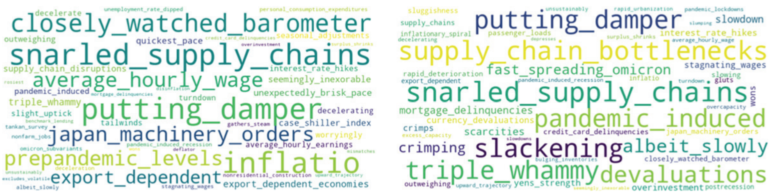
Figure 8. Word Clouds of the 50 Most Similar Words to the Tokens "Supply Chain" (left) and "Supply Chains" (right)

Note: These word clouds show the 50 most similar tokens to the vectors of the tokens "supply chain" (left-hand side) and "supply chain" (right-hand side) according to our results of word embedding. We excluded the words related to personal names, companies, countries, and regional names.

"supply chain bottlenecks," and "supply chain disruptions." The bigger the size of the words, the higher the similarity with the word of reference. For instance, Figure 6 shows that "supply" (left-hand side) and "supplies" (right-hand side) tend to appear more often close to words related to bottlenecks such as "shortages" or "scarcities" and to products that have suffered shortages since the COVID crisis and the Russian–Ukrainian war such as "antiviral_pills" or "nitrogen fertilizer."

According to Figure 7 the words "supply chain" (left) and "supply chains" (right) are related to sectors that have suffered supply

Figure 9. Word Clouds of the 50 Most Similar Words to the Tokens "Supply Chain Bottlenecks" (left) and "Supply Chain Disruptions" (right)



Note: These word clouds show the 50 most similar tokens to the vectors of the tokens "supply chain bottlenecks" (left-hand side) and "supply chain disruptions" (right-hand side) according to our results of word embedding. We excluded the words related to personal names, companies, countries, and regional names.

chain disruptions in the United States and Europe such as "semiconductor_manufacturing_equipment," "meat_processing_plants," or "chipmaking" and to trade policy terms such as "aluminium_tariffs" or "retaliatory_tariffs."

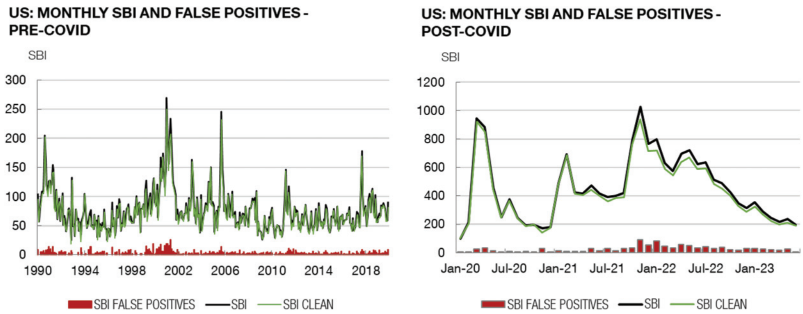
Figure 9 shows that the words "supply chain bottlenecks" and "supply chain disruptions" tend to appear close to several "words" with negative meanings such as "slowdown," "slackening," or "decelerating." Moreover, these words were often employed in the context of the pandemic, since they were often associated with COVID-related clauses, such as "fast_spreading_omicron" or "pandemic_induces," as well as to words related to the resulting economic crisis and higher prices, such as "inflationary_spiral."

2.3.4 The Index Is Robust to False Positives

An important concern when using the frequency of newspaper news related to one topic to identify an economic phenomenon, is that of false positives—that is, the possibility that our search words capture news reflecting an easing, rather than a worsening, of supply chain problems. To control for this, we build a "false positives sub-index."

In particular, in the English-based indices we build the sub-index by adding to our searches the following words, to be

Figure 10. U.S. SBI and False Positives



Note: Comparison between the U.S. monthly SBI, the contribution of false positives to the U.S. SBI, and the U.S. SBI cleaned from false positives. The contribution of false positives is computed as explained in Section 2.3.4. The cleaned SBI is calculated as the difference between the overall SBI and the false positive component. Left panel: January 1990–December 2019. Right panel: January 2020–June 2023. U.S. SBI is normalized to 100 throughout the 1990–2021 period.

found in a range of five words with respect to the others[12]: "ease, easing, eased, overcome, overcoming, overcame, loose, loosening, loosed, improve, improving, improvement, improved, remove, removing, removed, fade, fading, faded, restore, restoring, restored, eliminate, eliminating, eliminated, ameliorate, ameliorating, amelioration, alleviate, alleviating, alleviated, mitigate, mitigating, mitigation, mitigated, lessen, lessening, lessened, reduce, reducing, reduced, reduction, diminish, diminishing, diminished."

As shown in Figure 10 for the United States, false positives are fairly unusual, representing, on average, 4.2 percent of the overall SBI in the full time sample (4.1 percent and 5.4 percent in the pre-COVID and in the post-COVID sub-samples, respectively). Moreover, these false positives have a negligible effect on the overall index, since the correlation coefficient between the overall SBI and the "clean" component of the index exceeds 0.9 both in the full sample and in the pre- and post-COVID sub-samples. Even in the

[12]We restrict the distance to avoid capturing as false positives other related developments described in the news. However, the method is robust to changes in the size of the range.

post-COVID decline phase of global bottlenecks (starting in January 2022), the contribution of false positives to the overall index remains below 11 percent in all months, with the only exception of November 2020, in which it reached 18 percent.

To confirm our findings, we perform an event study around a policy change directly related to an easing of bottlenecks, the removal of China's zero-COVID strategy in the final months of 2022, when this problem could potentially be more acute. In particular, we calculate the impact of this policy change on the sub-index of false positives within the Chinese monthly SBI. The restrictive zero-COVID measures were removed after massive protests took place in several Chinese cities between November 24 and 27, 2022. On December 7, the zero-COVID strategy was effectively ended as key measures were removed, although the official end was announced on January 8, 2023. In Figure 11 we show that false positives account for a limited percentage of the overall SBI (about 11 percent) between April 2022 and June 2023, leaving the overall trend of the index fairly unaffected. The correlation between the overall SBI and the SBI cleaned from the false positive component is 0.9 throughout the sample period.

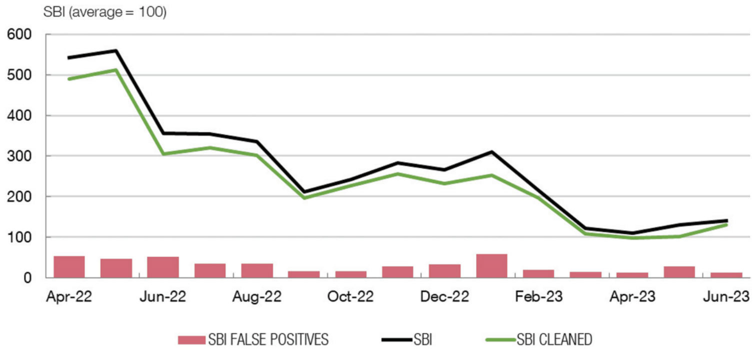
Overall, these exercises let us conclude that the presence of false positives is limited and does not affect significantly the evolution and the peaks of the SBI.

2.3.5 Relation with Other Measures

Our index seems to be a better measure of supply-side disruptions than the other measures available in at least three dimensions: it ensures the selection of only supply-side events, its high-frequency nature allows for a timelier analysis, and it covers the whole economy.

First, our text-based procedure guarantees the selection of only supply-side events. As shown in the previous section, the spikes of the index are related to supply-side bottlenecks. Before the COVID pandemic, we find several spikes that correspond closely to identified supply disruptions, such as strikes, Hurricane Katrina, or the Gulf War. After the COVID pandemic, although our index explodes, the spikes are related to the lack of global supplies such as semiconductors, raw materials, medical equipment, and COVID vaccines. This is confirmed first in the previous section by using a narrative approach

Figure 11. Chinese SBI and False Positives around the Dates of the Zero-COVID Policy Removal

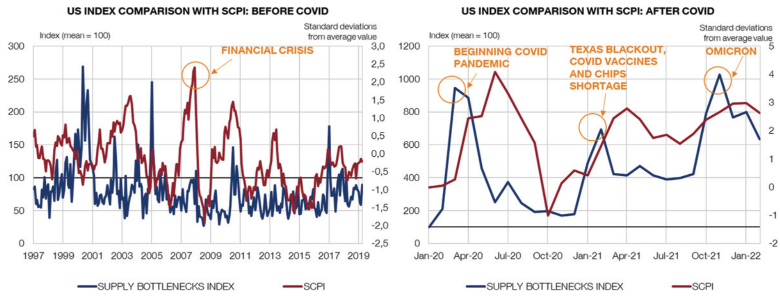


Note: Comparison between the Chinese monthly SBI, the contribution of false positives to the Chinese SBI, and the Chinese SBI cleaned from false positives around the dates of the zero-COVID policy removal. The contribution of false positives is computed as explained in Section 2.3.4. The cleaned SBI is calculated as the difference between the overall SBI and the false positive component. The zero-COVID policy was effectively removed on December 7, 2022; its official end was announced on January 8, 2023. China SBI is normalized to 100 throughout the 2010–21 period.

which confirms that most of the increase in the index around two specific events—the California energy crisis of 2001 and Hurricane Katrina in 2005—is in fact due to these events. In addition, using the word embedding technique (see previous section), we find that the words closer to our word criteria are related to supply chain pressures.

