Measuring Shortages Since 1900*

Dario Caldara Matteo Iacoviello David Yu

May 2024

PRELIMINARY AND INCOMPLETE DRAFT

Abstract

This paper introduces a monthly shortage index for the United States from 1900 to 2023, constructed using a sample of approximately 25 million newspaper articles. The index measures the intensity of shortages of labor, materials, goods, and energy by calculating the proportion of articles discussing shortages each month. The resulting index reveals significant variation in shortage intensity over time, with notable peaks during periods of economic turmoil and wars. We explore the relationship between the shortage index and key economic indicators, discussing potential applications for researchers, policymakers, and businesses.

KEYWORDS: Shortages; Textual Analysis.

JEL CLASSIFICATION: C43, E32, N11, N12.

*Corresponding author: Matteo Iacoviello (matteo.iacoviello@frb.gov). All authors are affiliated with the Federal Reserve Board. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

1 Introduction

Shortages, defined as a lack of sufficient supply to meet demand, have been a recurring feature of economic life throughout the 20th and early 21st centuries. The hallmark of the economics discipline is the study of the scarce allocation of resources. It is therefore to be expected that shortages could have significant impacts on consumers, businesses, and the overall functioning of the economy. Yet, despite their importance, there has been limited research on the long-term trends and patterns of shortages across various sectors.

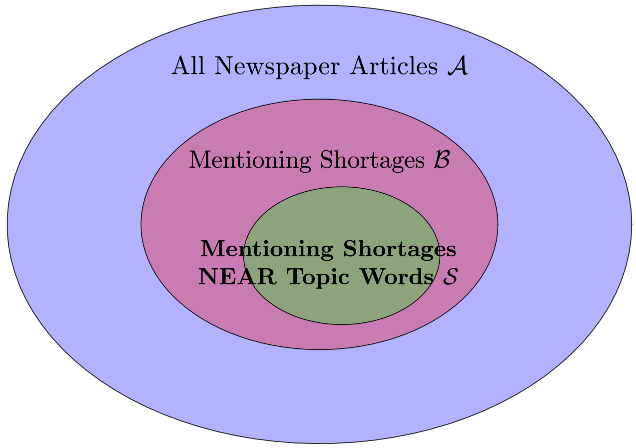
This paper aims to fill this gap by constructing a monthly shortage index for the United States using newspaper articles from 1900 to 2023. The shortage index is a news-based indicator of the intensity of shortages of labor, materials, goods, and energy in the United States. It is constructed using a sample of about 20,000 news articles per month from six major U.S. newspapers. In total, approximately 25 million articles are used in the construction of the index.

Our approach builds on previous work using news-based measures to track economic phenomena, such as the Economic Policy Uncertainty Index (Baker et al., 2016) and the Geopolitical Risk Index (Caldara and Iacoviello, 2022). However, to our knowledge, this is the first attempt to create a comprehensive shortage index for the United States spanning over a century. We hope that the resulting shortage index can provide a valuable tool for researchers, policymakers, and businesses to study the dynamics of shortages and their relationship to various economic, political, and social factors. By examining the index in conjunction with other economic indicators, we can gain insights into the causes and consequences of shortages and inform policy responses.

A number of other studies have also used news sources to construct indicators of shortages such as ours. Example include Bernanke and Blanchard (2023), Chen and Houle (2023), Lamont (1997), Pitschner (2022), Benigno et al. (2022), Burriel et al. (2023). The novelty of our approach is that our index is the first spanning over 125 years.

The remainder of the paper is structured as follows. Section 2 discusses the construction of the index, presents the index and discusses its evolution over time. Section 3 validates the index. Sections 4 and 5 explore the relationship between the shortage index and economic activity and inflation in the United States, using predictive regressions and a VAR, respectively. Section 6 concludes and discusses potential applications and future research directions.

Figure 1: Grouping of Newspaper Articles for the Construction of the Shortages Index.



2 The Shortage Index

In this section, we first discuss the construction of the shortage index. We then show how the index captures key episodes of shortages in U.S. history.

2.1 Construction of the Index

The shortage index is a monthly news-based indicator of the intensity of shortages of raw materials, goods, services and labor in the United States. It is constructed using a sample of about 20,000 news articles per month from 1900 through the end of 2023—for a total of about 25 million articles—published in the *Boston Globe*, the *Chicago Tribune*, the *Los Angeles Times*, *The New York Times*, *The Wall Street Journal*, and *The Washington Post*. Each month, the index counts the number of articles discussing energy, food, industry or labor shortages—the set $\mathcal{S}$ depicted in Figure 1— normalized by the total number of articles, the set $\mathcal{A}$. Higher values of the index indicates higher intensity of shortages. In what follows, we discuss the steps that led to the search query used to isolate the set of articles $\mathcal{S}$.

We start by constructing the set of articles $\mathcal{B}$, represented in by the pink area in Figure 1. The articles in this set contain at least one mention of a shortage word—namely 'shortage', 'scarcity', 'bottleneck' and 'rationing'—in conjunction with one or more economics words—such as the words 'economy,' 'market,' or 'commerce'. The 'shortage' words above are those more frequently associated with economically-relevant constraints to the production capacity of a country or to the availability of goods to consumers. The inclusion of at least one economics-related word in the search reduces the likelihood of false positives, that is, articles mentioning shortage words unrelated to the economic phenomenon that we intend to measure.[1]

We then draw from $\mathcal{B}$ a random sample a little over 3,300 articles, which we use to construct a list of the 1,000 most frequent collocates within five words of the 'shortage' words above. We select from this list words highlighting shortages in particular sectors of the economy or of particular goods. The most common words in the list (excluding stopwords) are oil, water, war, time, coal, days, food, cars, people, government, million, labor, state, home, steel, and fuel. In particular, we remove low-information words such as 'time' or 'days', as well as other words that convey little content about the topic at hand, such as 'people' or 'government'. The resulting list of collocates constitute our set of topic words that, for ease of exposition, we group into four categories related to food, industry, labor, and energy.

With these three lists of words (shortage words, economics words, and topic words), we construct the search query shown in Table 1. An article contributes to the shortages index—the set $\mathcal{S}$ in Figure 1—when two conditions are met: first, a shortage word must appear within five words (*N/5*) of a topic word; second, the article contains at least one economics word. If an article meets these two conditions and contains topic words from two categories, for instance both energy and food topic words, it is counted twice in the index. Thus, the number of shortage articles is then the sum of the articles in each of the four categories in that period. This definition allows us to weight articles that discuss multiple types of shortages more heavily in the overall index. In Section 3, we show that requiring shortage words to appear in close proximity to topic words is a critical part of our methodology. This step reduces the number of false positives and improves the accuracy of our search.