On the contrary, the widely used monthly PMI surveys on delivery times, backlogs, or purchased stocks seem to react to both demand and supply issues, as shown by Benigno et al. (2022). In turn, the measure proposed by these authors to try to correct these shortcomings of the monthly PMIs indicators of supply constraints by cleansing them of demand shocks, still falls short of our measure. In particular, when we compare our index for the United States to the Supply Chain Pressures Index (SCPI) proposed by Benigno et al. (2022), we find a moderate correlation between both indices for the pre-COVID period (see left-hand side of Figure 12). The highest spike in the SCPI index is related to the financial crisis—a period

Figure 12. Comparison of U.S. SBI with Federal Reserve Bank of New York's U.S. SCPI: before COVID (left) and after COVID (right)



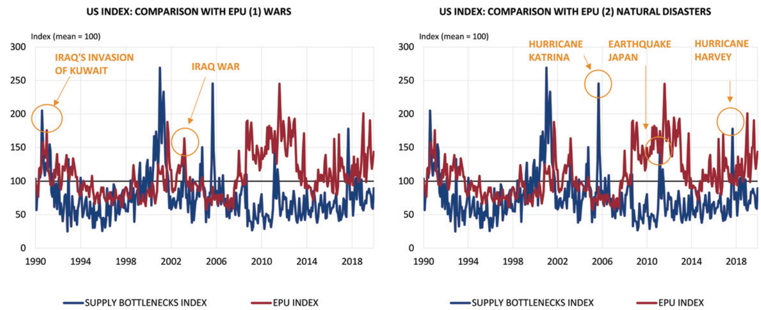
Note: U.S. SBI and Federal Reserve Bank of New York's U.S. SCPI (Benigno et al. 2022) from 1997 until March 2022. This index was discontinued in March 2022. Since that moment only a global index is available. The SBI is normalized to 100 throughout the 2001–21 period.

for which there is little evidence of supply bottlenecks—while the highest spike of our SBI is produced by the 2001 California blackout and energy crisis, followed by the impact of Hurricanes Rita and Katrina in 2005. Both indices capture the increase in supply disruptions after the Japan earthquake in 2011, but the SCPI shows little movement around Hurricane Katrina. During the pandemic period, on the contrary, the two indices are more correlated (see right-hand side of Figure 12).

Similar results are found when comparing the U.S. SBI with other more general measures of uncertainty, like the index of economic policy uncertainty (EPU) developed by Baker, Bloom, and Davis (2016). In Figure 13 we show that war events tend to increase both indices, while natural disasters only increase the SBI. Table C.1 in Appendix C reports the correlation of the monthly SBI and EPU with several economic variables in the pre-COVID period (results for the whole sample are similar, although in general the cross-correlation of economic variables increases). Interestingly, unlike the EPU, the SBI is not correlated with oil price or consumer sentiment developments.

Second, the high-frequency nature of the indicator, which can be retrieved daily, allows for real-time analysis of bottlenecks and

Figure 13. Comparison of U.S. SBI with U.S. EPU: Wars (left-hand side) and Natural Disasters (right-hand side)



Note: Comparison of U.S. SBI with U.S. EPU: wars (left-hand side) and natural disasters (right-hand side) from 1990 until 2019. The U.S. SBI is normalized to 100 throughout the 1990–2021 period.

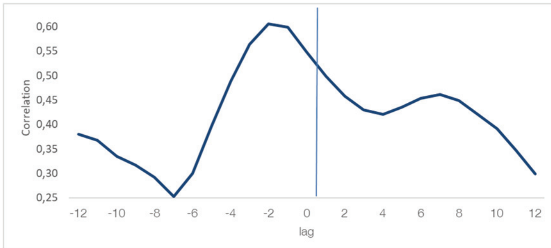
helps to better identify shocks to macro variables.[13] Our index displays a high correlation with some sub-components of the European Commission survey on production restrictions, as shown in Appendix C.[14] However, survey-based indicators, like this same survey, which is available at the quarterly frequency, or the monthly PMIs, tend to be more lagging than our measure of bottlenecks. In this sense, our index for the United States tends to lead the monthly one developed by Benigno et al. (2022). The dynamic maximum (monthly) correlation between the two indices (see Figure 14) is achieved with two lags of the news-based SBI. Furthermore, a Granger-causality test finds that the SBI causes (in the sense of Granger) the SCPI.[15] We observe this in two particular events such as in Hurricane Katrina and in the COVID crisis. For instance, as shown in Figure 15 (left panel), after Hurricane Katrina reached

[13]Other high-frequency indicators, such as the Baltic Dry Index or the Harpex Index for maritime transport, only cover specific sectors, being especially related to trade dynamics.

[14]The correlation is particularly high with the labor and machinery sub-components, and especially in the full time sample, which includes the post-COVID period.

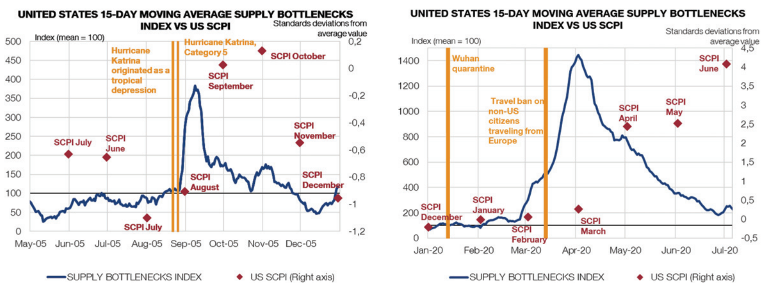
[15]A similar result was found when estimating the correlation between a similarly constructed SCPI and the SBI in the rest of the countries in our sample. Results are available upon request.

Figure 14. Dynamic Correlations of U.S. SBI with U.S. Supply Chain Pressure Index (1997–2022)



Note: Dynamic correlations from U.S. SBI with U.S. Supply Chain Pressure Index 1997 until March 2022. The U.S. SBI is normalized to 100 throughout the 1990–2021 period.

Figure 15. U.S. 15-Day Moving-Average Supply Bottlenecks Index vs. U.S. Supply Chain Pressure Index



Note: Evolution of the U.S. SBI (blue line, left axis) and U.S. Supply Chain Pressure Index from Benigno et al. (2022) (red dots, right axis), around Hurricane Katrina and the first wave of COVID-19. The U.S. SBI is normalized to 100 throughout the 1990–2021 period. The U.S. Supply Chain Pressure Index is measured in standard deviations from the average value.

Category 5 status at the end of August 2022, the U.S. SBI increased during the first half of September, a month before the U.S. SCPI data for September would have been available. This is even clearer during the COVID crisis (see right panel of Figure 13), when the SBI index started to increase in early February, reaching historical maxima during March, capturing the diverse problems in supply due to the COVID crisis, whereas the SCPI did not show any signs of bottlenecks until the beginning of May, when the data of April were available.

Third, our index spans a longer sample and covers the whole economy. In the U.S. case, the index is based on daily article searches from 11 nationwide newspapers since 1990, while the European indices start in the early or mid-2000s. Other supply bottlenecks indices commonly used only cover specific sectors, like the Harper and Baltic maritime trade indices (which are based on the prices of maritime trade across different locations), or lack a sufficiently big sample to provide inference, such as the Small Business Pulse Survey in the United States, or cover a more limited period, like the text-based index in Young et al. (2021), which uses quarterly S&P earnings calls as a source of information.

3. Macro Impact of Supply-Side Disruptions

To study the macro impact of the supply-side disruptions identified by the SBI, we follow Baker, Bloom, and Davis (2016) and construct a monthly VAR identified using a Cholesky decomposition in which we include the following seven variables, in the stated order: the bottlenecks index, the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index, plus a constant. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria.

The supply chain bottlenecks indices are clearly not purely exogenous variables (or shocks), since, for example, they are more binding when demand intensifies. To control with the VAR methodology for this potential feedback between activity and supply chain bottlenecks, we use the fact that bottlenecks are unlikely to react contemporaneously to activity. In fact, firms usually use inventories to accommodate demand shocks, and they increase their inventories when the supply chain risk is higher (Carreras Valle 2021). This means that the Cholesky identification proposed, placing the SBI first and the activity variables last, should be adequate. That is, we assume that shocks to the domestic variables may only be reflected with a lag in the bottlenecks index (as contemporaneous shocks will be absorbed by inventories), while supply chain disruptions may affect contemporaneously activity and prices.