The classification into four topics is supported by the Latent Dirichlet Allocation (LDA) analysis that we perform ex-post on a sample of articles satisfying our criterion for inclusion in the index. LDA is a popular unsupervised machine learning technique used for topic modeling in natural language processing, and is designed to discover hidden topics within a collection of documents by analyzing the co-occurrence of words in these documents. There are two inputs to the algorithm. The first is the corpus of documents of text to be analyzed. Here,

[1] Other potential synonyms of shortage, such as "lack" or "paucity" or "insufficiency," either have a wider range of meanings, or are less likely to be exclusively associated with economic shortages.

the corpus is a random sample of 13,623 abstracts of newspaper articles mentioning shortages and satisfying our criterion for inclusion in the index. This sample is about 4 percent of the approximately 330,000 articles that are included in our index from 1900 to 2023.[2] The second input is the number of clusters, or topics, which we set to four.

The results of the LDA analysis are illustrated and summarized in Figure 2. The most recurrent words for each topic are presented as word clouds in the panels to the left. Topic 1 focuses on energy, topic 2 on water, food and agricultural products, topic 3 on industrial products such as coal, steel, railroads, cars, and topic 4 on jobs. The stacked bar chart to the right visualizes the topic mixtures for each abstract by year, for a total of 13,623 bars, sorted by year. Each article straddles different topics. Early in the sample, industry-related and, to a lesser extent, food and water shortages dominate the conversation. Energy-related shortages are the most common topic throughout most of the 1970s. Labor-related shortages become more prevalent in the post-pandemic years.

2.2 Shortages In History

We now present the shortage index, examine spikes, and consider the historical context in which the spikes occurred. Figure 3 plots the shortage index at a monthly frequency from 1900 through the present. The index is calculated by taking the monthly share $\mathcal{S}/\mathcal{A}$, scaled dividing by its mean over the period 1900-2023 and multiplying by 100, so that the average value of the index over the sample is 100. In Table 2, we list the thirty largest spikes in the index, accompanied by a description of the key events surrounding each episode.[3]

Over its long history, the index exhibits considerable variation, and the episodes behind the spikes in the shortage index are related primarily to three themes: geopolitical events, labor shortages and energy shocks. First, adverse geopolitical events, especially wars, are associated with severe shortages. Most notably, the index rises dramatically during World War I. It surges during World War II, reaching a value above 1,000 (10 times larger than the sample mean) in

[2] Following standard practice, before using the words in the LDA analysis we remove stopwords and numbers. We also stem the words reducing them to a common root.

[3] To calculate spikes, we start with the residuals of a regression of the shortage index h_t against its value two months before and two months after. The largest residuals thus represent the largest surprises and form our list of candidate spikes. Next, we eliminate a candidate spike if it occurs in a month t in which the index itself is not a local maximum over the 13-month period $[t-6, t+6]$. This step ensures that the identified spikes are not just large residuals, but also (locally) peak values. Of the remaining observations, the ones with the thirty largest residual values are reported in Table 2.

January 1943. Second, many spikes are associated with labor shortages, especially those caused by strikes. These tend to occur towards the beginning of our sample (for example, coal-related strikes in 1903, 1919, and 1922). Strike-related shortages are less frequent in more recent years. Third, instead, post-World War II spikes are often associated with energy shortages, especially those relating to geopolitical turmoil in the Middle East. Oil supply issues crop up repeatedly, occurring at the same time as jumps in the index during the Suez Crisis, the oil shocks of the 1970s—associated with the only other reading of the index above 1,000—, and around the Iraqi invasion of Kuwait in 1990.

Figure 4 breaks down the shortage index by topic. This decomposition illustrates that the aforementioned jumps in the index largely reflect a spike in the energy component of our index, consistent with the oil events of the time. Fourth, the index increases multiple times around the Covid-19 pandemic. The first spike corresponds to shortages of medical equipment and nursing staff at the onset of the pandemic. The second spike is larger and occurs at the beginning of 2022 when global supply bottlenecks emerged, as many economies reopened following prolonged mobility restrictions in 2020 and 2021. This second spike, as seen in Figure 4, is mostly composed of increases in the labor and industry components.

Finally, we also compare our index to a global version. The global index includes articles which meet the requirements to be included in the original index, but also requires that an international word (such as the name of a country, major city, or related term) appears in the article. Figure 5 plots both the original index and the global counterpart. Both measures are fairly similar, as they spike around the same time. The main exception is the US-only spike in the mid-1970s, which occurred around the time of then-U.S. President Carter's proposal to conserve energy.

This section has described how we construct and descriptively interpret the index. In the next section, we assess the accuracy of our index.

3 Assessing the Accuracy of the Shortage Index

We conduct two separate exercises to assess the accuracy of the index. In the first, we verify that the newspaper articles included in the index mention concerns about shortages. In the second, we verify that the index is aligned with alternative measures of shortages for the period in which these alternatives exist and overlap with ours.

3.1 Validation of the Shortage Index

We verify that our index measures accurately shortages by minimizing Type-I and Type-II error. We sample the abstract of 872 articles belonging to the shortage set $\mathcal{S}$.[4] By construction, each of these articles contains at least one business-related word as well as one mention of scarcities, shortages or bottlenecks in proximity of a topic word such as energy, food, industry and labor. For each article, we extract the first snippet of text that contains references to shortages. We center the snippet around the shortage word, and set its length to 110 characters, drawing inspiration from Twitter's original 140-character limit, and striking a balance between brevity and computational and cognitive burden. For instance, examples of recent and old snippets in our sample are respectively "[A]lthough demand remains strong. ... the resulting supply shortage of german manufacturing goods could also...", from 2021; and "[...] men interested in the industries affected by shortage of steel are anxious to see the strike settled," from 1901.

We then use the Claude AI assistant (Anthropic, 2024) to determine whether each snippet mentions current or prospective shortages, rationing, scarcity, or bottlenecks related to goods, labor, materials, food, or water. Claude was instructed to return a table of results coding articles either as 1—shortage mentioned—, or zero—shortage not mentioned—or 99—unsure whether the existence of shortages was mentioned. In addition to the classification, Claude was asked to provide a brief explanation for the coding of each snippet.

Before the classification, we provided Claude with some examples of how we would code the snippets, and made sure that the training sample included false positive, mentioning for instance lack or end of shortages.[5] Use of AI for validation is not foolproof, but we found Claude did as good as a job as a human, for instance by extrapolating the context of a particular sentence to a particular country or person. For instance, for the sentence "economy

[4] Our search query to calculate the index relies on the six U.S. newspapers listed in Section 2. For technical reasons, abstracts are not available for these newspapers since 2015. For the period 2015-2023, we sample the abstract we used for the validation from a larger set of newspapers, including some U.K., Canadian, and Australian ones. A detailed list of the 872 abstracts and sources used for validation is available upon request from the authors. Abstract are short portions of text often containing the initial sentences or the initial paragraph of the entire article.

[5] The specific prompt was as follows. "I give you 872 snippets of text each about 110 characters long. For each of them, can you tell me whether they mention current or perspective shortages or rationing or scarcity or bottlenecks related to goods, labor, materials, food, water? Just return a table with yes=1, no=0, unsure=99, and a brief explanation. For instance. Article 1 mentions perspective shortages since it mentions that steel shortages will prevail in the near future, so it is a 1. Article 2 says steel shortages caused a plant closure, so it is coded 1. Article 3 says shortage of cars is crimping coal production, so 1. Article 4 mention shortage of cars, so 1. Article 10 mention shortage of workspace, so not really a work shortage, so 0. Article 329 says no shortage of cars has been experienced, so 0."

may be slowing but Lowe is banking on labour shortages gradually leading to an increase...", Claude classified the text as 1 and added that "Reserve Bank [of Australia] expecting labour shortages to lead to wage growth."

The results of the audit are in Table 3. Out of 872 articles belonging to the set set $\mathcal{S}$, only 6.3 percent were deemed by ClaudeAI as false positives.[6]

We then repeat the audit for a sample of 298 articles not belonging to the set $\mathcal{S}$. Out of these 298 articles, only one appears to mention shortages but is not captured by our search query ("recycling of newsprint was held back by a shortage of deinking plants"). Of note, our search query deliberately did not include the word "plants" since in preliminary attempts we found instances of false positives associated with this word.[7]

Finally, we confirm that restricting the search to include shortage words in proximity of words indicating goods, labor, food or energy improves the accuracy of the search. The share of articles mentioning economically-relevant shortages in the set that allows for, but does not require the presence of shortage words is 84.2 percent, corresponding to a Type I error of 15.8 percent, much larger than in our preferred search query. False positives included in this set—that are not captured by our preferred search query—include articles mentioning shortages of political campaign funds, lack of good baseball photos, legislative bottlenecks, and shortage of sunshine.

3.2 Comparison with Other Indicators of Supply Constraints

In this section, we compare our index with other, related measures of supply constraints.

In Figure 6, we plot our shortage index alongside the New York Fed Global Supply Chain Pressure (GSCPI) Index, the Supplier Delivery Index (SDI), and the Supply Bottlenecks Index (SBI) for the US. We standardize each of the variables to have mean 0 and variance 1. The GSCPI is published by the Federal Reserve Bank of New York and is designed to

[6] For instance, Claude classified the snippet "...says that while there is not necessarily a shortage of people wanting to work in management" as 0 with the explanation "No shortage of people wanting to work in management." Similarly, the snippet "a motive for mr. newt gingrich's knife job, had no shortage of conspiracy theories, most leading to the..." was classified as 0 with the explanation "Speaker's ouster sparked many conspiracy theories but not actual shortages." In some cases, Claude classified as 0 articles that we would have probably classified as 1. For instance, the snippet "canada's action today in temporarily suspending meat rationing" was classified as 0 since Claude gave more weight to the temporary suspension of the rationing rather than its existence.

[7] See for instance the article "Brighten Up Indoors With Colorful Plants" (Los Angeles Times, Feb. 4, 1996) that states "there's no shortage of plants with brightly colored foliage to liven up your kitchen."

measure supply chain conditions around the world, using data on both manufacturing and transportation costs. The SDI is published by the Institute of Supply Management (ISM), and captures the result of a monthly survey which asks firms whether they are experiencing longer or shorter wait times compared to the previous month. The value of the SDI is the share of respondents reporting longer wait times plus half the share of respondents reporting no change. The SBI is produced by Burriel et al. (2023) and uses a text-based newspaper search to quantify the level of supply chain issues. An advantage of our index relative to these indicators is that our index is available over a much longer period of time.

Figure 6 shows that our index is visually similar to these three inidcators. Over the entire existence of the GSCPI, the correlation between our index and the GSCPI is 0.73. Both measures increase sharply at the onset of Covid-19 in early 2020, and again in the beginning of 2022 as supply chain bottlenecks took hold.

There is a lower correlation between our index and the SDI. This comparison begins in 1976, when the SDI starts. Our measure has a correlation of 0.25 with the SDI. Both measures spike around the 1979 oil crisis and Covid-19. One possible explanation is that both events brought about severe delays in transportation (via fuel costs and supply bottlenecks, respectively), which may have led to shortages for manufacturers captured by the rapid increases in both indices.

Finally, our index has a correlation of 0.90 with the US SBI. Additionally, Burriel et al. (2023) produce indices for other countries (Germany, France, Italy, Spain, Great Britain, and China). Our index is similarly highly correlated with these indices for the overlapping sample period. These correlations suggest that our index is capturing similar movements as other related supply chain variables.

4 Shortages as Predictors of Inflation and Activity

Figure 7 illustrates a positive relationship between U.S. inflation and our indicator of shortages for a sample starting in 1940. In this section, we formally explore the relationship between shortages and near-term inflation and economic activity. Specifically, we estimate the following predictive regression:

$$\Delta Y_{t+h} = \alpha + \beta SHORTAGE_t + \Sigma_{i=0}^{p} \mathbf{X}_{t-p} + \varepsilon_{t+h}, \tag{1}$$

where $\Delta Y_{t+h} = \frac{400}{h}\ln(\frac{Y_{t+h}}{Y_t})$ is the annualized log change of a variable of interest Y_t between period t and forecast horizon h; $SHORTAGE_t$ denotes the level of the shortage index. $\mathbf{X}$ is a vector of control variables.

We use quarterly data from 1950 through 2023 from the National Income and Product Accounts (NIPA) for real per-capita GDP, personal consumption expenditure, and private fixed investment. We measure inflation for each category using the associated price deflators. For GDP and its price deflator, we extend the sample back to 1900 using data from Ramey and Zubairy (2018). Data on total population are also from Ramey and Zubairy (2018), which we extend through 2023 using the POP series from FRED.

For each price and economic activity indicator, we estimate regression (1) separately by OLS. As control variables, we include quarterly changes of the dependent variable and the associated economic indicator or price deflator, contemporaneously and with three lags. For instance, the predictive regression for real GDP growth includes contemporaneous and lagged values of both real GDP growth and GDP inflation.

We tabulate results for the one-year ahead regressions in Table 4, while results for the one- and eight-quarter horizons are reported in Table A.1 and Table A.2, respectively. To facilitate comparison across variables, we report standardized estimates of the coefficients β. A standardized coefficient represents the movement of the dependent variable (in standard deviation units) in response to a one standard deviation change in the explanatory variable.

The first two columns of Table 4 report estimates for the full sample. An increase in shortages is associated with a rise in inflation (first column) and a decline in economic activity (second column), the typical effects of supply-side disruptions. The inflationary effects of shortages are evenly distributed across GDP components, with the price of services consumption being the least impacted. While consumption of durable goods and private fixed investment decline, there is no statistically significant effect on the consumption of nondurable goods and of services.

To quantify the economic effects of shortages, take for instance the standardized coefficients of 0.25 and -0.25 estimated for durable consumption inflation and real growth, respectively. A one-standard deviation increase in the shortage index is associated with an increase in durable goods inflation of 0.75 percentage point and a decline in durable goods consumption growth of 1.75 percentage points. The coefficients for GDP imply an increase in inflation of 0.5 percentage point and a reduction in growth of 0.3 percentage points.