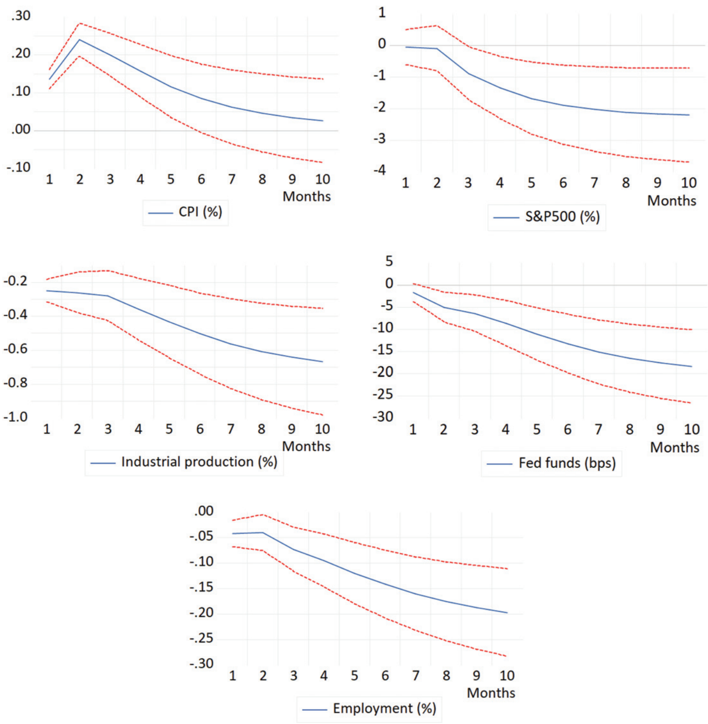
In this case, the recursive identification is compatible with the interpretation of the index as a proxy (or an instrument in the case of a regression framework, as explained in Plagborg-Møller and Wolf 2021) for supply problems. As supply problems are difficult to measure, researchers often rely on sign restrictions, which we deem unnecessary in our case, as the main spikes in the index refer to supply disruptions.

In our benchmark specification, we restrict the sample to the period from January 1999 to January 2020. We present impulse response functions (IRFs) to shocks in the VAR. As explained in Section 2.1, these shocks might have different sources. The impulse responses before the pandemic will show the average response of the economy to the structural shock, given the mix of shocks that form the SBI in that particular period.[16] As a result, out-of-sample inference of the impact of an SBI shock should take into account the source of the shock. For example, a supply chain malfunctioning might have a more delayed impact on the economy than a sudden disruption due to a natural disaster. On the other hand, the pandemic supply shock could have triggered aggregate demand effects (Guerrieri et al. 2022), which may not be a feature of more isolated supply shocks. Therefore, we avoid using the latest period, which is not comparable with the previous one as a result of the great negative effect of the COVID pandemic, and later we check that the results are comparable when extending the sample until 2022.

The results are presented in Figure 16. In particular, a shock of one standard deviation to the SBI (resulting in an increase of 60 points in the index over the whole sample) induces a significant decrease in employment of around 0.2 percentage point (pp) after 10 months, and a decrease in industrial production of 0.7 pp after 10 months. The effects on financial variables are more moderate, with a non-significant decrease in stock prices on impact and a decrease of around 2 percent after 10 months, together with a small (and non-significant during the first quarter) decrease in the federal funds rate. As for prices, the VAR evidence confirms the SBI shock is a pure

[16]This is also the case for different indices that try to capture the average response of the economy to a change in economic sentiment or in economic uncertainty, such as Baker, Bloom, and Davis (2016) or Caldara and Iacoviello (2022).

Figure 16. Impulse Responses to an SBI Shock in the United States (1990–2020)



Note: Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI, the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is an increase of 60 points in the SBI. The red lines denote one-standard-deviation confidence bands.

supply shock: prices rise significantly on impact, with CPI increasing by 0.25 pp in the first two months after the shock.

To illustrate the economic relevance of these results, it is worth calculating the impact of specific events as measured by the SBI. In particular, Hurricane Katrina in 2005 increased the U.S. SBI by around 150 basis points, which according to the VAR results would have implied an increase in the U.S. aggregate CPI by 0.75 pp after

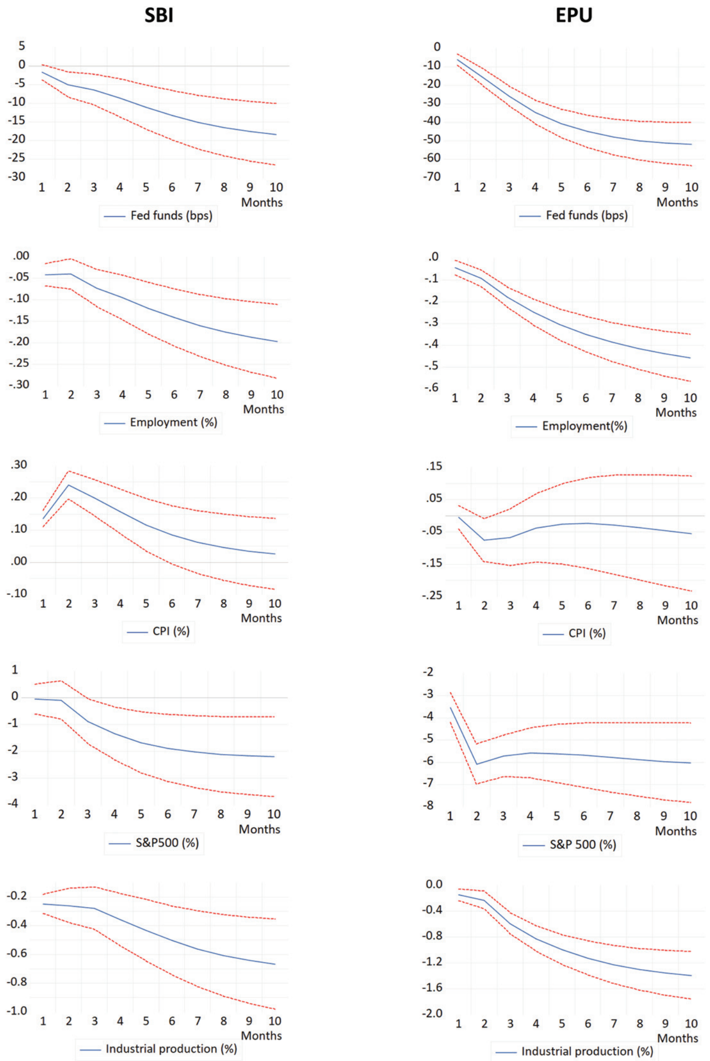
5 months and a contraction of U.S. aggregate industrial production by 1.5 pp after 10 months.

In Figure 17, we compare these results with those of a standard measure of economic policy uncertainty, the EPU by Baker, Bloom, and Davis (2016). The size of the shocks is the same as before (one standard deviation of the index, corresponding to an increase of 60 points in the index). The effects on industrial production and employment are also quite comparable. However, the EPU has a stronger impact on financial variables, which is consistent with the high relevance of uncertainty for stock prices. Interestingly, while the CPI is not affected by the EPU shock, it increases in the case of the SBI shock. As the SBI shock is a persistent supply shock, monetary policy faces a trade-off between prices and activity, which is reflected in the more cautious response of the federal funds rate in the case of the SBI shock (see, for example, Comin, Johnson, and Jones 2023 for a discussion on the role of monetary policy facing supply chain disruptions).

In Figure 18, we present several robustness exercises around our benchmark specification (blue line) for the response of the CPI index (left) and industrial production (right). First, we include the Michigan Index of Consumer Sentiment (orange line), ordered after the EPU index. It is well known that the response of economic variables to EPU is less strong when including forward-looking consumer variables. In the case of the SBI, the results remain unchanged. This is also evidence that past and future demand prospects are not affecting the index. Second, we change the ordering of variables, by putting the EPU first (green line). The significance of the results is not affected. Finally, we include the oil price as the first variable in the recursive VAR (red line). With this specification, we are not allowing for a contemporaneous effect of the bottlenecks index to the oil price, to avoid the possible concern that the SBI may be capturing mainly oil supply shocks. As can be seen, including oil prices slightly reduces the effect of the benchmark VAR, but it does not affect the significance of the results.

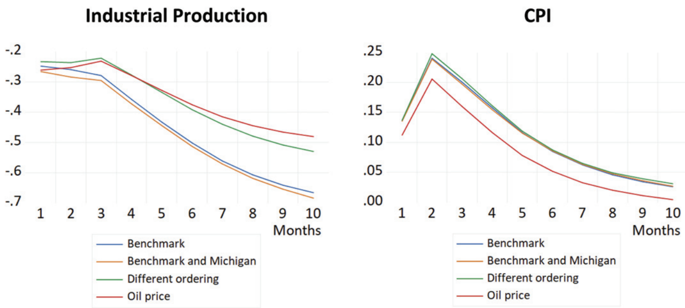
The next exercise is a comparison with a similar benchmark VAR computed using the SCPI as a bottlenecks indicator. As shown in Figure 19, the effects on the CPI are similar on impact (left-hand side), although more persistent in the case of the SCPI. However, the impact on industrial production (right-hand side) is

Figure 17. Impulse Responses to an SBI Shock (left column) and the EPU Index (right column) in the United States (1990–2020)



Note: Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI, the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is an increase of 60 points in the SBI (left) and 60 points in the EPU (right). The red lines denote one-standard-deviation confidence bands.