The remaining columns of Table 4 show that the results for the full sample hide notable time variation in the relationship between shortages, inflation and economic growth. In a sample running from 1950 through 2014, we find that the effects of shortages on inflation and activity are more precisely estimated. In addition, the reduction in economic growth is widespread, sparing only private consumption of services. In a sample starting in 2015 and encompassing the Covid pandemic, the effects on inflation are substantially larger, albeit less precisely estimated. The coefficients on economic growth become *positive*, although mostly not statistically significant. We interpret the estimates as evidence of a more prominent role of demand forces in driving shortages during and in the aftermath of the Covid-19 pandemic compared to the pre-Covid sample.

The estimates for the sample starting in 2015 are consistent with the U.S. experience since the Covid pandemic. Strong demand and weak supply both contribute to the emergence of shortages. Both demand and supply forces push prices in the same direction—and have contributed to the rise of inflation—while having opposite effects on economic activity, thus contributing to the resilience of economic activity.

One might wonder whether the Covid-19 experience has been unique, or whether other historical episodes of shortages were also associated with a role for private demand. We investigate this question running regression (1) on a rolling sample using a 30-year window. We focus on real GDP growth and inflation to leverage data prior to World War II. Figure 8 shows the results for inflation (top panel) and real GDP growth (bottom panel).

Starting with World War II, shortages have consistently exerted inflationary effects. The 10 years prior to the pandemic are a notable exception, due to the fact that in the three decades prior to the pandemic, the U.S. did not experience episodes of severe shortages against a background of remarkable stable inflation.

Shortages have exerted economically meaningful and statistically significant adverse effects on economic activity starting in the 1970s up until the Covid-19 pandemic. In contrast, an increase in our index is associated with higher activity around just two historical episodes: the Covid pandemic and World War II. Rationing, which was commonplace during the war, implies that demand outstripped supply. Thus both episodes, through their own unique circumstances, were times in which high demand propped up economic activity. Furthermore, the imposition of price caps during the war may have contributed to keeping inflation more muted than expected.

In the next section, we take a different approach in investigating how shortages interact with demand and supply factors, estimating a structural VAR model.

5 Shortages and Activity: A VAR Analysis

In this section, we present a simple structural VAR model of the US economy that incorporates shortages. The idea is to decompose movements in shortages, GDP and inflation into mutually orthogonal components with an economic interpretation.

Consider a model based on quarterly data for economic activity, inflation, and shortages summarized by the vector $\mathbf{X}_t = (y_t, \pi_t, h_t)'$. Economic activity is measured by four-quarter change in log GDP, inflation is measured by the four-quarter change in the log of the GDP deflator, and shortages are expressed in levels (and standardized). All series are demeaned.

The economy has a vector autoregressive representation given by:

$$\mathbf{A}\mathbf{X}_t = \sum_{j=1}^{p} \boldsymbol{\alpha}_j \mathbf{X}_{t-j} + \mathbf{B}\mathbf{u}_t, \tag{2}$$

where $\mathbf{u}_t = (u^S, u^D, u^H)'$ is a vector of structural shocks described below, p is the lag length, and $\mathbf{A}$, $\mathbf{B}$, and $\boldsymbol{\alpha}_j$ for $j = 1, ..., p$ are matrices of structural parameters. The structural shocks have zero mean and variance–covariance matrix $E[\mathbf{u}_t \mathbf{u}_t'] = \boldsymbol{\Sigma}_u$. Without loss of generality, we normalize one entry on each row of $\mathbf{A}$ to 1 and we assume that $\boldsymbol{\Sigma}_u$ is a diagonal matrix.

Abstracting from lagged terms, the following three equations describe the joint modeling of shortages and economic activity, and summarize the contemporaneous restrictions that we impose on the parameters in the matrices $\mathbf{A}$ and $\mathbf{B}$:

$$y = \kappa\pi + u^S, \tag{3}$$

$$y = -\delta\pi + u^D, \tag{4}$$

$$h = u^H - \theta_S u^S + \theta_D u^D. \tag{5}$$

Equation (3) is an aggregate supply equation: total production is positively related to prices ($\kappa > 0$), and subject to supply shocks u^S. Equation (4) is an aggregate demand equation: it states that aggregate demand y is inversely related to inflation ($\delta > 0$), and subject to demand shocks u^D. The model does not allow shortage shocks to impact demand and supply within a quarter. Thus, the effects of shortages on economic activity and prices happen with at least a one-quarter delay and depend on the lagged feedback from shortages to GDP and prices captured by the coefficients $\boldsymbol{\alpha}_j$ for $j = 1, ..., p$.

Equation (5) assumes that shortages reflect both "regular" business cycle movements caused by supply and demand shocks, and an "exogenous" component that proxies for newsworthy disruptions to the regular flow of goods, services and factors of production in an economy. Under this interpretation, innovations to u^H may capture unusual combination of shocks that are not captured by the u^D and u^S terms, such as atypical market adjustment in response to sudden shifts in economic conditions, a shock to regulation—such as mandated price ceilings or quantity rationing—that disrupts the regular functioning of a market economy, panic buying that suddenly causes rationing of certain goods, or weather events or geopolitical shocks that impede the regular flow of goods in an economy.

The matrices summarizing the system are therefore:

$$\mathbf{A} = \begin{bmatrix} 1 & -\kappa & 0 \\ 1 & \delta & 0 \\ 0 & 0 & 1 \end{bmatrix}; \ \mathbf{B} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -\theta_S & \theta_D & 1 \end{bmatrix}, \tag{6}$$

with the impact matrix relating variables at time t to structural shocks given by:

$$\mathbf{C} = \mathbf{A}^{-1}\mathbf{B} \equiv \begin{bmatrix} \frac{\delta}{\kappa+\delta} & \frac{\kappa}{\kappa+\delta} & 0 \\ \frac{-1}{\kappa+\delta} & \frac{1}{\kappa+\delta} & 0 \\ -\theta_S & \theta_D & 1 \end{bmatrix}. \tag{7}$$

Following Baumeister and Hamilton (2019), we view identification and estimation of this structural VAR model as a special case of a Bayesian VAR with prior restrictions imposed on the parameters of the matrices $\mathbf{A}$ and $\mathbf{B}$. To see why, consider the example in which one assumes a vertical within-quarter aggregate supply curve, so that $\kappa = 0$. The matrix $\mathbf{C} = \mathbf{A}^{-1}\mathbf{B}$ relating variables to structural shocks becomes lower triangular and the VAR model has a familiar recursive interpretation with variables ordered as (y_t, π_t, h_t).

Rather than fixing the slope of either the aggregate demand or the aggregate supply curve to identify the shocks—which would suffice to exactly identify the shocks—we estimate directly the structural parameters of the matrices $\mathbf{A}$ and $\mathbf{B}$ imposing prior distributions, which are plotted in red in Figure 9. Specifically, the priors for κ and δ are normally distributed with mean 2 and 1, respectively, and standard deviation 1 and 0.5. At the prior mean, the slope of the aggregate supply curve implies that in the short-run desired inflation rises 0.5 percentage point in response to a 1 percent increase in production. The slope of the aggregate demand curve implies that on impact a 1 percent contraction in GDP raises inflation by 1 percentage point. The support of the prior densities is wide, encompassing substantially smaller and larger elasticity values. As discussed in the empirical results, the data and the model structure lead to a substantial revision both in the location and spread of these distributions.

We set the priors for θ_S and θ_D so that they are drawn from an inverse gamma distribution with mean 0.25 and standard deviation 0.5. This choice of priors embeds the assumption that shortages, and associated news, can arise in response to standard demand and supply shocks within a quarter. Of note, implicit in our choice of priors is the assumption that expansionary demand shocks can only be associated with an increase in shortages, and that expansionary supply shocks can only be associated with a decrease in shortages (that, is, the support of θ_S and θ_D is positive).

The prior mean for the coefficients $\boldsymbol{\alpha}_j$ is set to 0.8 for the fist lag, and to 0 for subsequent lags.[8]

We estimate the model on quarterly data from 1950 through 2023 using standard Bayesian techniques. To construct the estimates of interest, we take 50,000 draws from the posterior distribution using a Random Walk Metropolis-Hastings algorithm.

Empirical Results

Figure 9 reports prior and posterior parameters distributions. Of note, the slope of the supply curve implies that a demand shock that raises GDP growth by 1 percentage point leads on impact to an increase in inflation of around 0.25 percentage points; and the slope of the demand curve implies that a supply shock that reduces GDP by 1 percentage point leads to an increase in inflation of about 0.5 percentage points. Additionally, shortages increases in response to expansionary demand shocks and decline in response to contractionary supply shocks.

Figure 10 reports the impulse responses to the estimated shocks in the model.

The full historical decomposition of the model is reported in Figure 11. Not all shortages

[8] The lagged coefficients $\boldsymbol{\alpha}_j$ are normally distributed with a tighter standard deviation the higher the lag order as in the VAR priors discussed in Doan et al. (1984) (we use 0.25 for the first lag and of 0.125 for the second lag). The prior on the standard deviation of the structural shocks is an inverse gamma with mean 1 and standard deviation 0.5.

are created equal. A large part of the shortages in the 1950s are driven by demand shocks, associated with the Korean war, pent-up demand after World War II, and the rapid economic recovery that accompanied the transitioning from a wartime to a peacetime economy. The oil shocks of the 1970s and 1980s drove an unusual rise in shortages.

Figure 12 reports the role of shortage shocks between 2020 and 2023. As the estimated effect of shortage shocks on inflation is long-lived, the identified shortages shocks account for a large share of the post-pandemic rise in inflation.

Discussion

We conclude this section with a brief discussion on why we estimate the effects of shortage shocks by imposing over-identifying restrictions relative to, say, a standard recursive VAR. As shortages are assumed to respond contemporaneously to demand and supply shocks, the identification of shortage shocks and their effects is largely independent of the specific assumptions that we make regarding the slope of the aggregate supply and the aggregate demand curve. However, the obvious advantage of a fully identified model such as ours is that it leads to an interpretation of shortage movements that is more natural and economically palatable. Consider two alternative versions of the model that are closer to a recursive identification scheme, with all parameters estimated without imposing prior restrictions on their magnitude or sign. In the first alternative version, when we assume that $\kappa = 0$, the resulting estimate of δ is close to 10, but the estimated demand and supply shocks make little economic sense. Supply shock move output a lot, but lead to very small movements in inflation as the aggregate demand curve is very flat. Demand shocks that increase inflation do not move output on impact by construction, but lead to a counterfactual decline in output in successive periods. Of course, one could relabel these shocks as adverse supply shocks, but the remaining shock moving prices and output also generates a negative comovement between the two variables, so no primitive economic shock moves output and inflation in the same direction. In the second alternative version, when we assume that $\kappa = 100$, so that the Phillips curve is essentially flat in the short run, the resulting estimate of δ is -0.24, so that the aggregate demand curve is upward sloping. Both estimated demand and supply shocks generate positive comovement between output and inflation, so that no primitive economic shock moves output and inflation in opposite directions. In sum, versions of the model estimated without imposing restrictions on the slope of the economy-wide aggregate demand and supply curve lead to a contrived interpretation of what drives movements in shortages. Our identification strategy, by contrast, places minimal restrictions that allow a far more natural interpretation of the forces driving shortages and the business cycle.

6 Conclusions

Concerns about supply limitations and resource constraints have been a very common theme in press coverage over the past century, whether during wartime, periods of economic upheaval, or as a result of natural disasters or trade disruptions. The specific markets impacted by shortages have evolved with changes in technology and consumption patterns, but the fundamental economic challenges of matching limited supplies with variable demand have remained a persistent source of public anxiety and policy debates. Policymakers and industries have responded to shortages with a variety of coping strategies including rationing essential goods, developing substitutes and alternatives, investing in expanded productive capacity, and promoting conservation. The recurrence of shortage events across decades shows the difficulty of permanently eliminating vulnerabilities in the face of population growth, rising living standards, geopolitical instability and environmental pressures. This paper has presented a monthly index of shortages going back to 1900. We hope that this analysis can prove useful to researchers.

References

ANTHROPIC (2024): "Claude," Conversational AI model developed by Anthropic, version from March 30, 2024. Available at https://www.anthropic.com.

BAKER, S. R., N. BLOOM, AND S. J. DAVIS (2016): "Measuring Economic Policy Uncertainty," *The Quarterly Journal of Economics*, 131, 1593.

BAUMEISTER, C. AND J. D. HAMILTON (2019): "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks," *American Economic Review*, 109, 1873–1910.

BENIGNO, G., J. DI GIOVANNI, J. J. GROEN, AND A. I. NOBLE (2022): "The GSCPI: A new barometer of global supply chain pressures," *FRB of New York Staff Report*.

BERNANKE, B. AND O. BLANCHARD (2023): "What caused the US pandemic-era inflation?" *Peterson Institute for International Economics Working Paper*.

BURRIEL, P., I. KATARYNIUK, C. MORENO PÉREZ, AND F. VIANI (2023): "A new supply bottlenecks index based on newspaper data," *Banco de Espana Working Paper*.

CALDARA, D. AND M. IACOVIELLO (2022): "Measuring geopolitical risk," *American Economic Review*, 112, 1194–1225.

CHEN, L. AND S. HOULE (2023): "Turning Words into Numbers: Measuring News Media Coverage of Shortages," Tech. rep., Bank of Canada.

DOAN, T., R. LITTERMAN, AND C. SIMS (1984): "Forecasting and conditional projection using realistic prior distributions," *Econometric Reviews*, 3, 1–100.