Figure 18. Impulse Responses of Industrial Production (left) and CPI (right) to an SBI Shock (robustness)



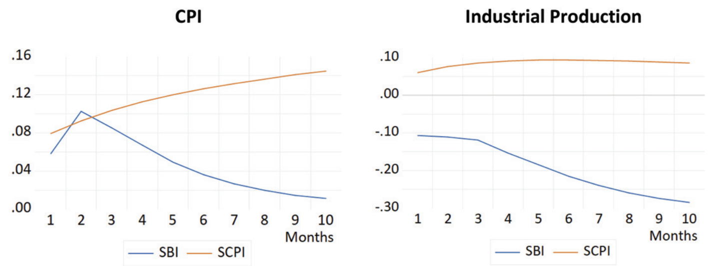
Note: Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition. The figure shows the response of industrial production to the SBI shock in the benchmark specification (see notes to Figure 13). The orange line includes eight variables in the stated order: SBI, the economic policy uncertainty index, the Michigan Index of Consumer Sentiment, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. The green line includes seven variables in this order: the economic policy uncertainty index, the SBI, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. Finally, the red line includes eight endogenous variables, adding the real oil price as the first variable in the recursive specification. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is normalized in all specifications to show an increase of 60 points in the SBI.

completely different. Counterfactually, the shock to SCPI increases (non-significantly) industrial production, while the SBI shock decreases it. We conclude that the SBI is more related to the supply side of bottlenecks.

For robustness, we also report in Figure 20 the impulse responses of a VAR estimated using data for the whole sample available, from January 1990 until May 2022.[17] Although qualitatively the results are not changed, some differences in the dynamics appear. First, the

[17] The large and persistent spike in the SBI after the pandemic can be thought of as a measure of the prominent importance of these shocks or as a structural change, and therefore it warrants some caution when interpreting the results using the whole sample.

Figure 19. Impulse Responses of CPI (left) and Industrial Production (right) to a One-Standard-Deviation SBI or SCPI Shock in the United States (1990–2020)

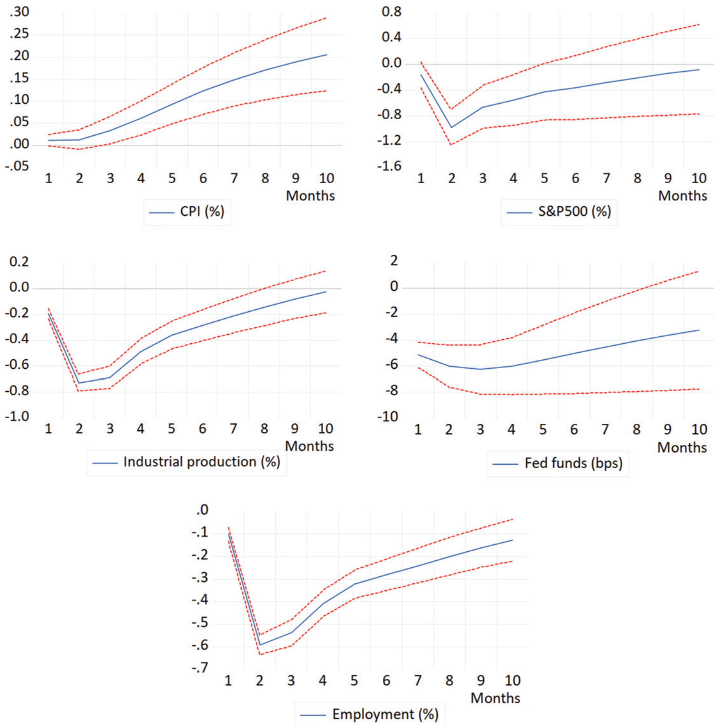


Note: Monthly VAR from January 1990 to January 2020 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI (blue) or the SCPI (orange), the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags in all specifications, following the Schwarz and Hannan-Quinn criteria. The shock is a one-standard-deviation increase in the SBI (blue) or the SCPI (orange).

response of CPI is much more persistent than before. Second, the response of industrial production and employment is more immediate than in the previous exercises, with an immediate fall. This could be caused by the pandemic itself, as it created a very important and sudden bottlenecks shock, but also because of the different mix of shocks forming the SBI after this period and the response to them of supply chains during and after the pandemic (Bonadio et al. 2021).

Finally, we estimate a panel VAR for six countries (United States, United Kingdom, Spain, Italy, France, and Germany). The sample ranges from January 2007 to January 2020, given the restrictions on newspaper availability across countries. The shock is also one standard deviation, equal to a 60-point increase in the index. The panel VAR includes equivalent variables to the ones used before, but we use the unemployment rate, which is available at monthly frequency for all countries. In any case, as shown in Figure 21, the results for unemployment, industrial production, and the CPI are qualitatively similar to the ones presented before, although noisier, as is expected due to the shorter and more heterogeneous sample.

Figure 20. Impulse Responses to a One-Standard-Deviation SBI Innovation in the United States (January 1990–May 2022)

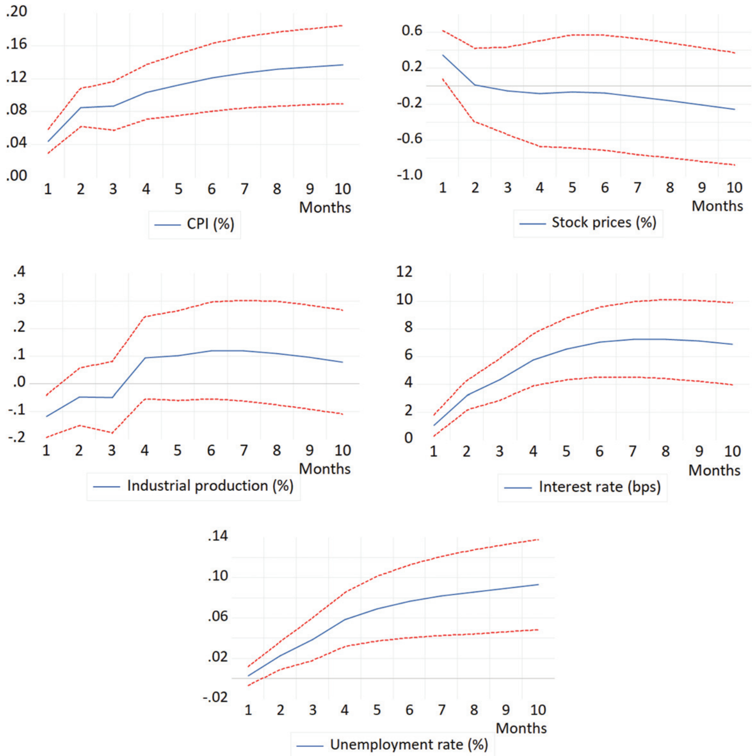


Note: Monthly VAR from January 1990 to May 2022 identified using a Cholesky decomposition in which we include seven variables, in the stated order: the SBI (blue) or the SCPI (orange), the economic policy uncertainty index, the stock price index (S&P 500), the official interest rate (federal funds), log employment, log industrial production, and log consumer price index. We include two lags following the Schwarz and Hannan-Quinn criteria. The red lines denote one standard deviation confidence bands. The shock is normalized in all specifications to show an increase of 60 points in the SBI.

4. Conclusions

We construct an index of supply bottlenecks using newspaper articles. An audit exercise based on a comparison with other possible sources of information, a human-based analysis of the main spikes,

Figure 21. Impulse Responses to a One-Standard-Deviation SBI in the United States, United Kingdom, Germany, France, Italy, and Spain (pre-COVID sample)



Note: Monthly panel VAR from January 2007 to January 2020 identified using a Cholesky decomposition. The countries included are the United States, the United Kingdom, Germany, France, Italy, and Spain. We include seven variables: the SBI, the EPU index of each country, a stock price index, the official interest rate, the unemployment rate, log industrial production, and log CPI. We include three lags following the Schwarz and Hannan-Quinn criteria. The red lines denote one-standard-deviation confidence bands. The shock is an increase of 60 points in the SBI.

and the use of machine learning techniques over a sample of articles let us conclude that the index captures the main events previously identified in the literature as leading to supply disruptions—including wars, natural disasters, strikes, and the notable supply chain bottlenecks during the COVID-19 pandemic. The index is calculated for the United States, the United Kingdom, the main economies in the euro area, and China.

The econometric analysis shows that supply bottlenecks have important effects on the economy, leading to a decrease in industrial production and employment and an increase in prices. As a consequence, the index is a good proxy for supply shocks (of different natures) affecting the economy. Overall, the evidence presented in this paper supports the view that supply bottlenecks should be carefully monitored and addressed by policymakers.

Appendix A. Definition of the Index, Newspapers Used, and Data Sample

A.1 Definition of the SBI

(i) Define NR_t^i as the number of articles containing the words selected in each newspaper $i = 1, 2, \dots p$ and time period t.

(ii) Let $X_t^i = \frac{NR_t^i}{N_t^i}$ be the relative frequency rescaled by the total number of articles in the same newspaper and period $t(N_t^i)$, to account for the fact that the overall volume of articles varies across newspapers and time, and let T_1 and T_2 denote the time intervals used in the standardization and normalization calculations.

(iii) Compute the variance and mean of variable X_t^i, in the interval T_1 for each newspaper i:

$$\sigma_{T_1}^{X^i} = \sqrt{\sum_{T_1} \left(\frac{NR_t^i}{N_t^i} - \mu_{T_1}^{X^i} \right)^2 / T_1}, \mu_{T_1}^{X^i} = \sum_{T_1} \frac{NR_t^i}{N_t^i} / T_1.$$

(iv) Standardize X_t^i by dividing through by the standard deviation for all t. This operation yields, for each newspaper, a series $Y_t^i = \frac{X_t^i}{\sigma_{T_1}^{X^i}}$ with unit standard deviation in the interval T_1.

(v) Compute the mean over the p newspapers of Y_t^i in each period t to obtain the series $Z_t = \sum_p Y_t^i/p$.

(vi) Compute $M = \sum_{T_2} Z_t/T_2$, the mean value of Z_t in the interval T_2.

(vii) Multiply Z_t by $(100/M)$ for all t to obtain the normalized SBI time-series index $SBI_t = Z_t \frac{100}{M}$.

Therefore, putting all together, we have

$$SBI_t = \frac{\sum_p \frac{X_t^i}{\sigma_{T_1}^{X^i}}/p}{\sum_{T_2}\left(\sum_p \frac{X_t^i}{\sigma_{T_1}^{X^i}}/p\right)/T_2} 100.$$

We can calculate the contributions of a subset of news on the index—for example, those related to a particular event like Hurricane Katrina—in the following manner. Count the number of news amongst those including the selected words which also contain a word describing that event ($NR_t^{S,i}$) and defined the rescaled frequency of this set of news as $X_t^{S,i} = \frac{NR_t^{S,i}}{N_t^i}$. In the current example we would add the word “Katrina.” Then the contribution of this event to the SBI (${SBI^S}_t$) would be as follows:

$$SBI_t^S = \frac{\sum_p \left(\frac{X_t^{S,i}}{\sigma_{T_1}^{X^i}}\right)/p}{\sum_{T_2}\left(\sum_p \frac{X_t^i}{\sigma_{T_1}^{X^i}}/p\right)/T_2} 100.$$

A.2 Newspapers and Sample

The time period covered for the United States goes from January 1, 1990 until May 2022. The newspapers used are the following (in parentheses is the time they join the index if they did it later than January 1990 due to lack of data): the *Los Angeles Times*, the *San Francisco Chronicle*, the *Houston Chronicle*, the *New York Times*, the *Washington Post* (December 1997), the *Chicago Tribune* (January 2000), the *Wall Street Journal* (April 2001), the *Miami*

Herald (June 2001), the *Boston Globe* (September 2001), *USA Today* (February 2002), and the *Dallas Morning News* (May 2003).

The newspapers used for the United Kingdom are the following: the *Times*, the *Independent*, the *Guardian*, the *Telegraph*, the *Daily Mirror*, the *Daily Express*, the *Daily Mail*, the *Evening Standard*, the *Sun*, and the *Sunday Times*. The time sample starts January 1, 2001.

In the case of France, we adapt the words into the French language. In particular, we use the following words for each group:

1. chaine d'approvisionnement, chaines d'approvisionnement, chaine logistique, chaines logistiques, approvisionnement, approvisionnements;

2. goulot d'étranglement, goulots d'étranglement, pénurie, pénuries, perturbation, perturbations, problème, problèmes, rareté, raretés, absence de, absences de, manque de, retard, retards, délai, délais.

The sample starts on January 1, 2006. The newspapers used are the following (in parentheses is the time they join the index if they did it later than January 2006 due to lack of data): *Le Figaro, Le Monde, Les Echos, Le Progrès, Agence France Presse, Sud Ouest, Ouest France*, and *Midi Libre* (September 2006).

For Italy, we adapted the search words into Italian:

1. catena di approvvigionamento, catene di approvvigionamento, supply chain, supply chains, catena di fornitura, catena di forniture, fornitura, forniture, catena logistica, catene logistiche;

2. collo di bottiglia, rallentamento, rallentamenti, congestione, scarsità, carenza, carenze, assenza, assenze, interruzione, perturbazione, interruzioni, perturbazioni, problema, problemi, difficoltá, penuria, mancanza, mancanze, ritardo, ritardi, arretrato, arretrati, inevaso, inevasi.

The sample starts on January 1, 2007. The Italian newspapers used are the following: *ANSA, Agenzia Giornalistica Italia, Corriere* *della Sera, La Stampa, Il Sole 24 ore, La Repubblica, Il Giornale, La Nazione, Il Resto del Carlino, Il Giorno.*

For Spain, we adapted the search words into Spanish:

1. cadena de suministro, cadena de suministros, cadenas de suministro, cadenas de suministros, suministro, suministros;

2. cuello de botella, cuellos de botella, escasez, escaseces, interrupción, perturbación, paralización, interrupciones, perturbaciones, paralizaciones, problema, dificultad, problemas, dificultades, carencia, carencias, falta de, atraso, retraso, atrasos, retrasos.

The sample starts on January 1, 2007. The Spanish newspapers used are the following (in parentheses is the time they join the index if they did it later than January 2007 due to lack of data): *ABC*, *El Mundo, El País, El Economista* (May 2008), *Expansión*, and *Cinco Días.*

For Germany, we adapted the search words into German. However, we created a new group of words due to the characteristics of the German language that have words that by itself mean "supply bottleneck," such as "Versorgungsengpass." Thus, in the German search, we count the article as 1 if we find the same search as for the other languages (group 1 and 2 simultaneously) or any word belonging to group 3.

1. Lieferkette, Lieferketten, Lieferung, Beschaffung, Lieferungen, Beschaffungen.

2. Engpass, Kapazitätsengpass, Mangel, Knappheit, Mängel, Knappheiten, Störung, Betriebsstörung, Störungen, Betriebsstörungen, Problem, Probleme, Verknappung, Verknappungen, Fehlen von, Verzug, Verzögerung, Verspätung, Verzögerungen, Verspätungen, Rückstand, Nachholbedarf, Rückstau, Arbeitsrückstand, Rückstände, Arbeitsrückstände, Schwierigkeit, Schwierigkeiten.

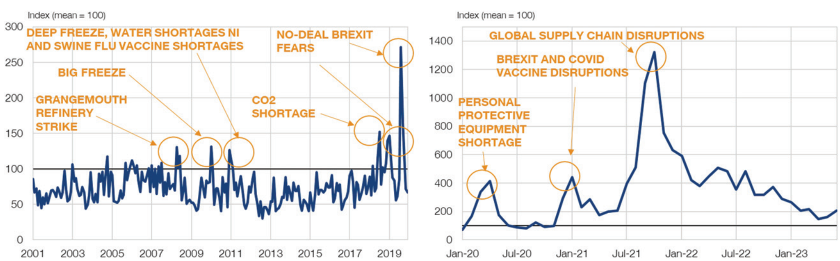
3. Lieferengpass, Lieferengpässe, Versorgungsengpass, Versorgungsengpässe, Beschaffungsprobleme, Lieferrückstand.

The sample starts on January 1, 2007. The German newspapers used are the following (in parentheses is the time they join the index if they did it later than January 2007 due to lack of data): *Die Welt, Frankfurter Allgemeine Zeitung* (March 2013), *Handelsblatt* (March 2013), *Die Welt, Der Tagesspiegel, Die Tageszeitung, Bild* (April 2013), *Rheinische Post, Frankfurter Rundschau, Stuttgarter Zeitung*, and *Berliner Morgenpost.*

For China, the sample starts on January 1, 2010. The newspapers used are the following: the *Wall Street Journal, China Daily*, the *South China Morning Post, Reuters News*, and *Dow Jones Institutional News.* We restrict our search to include only news related to China.

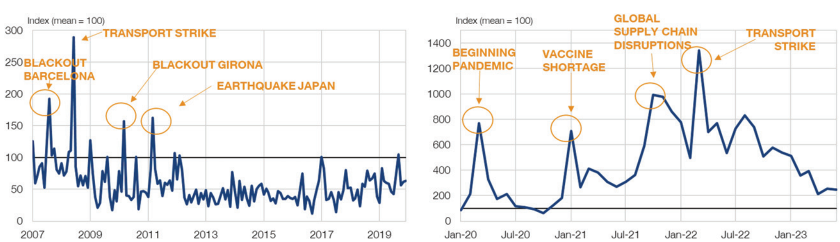
Appendix B. Explanations of Spikes in the SBI (Rest of Countries)

Figure B.1. United Kingdom Supply Bottlenecks Index



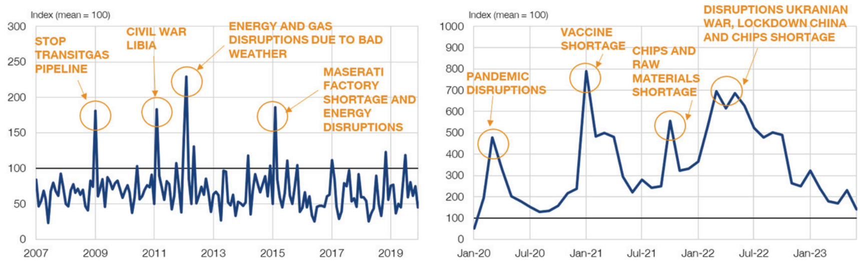
Note: U.K. SBI from 2001 until June 2023. U.K. SBI is normalized to 100 throughout the 2001–21 period. We describe in yellow the main events behind the spikes of the U.K. SBI.