LAMONT, O. (1997): "Do" shortages" cause inflation?" in *Reducing Inflation: Motivation and Strategy*, University of Chicago Press, 281–306.

NEWEY, W. K. AND K. D. WEST (1987): "Hypothesis testing with efficient method of moments estimation," *International Economic Review*, 777–787.

PITSCHNER, S. (2022): "Supply chain disruptions and labor shortages: COVID in perspective," *Economics Letters*, 221, 110895.

Ramey, V. A. and S. Zubairy (2018): “Government spending multipliers in good times and in bad: evidence from US historical data,” *Journal of Political Economy*, 126, 850–901.

Table 1: Search Query

Search Name	**Search Query**	**Peak Month**
Energy Shortages	(*shortages* N/5 *energy*) AND *economics*	Dec-1973
Food Shortages	(*shortages* N/5 *food*) AND *economics*	Mar-1943
Industry Shortages	(*shortages* N/5 *industry*) AND *economics*	Aug-1942
Labor Shortages	(*shortages* N/5 *labor*) AND *economics*	Jan-2022
Articles	*articles*	–

Topic Sets	**Components**
shortages	`shortage* OR bottleneck* OR scarcit* OR rationing*`
energy	`oil OR gas OR coal OR fuel OR fuels OR gasoline OR energy OR heating OR petroleum OR electricity OR refinery OR pipeline OR petrol`
food	`food OR wheat OR meat OR milk OR crop OR crops OR grain OR farm OR agriculture OR famine OR feed OR farmer OR farmers OR water OR fertilizer OR drought`
industry	`steel OR copper OR iron OR metal* OR automotive OR textile OR machinery OR equipment OR transportation OR railway OR airline OR freight OR shipping OR transit OR deliveries OR shipment* OR ships OR chip* OR semiconductor* OR infrastructure OR materials OR distribution OR car OR cars OR parts OR goods OR material OR auto OR computer OR ‘supply chain’ OR components`
labor	`labor OR workers OR job* OR work OR employment OR manpower OR worker OR staff OR professional* OR technician* OR staffing OR skills OR workforce OR` personnel OR strike* OR union*
economics	`economic OR industr* OR production OR manufactur* OR economy OR trade OR commerce OR business OR budget OR tax OR fiscal OR corporation OR market OR price OR capacity OR company OR demand OR sales OR factory OR wages OR suppl*`
articles	`the AND be AND to AND of AND and AND at AND in`

Note: The truncation character (*) denotes a search including all possible endings of a word, e.g. “scarcit*” includes “scarcity” and “scarcities”.

Table 2: Largest Shortage Surprises

Month	Index	Surprise	Event
Jan-1903	166	118	Nationwide coal shortages
Dec-1906	182	108	Shortage of coal and freight cars in Midwest
Nov-1916	225	106	Nationwide coal shortages
Jan-1918	552	319	Fuel and coal shortages
Dec-1919	286	115	Fuel and coal shortages due to war, strikes
Jul-1920	303	97	Freight car shortage affects coal and steel transportation
Aug-1922	268	135	Coal shortage due to strikes
Aug-1930	89	53	Drought leads to food and water shortages
Jul-1934	128	71	Strike by Teamsters unions in the West Coast
Sep-1939	145	76	Steel shortage due to the beginning of WW2
Aug-1941	493	138	War-related energy, materials and labor shortages
Jan-1943	1036	203	War-related oil, labor and food shortages
Jan-1945	538	174	War-related widespread shortages
Aug-1945	531	144	Labor shortages at the end of war
May-1946	563	180	Strikes by coal workers and fuel shortages
Jan-1948	439	167	Metal, fuel and food shortages
Feb-1950	216	96	Coal shortages amid strikes
Jan-1951	273	102	Labor shortages due to demand from defense industries
Jan-1952	259	120	Nationwide and worldwide shortages
Dec-1956	164	75	Oil shortages due to Suez crisis
Dec-1973	1036	471	Gasoline shortages due to 1973 oil crisis
Jan-1975	255	84	Concerns about gasoline rationing
Feb-1977	403	284	Carter's appeal on energy conservation
Feb-1978	151	66	Concerns about energy shortages
May-1979	553	201	Concerns about energy shortages
Aug-1981	146	49	Gasoline shortages due to 1979 oil crisis
Aug-1990	153	61	Concerns about energy shortages
Apr-2020	284	191	Medical shortages due to COVID-19 pandemic
Jan-2022	529	112	Labor shortages
Oct-2023	205	51	Food shortages in Gaza

Note: The table lists the largest shocks to the shortage index. For this table, the shocks are constructed using the residuals of an autoregression and a condition on local maxima.

Table 3: Validation of the Shortage Index

Set	**Share of Total Newspaper Articles in Set**	**Validation Sample**	**Articles Mentioning Actual Shortages**	**Type I Error**	**Type II Error**
Shortages AND Topic Words $\mathcal{S}$	1.58%	872	817	6.30%	–
Not Shortages $\mathcal{A} \setminus \mathcal{S}$	98.42%	298	1	–	0.33%
All Shortages $\mathcal{B}$	2.93%	334	284	14.97%	–

Note: Validation of the Shortage Index using a sample of newspaper articles used or not used to construct the index.

Table 4: Predicted Effect of Shortages on Prices and Quantities (4-quarters ahead)

	(1) 1950Q1–2023Q4		(2) 1950Q1–2014Q4		(3) 2015Q1–2023Q4	
	Prices	Quantities	Prices	Quantities	Prices	Quantities
GDP	0.19**	-0.13	0.22***	-0.21***	1.02***	0.15
	(2.04)	(-1.32)	(3.54)	(-3.13)	(4.12)	(0.57)
PCE Durables	0.25*	-0.25***	0.37***	-0.33***	1.10	1.61*
	(1.70)	(-3.13)	(8.14)	(-3.99)	(1.31)	(1.73)
PCE Nondurables	0.31***	-0.15	0.37***	-0.23***	0.83*	0.23
	(2.94)	(-1.61)	(3.64)	(-2.78)	(1.85)	(0.52)
PCE Services	0.18***	-0.02	0.19***	-0.05	1.17***	0.90**
	(4.14)	(-0.24)	(4.79)	(-0.50)	(6.85)	(2.47)
Investment	0.28***	-0.25***	0.32***	-0.31***	1.27***	0.05
	(2.70)	(-3.51)	(5.73)	(-5.15)	(3.21)	(0.08)
Obs.	292	292	260	260	32	32

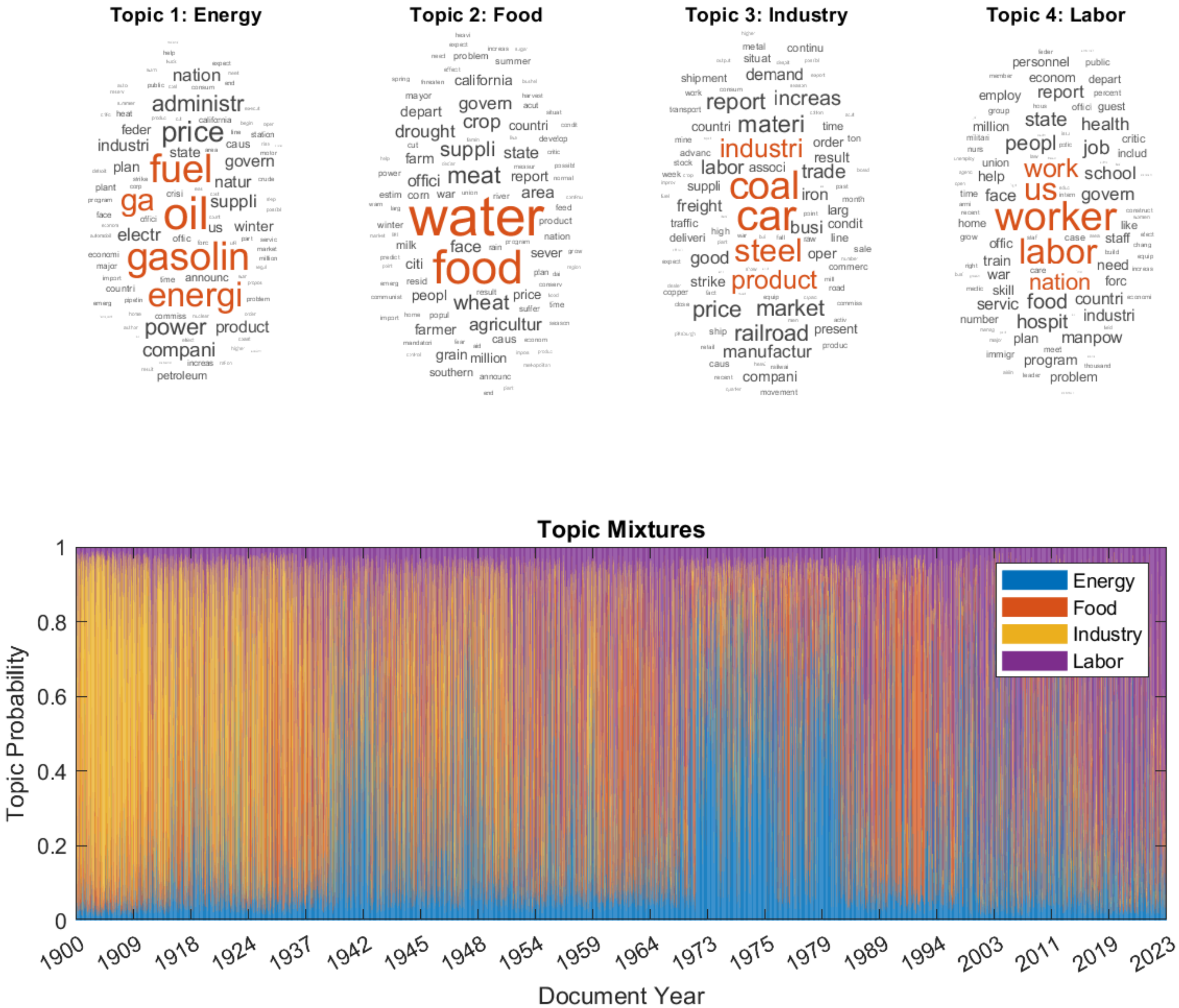
Note: The table reports standardized coefficients of predictive regressions of economic activity and inflation on the shortage index. The dependent variable for each regression is the log difference between $t+4$ and t of the variable listed in each row, both its real quantity and its associated price deflator. Each regression includes as controls the quarterly changes of the dependent variable and the associated economic indicator or price deflator, contemporaneously and with three lags. Data are quarterly. The full sample, reported in the first two columns, runs from 1950Q1 to 2023Q4. We also partition the sample into two periods: a "pre-Covid" period that runs from 1950Q1 to 2014Q4, and a "Covid" period which runs from 2015Q1 to 2023Q4. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses and computed according to Newey and West (1987). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Predicted Effect of Shortages on Prices and Quantities (with controls)

	(1) 1950Q1–2023Q4		(2) 1950Q1–2014Q4		(3) 2015Q1–2023Q4	
	Prices	Quantities	Prices	Quantities	Prices	Quantities
GDP	0.19**	-0.13	0.22***	-0.21***	1.02***	0.15
	(2.04)	(-1.32)	(3.54)	(-3.13)	(4.12)	(0.57)
Oil	0.16	-0.23**	0.22***	-0.38***	0.90*	0.16
	(1.64)	(-2.14)	(5.21)	(-4.03)	(1.88)	(0.36)
Commodities	0.19*	-0.21**	0.24***	-0.33***	0.92**	0.06
	(1.91)	(-2.02)	(6.11)	(-3.51)	(2.11)	(0.18)
Wages	0.17*	-0.20**	0.24***	-0.31***	0.36	0.65
	(1.67)	(-2.21)	(7.26)	(-4.00)	(0.74)	(0.95)
Inf. Exp. (1 Yr.)	0.25	0.00	0.00	-0.32**	1.14***	0.25
	(1.55)	(0.01)	(0.03)	(-2.31)	(4.93)	(0.70)