Figure B.2. Spain Supply Bottlenecks Index



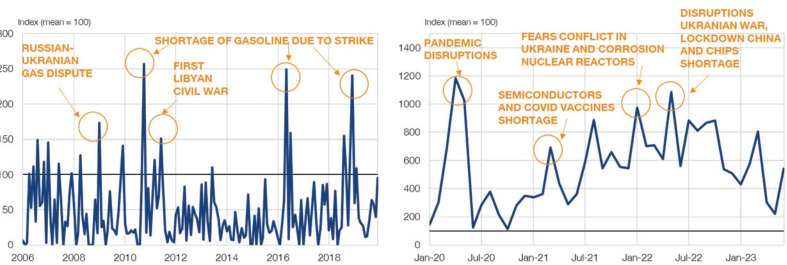
Note: Spain SBI from 2007 until June 2023. The Spain SBI is normalized to 100 throughout the 2007–21 period. We describe in yellow the main events behind the spikes of the Spain SBI.

Figure B.3. Italy Supply Bottlenecks Index



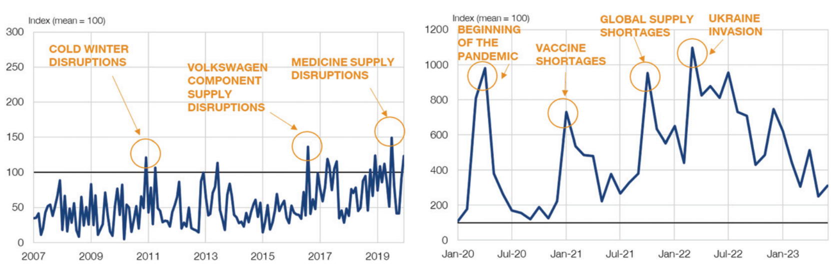
Note: Italy SBI from 2007 until June 2023. Italy SBI is normalized to 100 throughout the 2007–21 period. We describe in yellow the main events behind the spikes of the Italy SBI.

Figure B.4. France Supply Bottlenecks Index



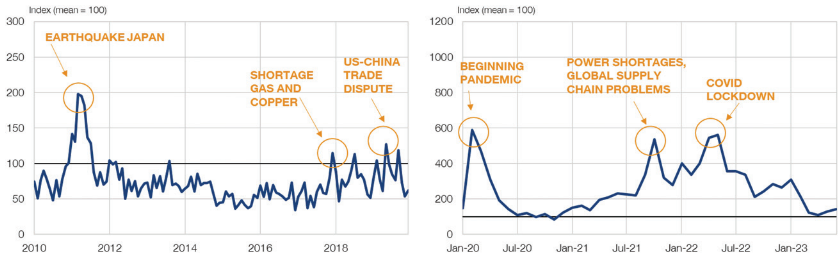
Note: France SBI from 2006 until June 2023. France SBI is normalized to 100 throughout the 2006–21 period. We describe in yellow the main behind the spikes of the France SBI.

Figure B.5. Germany Supply Bottlenecks Index



Note: Germany SBI from 2007 until June 2023. Germany SBI is normalized to 100 throughout the 2007–21 period. We describe in yellow the main events behind the spikes of the Germany SBI.

Figure B.6. China Supply Bottlenecks Index



Note: China SBI from January 2010 until June 2023. China SBI is normalized to 100 throughout the 2010–21 period. We describe in yellow the main behind the spikes of the China SBI.

Appendix C. Comparison with Other Measures

Table C.1. Correlations of SBI with EPU and Michigan Index of Consumer Sentiment Measures (1990–2019)

Variable	SBI	EPU	Consumer Sentiment
SBI	1.000	–0.039	0.116
EPU	–0.039	1.000	–0.589
FI	–0.010	0.096	0.230
IPI	–0.027	0.099	0.091
IR	0.308	–0.482	0.376
OIL	–0.098	0.402	–0.454
CPI	–0.163	0.330	–0.123
Sentiment	0.116	–0.589	1.000
PPI	–0.180	0.392	–0.210
Employment	–0.060	0.176	0.064
VIX	0.035	0.374	–0.339

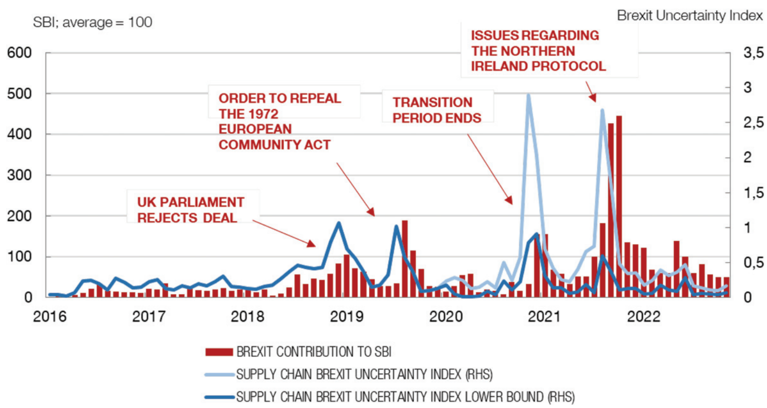
Note: Correlation of U.S. SBI with the EPU, the Michigan Index of Consumer Sentiment, the S&P 500 (FI), industrial production index (IPI), the federal funds rate (IR), the Brent oil price, the CPI, producer price index, employment, and the VIX. With the exception of the EPU and the SBI, the rest of the variables are retrieved from the Federal Reserve Economic Data (FRED) statistical database of the Federal Reserve Bank of St. Louis.

Table C.2. Correlations of SBI with the Machinery and Labor Sub-components of the European Commission Survey on Production Restrictions

	DEU	FRA	ITA	ESP	EMU
SBI—Labor					
2007:Q1–2019:Q4	0.51	0.21	–0.22	0.16	0.26
2007:Q1–2023:Q2	0.68	0.50	0.52	0.71	0.70
SBI—Machinery					
2007:Q1–2019:Q4	0.31	0.25	–0.11	0.19	0.38
2007:Q1–2023:Q2	0.44	0.22	0.37	0.48	0.67
SBI—Labor and Machinery					
2007:Q1–2019:Q4	0.55	0.23	–0.21	–0.07	0.31
2007:Q1–2023:Q2	0.80	0.56	0.52	0.70	0.78

Note: Correlation of Germany, France, Italy, Spain, and EMU SBI with the respective machinery and labor sub-components of the European Commission survey on production restrictions. EMU SBI is computed as the average of the SBI of the four main EU economies. European Commission indices are normalized.

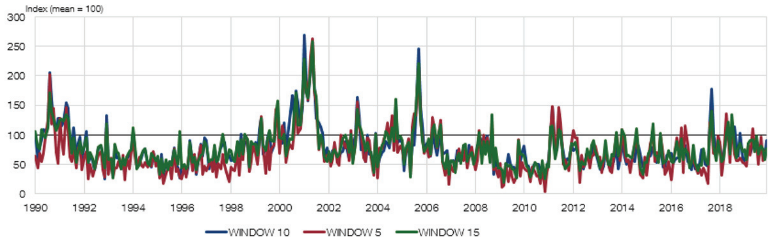
Figure C.1. Comparison of UK Brexit-Related SBI with the Supply Chain Brexit Uncertainty Index (2016–22)



Note: Comparison between the Brexit-related component of the U.K. monthly SBI and the supply chain component of the Brexit Uncertainty Index (Chung, Dai, and Elliott 2022). The Brexit contribution to the U.K. SBI is calculated as explained in Appendix A.

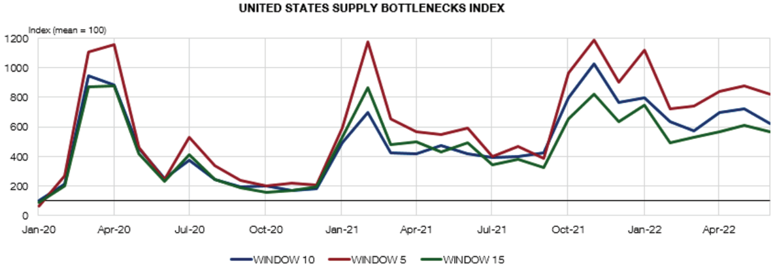
Appendix D. Different Windows for News Search

Figure D.1. U.S. Monthly SBI with Different Search Windows before COVID-19



Note: U.S. SBI from 1990 until the end of 2019. The SBI is normalized to 100 throughout the 1990–2021 period. We create two groups of words, one with the terms “supply” and “supply chain” that aim to capture the nature of the article, and another related to negative sentiment, such as “bottleneck” and “shortage.” Then we search, within a predefined window, for a coincidence of one word of the first group with another of the second group. Windows 5, 10, and 15 indicate for each U.S. SBI the maximum number of words between the two groups of words in our search.

Figure D.2. U.S. Monthly SBI with Different Search Windows after COVID-19



Note: U.S. SBI from 2020 until the end of June 2022. The SBI is normalized to 100 throughout the 1990–2021 period. We create two groups of words, one with the terms “supply” and “supply chain” that aim to capture the nature of the article, and another related to negative sentiment, such as ”bottleneck” and ”shortage.” Then we search, within a predefined window, for a coincidence of one word of the first group with another of the second group. Windows 5, 10, and 15 indicate for each U.S. SBI the maximum number of words between the two groups of words in our search.

Appendix E. Audit of the Main Events

This appendix lists the events behind the spikes of each national SBI to ensure that they capture correctly supply disruptions. For each country, we classify as spikes all the observations that are one standard deviation above the mean, using sample-specific mean and standard deviation for the pre-COVID and the post-COVID sample. To deduce the main events behind the spikes of each national SBI, we read all the articles that comply with our SBI searches.

United States

Pre-COVID:
Jul. 1990 (SBI=116): rhodium shortage, risk of water shortages in California
Aug. 1990 (SBI=205): risk of oil supply shortages due to Gulf War
Sept. 1990 (SBI=161): risk of oil supply shortages due to Gulf War
Oct. 1990 (SBI=120): risk of oil and propane supply shortages due to Gulf War
Dec. 1990 (SBI=127): risk of oil supply shortages due to Gulf War
Jan. 1991 (SBI=128): risk of oil supply shortages due to Gulf War
Feb. 1991 (SBI=115): risk of water shortages in California, shortages in military supplies, vulnerability to oil supply shortages
Mar. 1991 (SBI=122): risk of water shortages in California, vulnerability to oil supply shortages
Apr. 1991 (SBI=154): risk of water shortages in California
May 1991 (SBI=145): risk of water shortages in California
Aug. 1991 (SBI=111): risk of oil supply shortages from Soviet Union, copper supply shortages, risk of water shortages in California
Dec. 1992 (SBI=132): risk of shortages in steel and lumber production, risk of supply shortages of palladium from Russia and South Africa
Apr. 1999 (SBI=127): gasoline supply shortages, risk of supply shortages of palladium from Russia
Nov. 1999 (SBI=123): risk of Y2K-related disruptions, supply disruptions for electronics makers due to Taiwan earthquake
Dec. 1999 (SBI=131): risk of Y2K-related disruptions
Mar. 2000 (SBI=120): risk of oil, gas, and gasoline supply shortages, risk of water shortages in California

Jun. 2000 (SBI=124): debate on oil and gasoline supply shortages (related to gasoline price spikes)
Jul. 2000 (SBI=167): debate on oil and gasoline supply shortages, risk of electricity shortages in California
Aug. 2000 (SBI=131): risk of heating oil shortage for the coming winter, risk of electricity shortages in California, tire shortages due to Bridgestone/Firestone Inc. tire recall, blood shortage
Sept. 2000 (SBI=174): risk of energy crisis (oil and electricity), flu vaccine shortage
Oct. 2000 (SBI=153): risk of energy crisis (oil and electricity), flu vaccine shortage, supply shortages to electronics firms
Nov. 2000 (SBI=116): risk of energy crisis (oil and electricity), flu vaccine shortage
Dec. 2000 (SBI=146): risk of energy crisis (electricity), supply shortages to electronics firms
Jan. 2001 (SBI=269): blackouts and energy crisis in California
Feb. 2001 (SBI=198): California energy crisis, tetanus vaccine shortage
Mar. 2001 (SBI=156): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California
Apr. 2001 (SBI=212): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California
May 2001 (SBI=233): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California
Jun. 2001 (SBI=183): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California, blood shortages related to mad cow disease
Jul. 2001 (SBI=128): risk of energy crisis in several states and at the national level (oil, gas, and electricity), electricity energy crisis in California, blood shortages
Aug. 2001 (SBI=120): risk of energy crisis in several states and at the national level (mostly gasoline and electricity), blood shortages
Sept. 2001 (SBI=114): risk of energy crisis in several states and at the national level (mostly gas and gasoline)

Mar. 2003 (SBI=163): disruptions in oil supply due to Iraq War and to political unrest in Nigeria and Venezuela, supply shortages to U.S. troops in Iraq
Apr. 2003 (SBI=131): risk of oil shortages due to Iraq War, supply shortages to U.S. troops in Iraq
Aug. 2004 (SBI=126): risk of oil shortages due to disruptions from Russia's top oil producer (Yukos), Iraq War, and election in Venezuela, flu vaccine shortage
Oct. 2004 (SBI=150): risk of oil shortages due to disruptions from Russia's top oil producer (Yukos), Iraq War, and election in Venezuela, flu vaccine shortage, delays in Los Angeles and Long Beach ports
Aug. 2005 (SBI=130): Hurricane Katrina supply disruptions (fears of oil supply disruptions due to damage at Gulf Coast refineries)
Sept. 2005 (SBI=245): Hurricane Rita and Hurricane Katrina supply disruptions (fears of oil supply disruptions due to damage at Gulf Coast refineries)
Oct. 2005 (SBI=147): Hurricane Wilma supply disruptions, discussion of supply disruptions of Hurricane Rita and Hurricane Katrina, flu vaccine shortage
Nov. 2005 (SBI=115): past hurricanes disruptions (especially construction materials), flu vaccine shortage
Mar. 2011 (SBI=146): Tôhoku earthquake and tsunami supply chain disruptions (auto makers, batteries, etc.), fears of oil disruptions due to military intervention and conflict in Libya
Jun. 2011 (SBI=118): disruptions of oil in Libya, supply disruptions related to Tôhoku earthquake
Aug. 2017 (SBI=118): fears of oil disruptions and supply disruption caused by Hurricane Harvey
Sept. 2017 (SBI=178): supply disruption in Puerto Rico after Hurricane Maria and supply disruptions caused by Hurricanes Irma and Harvey
Aug. 2018 (SBI=114): fears of supply disruptions due to trade-war tensions with China

Post-COVID:
Mar. 2020 (SBI=946): pandemic disruptions
Apr. 2020 (SBI=885): pandemic disruptions

Oct. 2021 (SBI=794): pandemic-related disruptions and congestion in Long Beach and Los Angeles ports
Nov. 2021 (SBI=1028): pandemic-related disruptions and congestion in Long Beach and Los Angeles ports
Dec. 2021 (SBI=767): pandemic-related disruptions (omicron)
Jan. 2022 (SBI=798): pandemic-related disruptions (omicron), chip shortages, risk of oil and gas disruptions related to RUS–UKR war

United Kingdom

Pre-COVID:
Jan. 2003 (SBI=106): school staff supply shortages
Oct. 2004 (SBI=117): risk of oil supply shortages, flu vaccine shortages
Sep. 2005 (SBI=108): gasoline and organic milk supply shortages
Dec. 2005 (SBI=105): petrol supply shortages due to a fire in the oil terminal Hemel Hempstead
Jan. 2006 (SBI=112): risk of gas shortages
Feb. 2006 (SBI=103): oxygen supply shortages
Apr. 2006 (SBI=105): energy supply shortages
Nov. 2006 (SBI=101): winter flu vaccine shortages
Jan. 2007 (SBI=105): disruption to power supplies due to storms in London and the southeast
May. 2007 (SBI=103): housing-sector supply shortages
Jul. 2007 (SBI=108): food supply shortages due to floods from heavy rains
Apr. 2008 (SBI=130): Grangemouth refinery strike
May. 2008 (SBI=101): beef supply shortages, oil supply disruptions
Jun. 2008 (SBI=118): scarce oil supply, fuel supply problems
Jan. 2010 (SBI=131): disruptions related to Big Freeze
Dec. 2010 (SBI=126): disruptions related to Big Freeze, swine flu vaccine shortages
Jan. 2011 (SBI=114): water supply disruptions, swine flu vaccine shortages
Jun. 2018 (SBI=115): CO2 shortages, risk of supply disruptions associated with possible no-deal Brexit
Jul. 2018 (SBI=152): risk of supply disruptions associated with possible no-deal Brexit

Sep. 2018 (SBI=102): risk of supply disruptions associated with possible no-deal Brexit
Nov. 2018 (SBI=108): winter flu vaccine shortages, risk of supply disruptions associated with possible no-deal Brexit
Dec. 2018 (SBI=140): risk of supply disruptions associated with possible no-deal Brexit
Jan 2019 (SBI=146): risk of supply disruptions associated with possible no-deal Brexit
Feb. 2019 (SBI=114): risk of supply disruptions associated with possible no-deal Brexit
Aug. 2019 (SBI=272): drugs supply shortages, risk of supply disruptions associated with possible no-deal Brexit
Sept. 2019 (SBI=166): drugs supply shortages, risk of supply disruptions associated with possible no-deal Brexit
Oct. 2019 (SBI=117): drugs supply shortages, risk of supply disruptions associated with possible no-deal Brexit

Post-COVID:
Sept. 2021 (SBI=1104): delays and supply shortages related to COVID and Brexit
Oct. 2021 (SBI=1323): delays and supply shortages related to COVID and Brexit
Nov. 2021 (SBI=755): delays and supply shortages related to COVID and Brexit

Spain

Pre-COVID:
Jan. 2007 (SBI=126): interruptions in electricity supply due to adverse weather conditions
Jul. 2007 (SBI=125): interruptions in electricity supply in Barcelona
Aug. 2007 (SBI=192): interruptions in electricity supply in Barcelona and Valencia
Sep. 2007 (SBI=103): storm-related disruptions in southern regions, risk of oil supply disruptions associated with price spikes
Oct. 2007 (SBI=114): disruptions in electricity supply (particularly power outages in Barcelona, Leon, and Sevilla)
Apr. 2008 (SBI=109): risk of water shortages due to extreme heat
May. 2008 (SBI=111): risk of water shortages due to extreme heat, risk of oil supply disruptions associated with price spikes

Jun. 2008 (SBI=289): transport strike
Jan. 2009 (SBI=127): storm-related disruptions in northern regions
Aug. 2009 (SBI=101): water and electricity shortages in southern regions (particularly in Sevilla and Cadiz)
Mar. 2010 (SBI=157): interruptions in electricity supply in Girona due to adverse weather conditions
Aug. 2010 (SBI=101): interruptions in electricity supply in coastal areas
Mar. 2011 (SBI=163): supply interruptions related to the Fukushima earthquake
Dec. 2011 (SBI=107): gas supply disruptions from the Algeria-Spain pipeline
Feb. 2012 (SBI=104): shortage of selected medicaments
Jan. 2017 (SBI=101): bacterial meningitis vaccine shortages, cold weather supply disruptions
Sep. 2019 (SBI=105): power outage in Canary Islands, risk of supply disruptions associated with possible no-deal Brexit

Post-COVID:
Oct. 2021 (SBI=993): chip shortages, risks to gas supply from Algeria
Nov. 2021 (SBI=978): pandemic-related disruptions
Mar. 2022 (SBI=1344): transport strike

Italy

Pre-COVID:
Jan. 2009 (SBI=180): interruption of gas supply from Russia
Jun. 2010 (SBI=103): gas supply disruptions due to disagreement between Belarus and Russia
Feb. 2011 (SBI=183): risk of gas interruption from Libya, due to civil war
Oct. 2011 (SBI=107): hospitals supply shortages, supply disruptions due to earthquake in Liguria
Jan. 2012 (SBI=142): electricity and gas disruptions due to bad weather
Feb. 2012 (SBI=229): electricity and gas disruptions due to bad weather
May 2012 (SBI=130): refunds for bad weather in January

Mar. 2014 (SBI=118): risk of gas supply disruptions due to the Ukrainian crisis
Dec. 2014 (SBI=104): cold weather disruptions in gas supply
Feb. 2015 (SBI=186): Maserati factory supply shortages, electricity supply disruptions
Jul. 2015 (SB1=111): water supply disruptions
Nov. 2015 (SBI=105): water supply shortages, Alfa Romeo factory supply disruptions
Jan. 2017 (SBI=112): cold weather supply disruptions
Nov. 2018 (SBI=123): energy and water supply disruptions due to bad weather
Jul. 2018 (SBI=118): shortage of selected medicaments

Post-COVID:
Jan. 2021 (SBI=789): vaccine shortages
Oct. 2021 (SBI=555): chips and raw material shortage
Mar. 2022 (SBI=696): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
Apr. 2022 (SBI=614): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
May 2022 (SBI=686): risk of oil and gas stop from Russia
Jun. 2022 (SBI=628): risk of oil and gas stop from Russia

France

Pre-COVID:
Apr. 2006 (SBI=101): water supply shortages due to low levels of underground water reserves
Jun. 2006 (SBI=111): steel supply shortages
Aug. 2006 (SBI=149): water supply shortages
Nov. 2006 (SBI=119): diverse supply shortages (electricity, electronic components, textile manufacturers' input materials)
Jan. 2007 (SBI=146): roads blocked by snowed caused supply disruptions in the factories of Peugeot-Citroën, gas disruptions due to 2007 Russia–Belarus energy dispute
Jun. 2007 (SBI=116): fish market supply disruptions
Dec. 2007 (SBI=102): transport strike, water supply issues, problems in input supplies to auto industry
Apr. 2008 (SBI=127): organic food supply shortages, strike in Coca-Cola factory

Jan. 2009 (SBI=173): interruption of gas supply from Russia
Dec. 2009 (SBI=141): oil supply disruptions due to a pipeline rupture, energy supply disruptions due to multiple worker strikes
Oct. 2010 (SBI=257): oil shortages due to pension reform strike
Mar. 2011 (SBI=121): supply problems related to the Fukushima earthquake
Jun. 2011 (SBI=151): oil supply disruptions from Libya, due to civil war
Jun. 2013 (SBI=110): crops supply shortages due to hailstorms and heavy rains
May. 2016 (SBI=249): oil shortages due to new labor law strike
Jul. 2016 (SBI=159): fuel shortages due to strikes, bad weather supply disruptions
Aug. 2018 (SBI=155): different supply problems
Sep. 2018 (SBI=110): bitumen supply shortages
Nov. 2018 (SBI=145): oil shortages due to Gilets Jaunes strike
Dec. 2018 (SBI=240): oil shortages due to Gilets Jaunes strike
Feb. 2019 (SBI=109): supply shortage of medicines

Post-COVID:
Apr. 2020 (SBI=1182): pandemic disruptions
May. 2020 (SBI=1026): pandemic disruptions
Aug. 2021 (SBI=885): pandemic-related disruptions (semiconductors and raw materials)
Jan. 2022 (SBI=973): chip shortages, risk of oil and gas disruptions related to RUS–UKR war, problems with nuclear power stations over corrosion
May. 2022 (SBI=1086): supply shortages, risk of oil and gas disruptions related to RUS–UKR war, problems with nuclear power stations over corrosion
Jul. 2022 (SBI=884): supply shortages, risk of oil and gas disruptions related to RUS–UKR war

Germany

Pre-COVID:
Dec. 2007 (SBI=89): Mercedes Benz and Sharp TV key components supply disruptions
Dec. 2010 (SBI=121): cold weather supply disruptions

Apr. 2011 (SBI=107): electricity companies supply disruptions due to shutdowns in gas and coal power plants
Nov. 2012 (SBI=87): delay in delivery of new regional transportation trains intended for winter
Dec. 2012 (SBI=100): supply shortages of medicines, domestic train manufacturers supply disruptions
Jun. 2013 (SBI=113): long-distance trains supply shortages
Nov. 2013 (SBI=84): medicines supply disruptions
Aug. 2016 (SBI=136): Volkswagen key component supply disruptions
Dec. 2016 (SBI=99): medicines supply disruptions
Apr. 2017 (SBI=119): medicines supply disruptions (particularly anesthetic deliveries)
May. 2017 (SBI=109): BMW components supply disruptions
Jul. 2017 (SBI=105): Bayern painkillers supply shortages
Aug. 2017 (SBI=116): disruptions in egg supply, closure of Rhine Valley railway route
Jul. 2018 (SBI=88): risk of water shortages due to extreme heat
Aug. 2018 (SBI=95): risks for German car manufacturers due to U.S. and Mexico free-trade agreement, shortage of truck drivers
Oct. 2018 (SBI=104): fuel delivery shortages by maritime routes due to low water levels, Frankfurt Airbus plant production disruptions
Dec. 2018 (SBI=124): flu vaccines supply disruptions
Feb. 2019 (SBI=109): construction materials supply disruptions (particularly sand)
Mar. 2019 (SBI=86): medicines supply disruptions (particularly oxytocin)
Apr. 2019 (SBI=113): power generation supply disruptions due to energy transition, risk of supply disruptions associated with possible no-deal Brexit
May. 2019 (SBI=87): Loewe supply disruptions; closure of Russian oil pipeline
Jul. 2019 (SBI=149): medicines supply disruptions
Nov. 2019 (SBI=91): multi-day strike in Amazon, Leipzig, medicines supply disruptions (particularly antidepressants and epilepsy related)
Dec. 2019 (SBI=123): medicines supply disruptions

Post-COVID:
Mar. 2020 (SBI=809): pandemic disruptions
Apr. 2020 (SBI=980): pandemic disruptions
Oct. 2021 (SBI=952): pandemic-related disruptions (particularly chip shortages)
Mar. 2022 (SBI=1096): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
Apr. 2022 (SBI=824): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
May. 2022 (SBI=878): chip shortages, risk of oil and gas disruptions related to RUS–UKR war
Jun. 2022 (SBI=812): chip shortages, risk of oil and gas disruptions related to RUS–UKR war

China

Pre-COVID:
Jan. 2011 (SBI=142): cold weather disruptions in transportation and energy supply, steelmakers supply shortages due to floodwaters disrupting vital coal supplies from Australia
Feb. 2011 (SBI=130): farm products supply shortages (particularly vegetables and grain), refined oil products supply shortages
Mar. 2011 (SBI=198): supply interruptions related to the Fukushima earthquake
Apr. 2011 (SBI=195): supply interruptions related to the Fukushima earthquake (particularly car makers), power outages supply disruptions in aluminum and lead-acid battery industries
May. 2011 (SBI=182): power generation supply disruptions due to a shift in investment to new energies, supply disruptions related to a drought along the Yangtze River
Jun. 2011 (SBI=137): energy supply shortages
Jul. 2011 (SBI=128): energy and copper supply shortages
Jan. 2012 (SBI=104): fuel supply shortages
Dec. 2017 (SBI=115): gas supply shortages
Jul. 2018 (SBI=113): tariff war with the United States resulting in supply shortages of soybeans, sport-utility vehicles, and chemicals
Feb. 2019 (SBI=104): risk of supply disruptions associated with a possible no-tariff relief with the United States, iron ore supply shortages

May. 2019 (SBI=127): copper supply shortages, housing supply shortages in Hong Kong
Sep. 2019 (SBI=119): nickel ore supply disruptions, pork supply shortage caused by African swine fever

Post-COVID:
Feb. 2020 (SBI=590): pandemic disruptions
Mar. 2020 (SBI=469): pandemic disruptions
Oct. 2021 (SBI=536): energy supply disruptions related to shortage of coal supply, labor force shortages related to pandemic restrictions
Apr. 2022 (SBI=545): manufacturers supply shortages related to pandemic disruptions
May. 2022 (SBI=560): labor force shortages related to pandemic restrictions

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