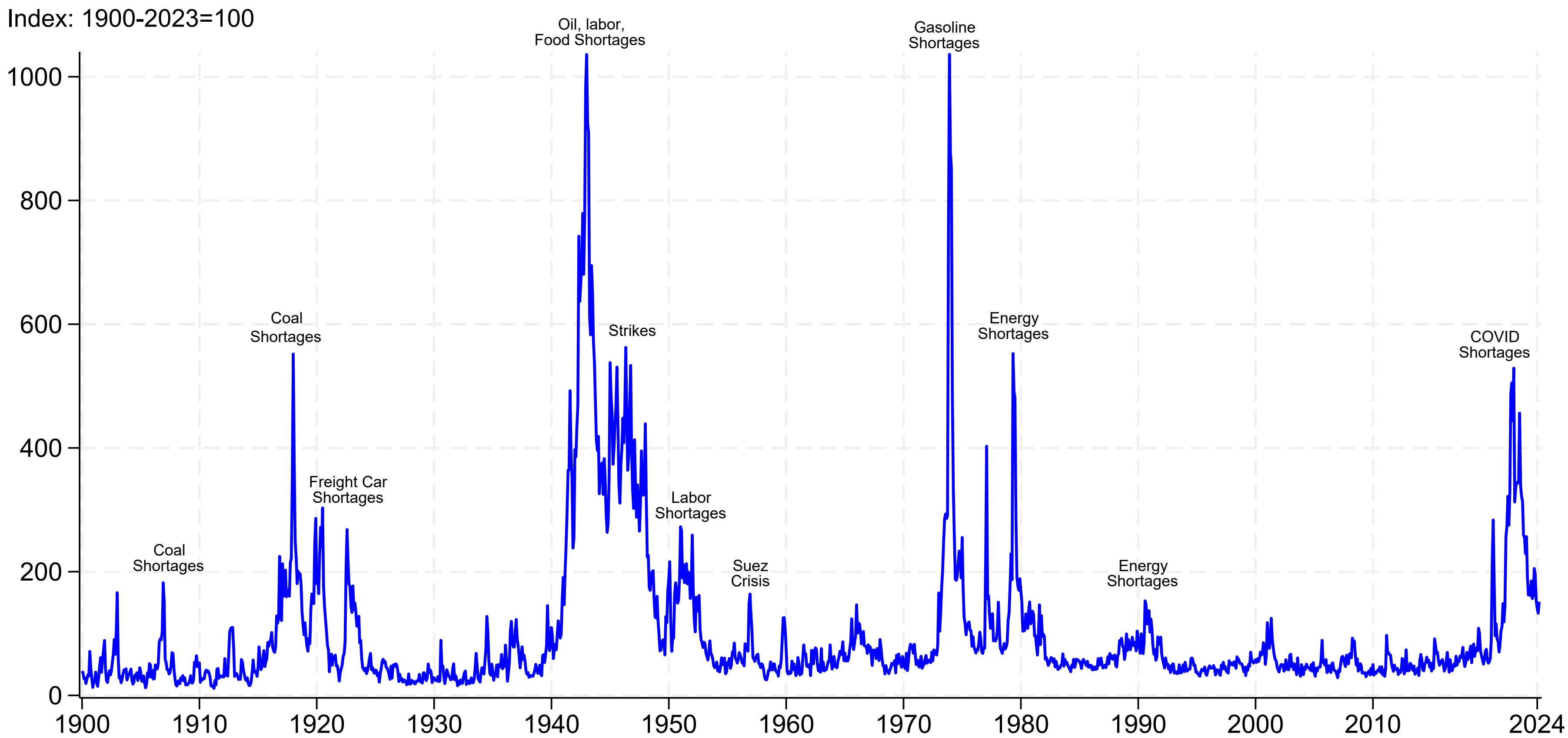
[1] Note: The table reports standardized coefficients of predictive regressions of economic activity and inflation on the shortage index. The dependent variable for each regression is the log difference between $t+4$ and t of GDP, both real GDP and GDP deflator. Each regression includes as controls the quarterly changes of the dependent variable and the associated economic indicator or price deflator, contemporaneously and with three lags. In each row, we add the listed variable as an additional control. Data are quarterly. The full sample, reported in the first two columns, runs from 1950Q1 to 2023Q4. We also partition the sample into two periods: a "pre-Covid" period that runs from 1950Q1 to 2014Q4, and a "Covid" period which runs from 2015Q1 to 2023Q4. Due to data limitations, the wage regressions start in 1964Q1, and the inflation expectation regressions start in 1982Q1. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses and computed according to Newey and West (1987). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Topic Classification for the Index



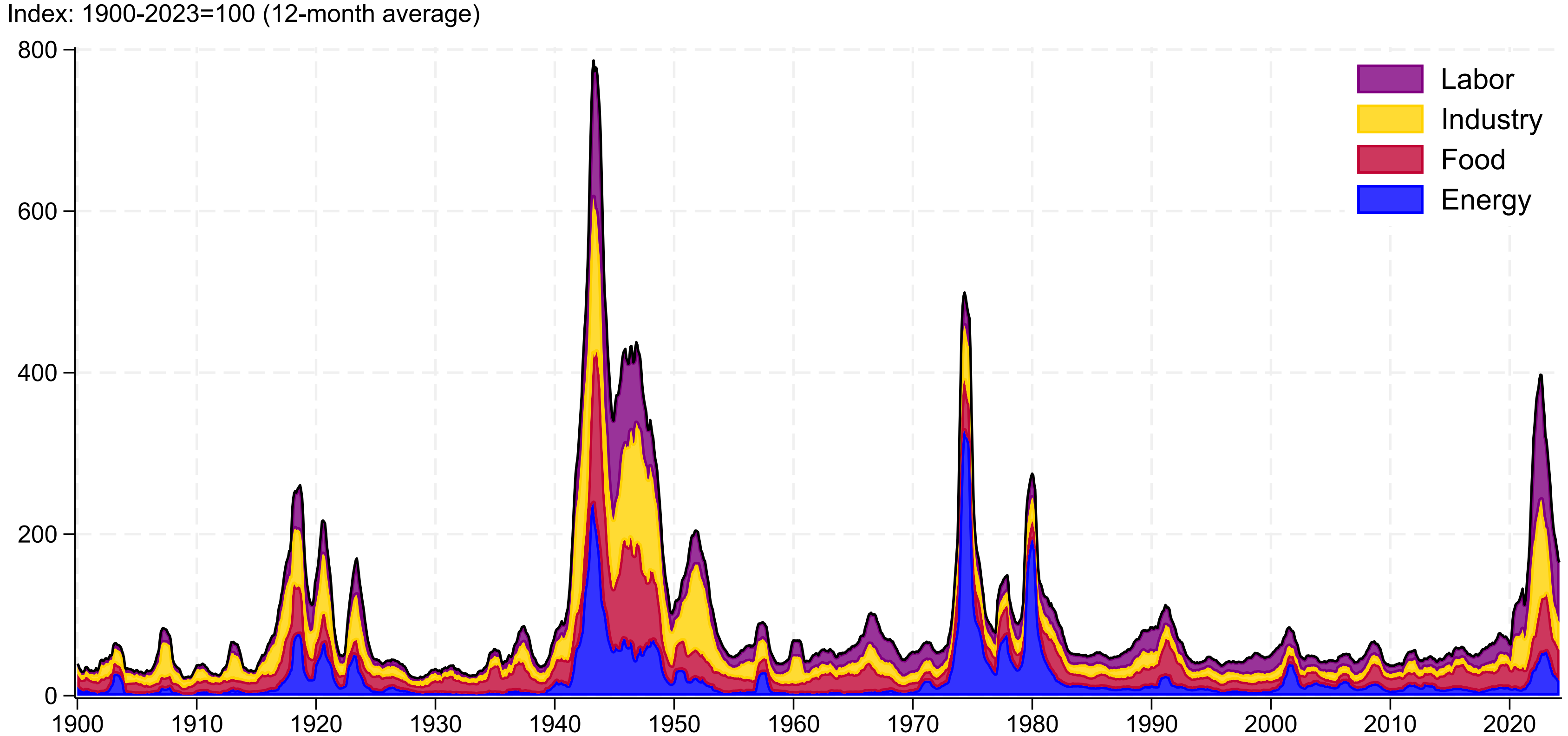
Note: Topic classification for a large sample of articles used in the construction of the Shortage Index. The top four rows indicate the four most influential topics chosen by LDA analysis on the articles. The bottom rows show topic probability by article, sorting the articles by time.

Figure 3: The Shortage Index



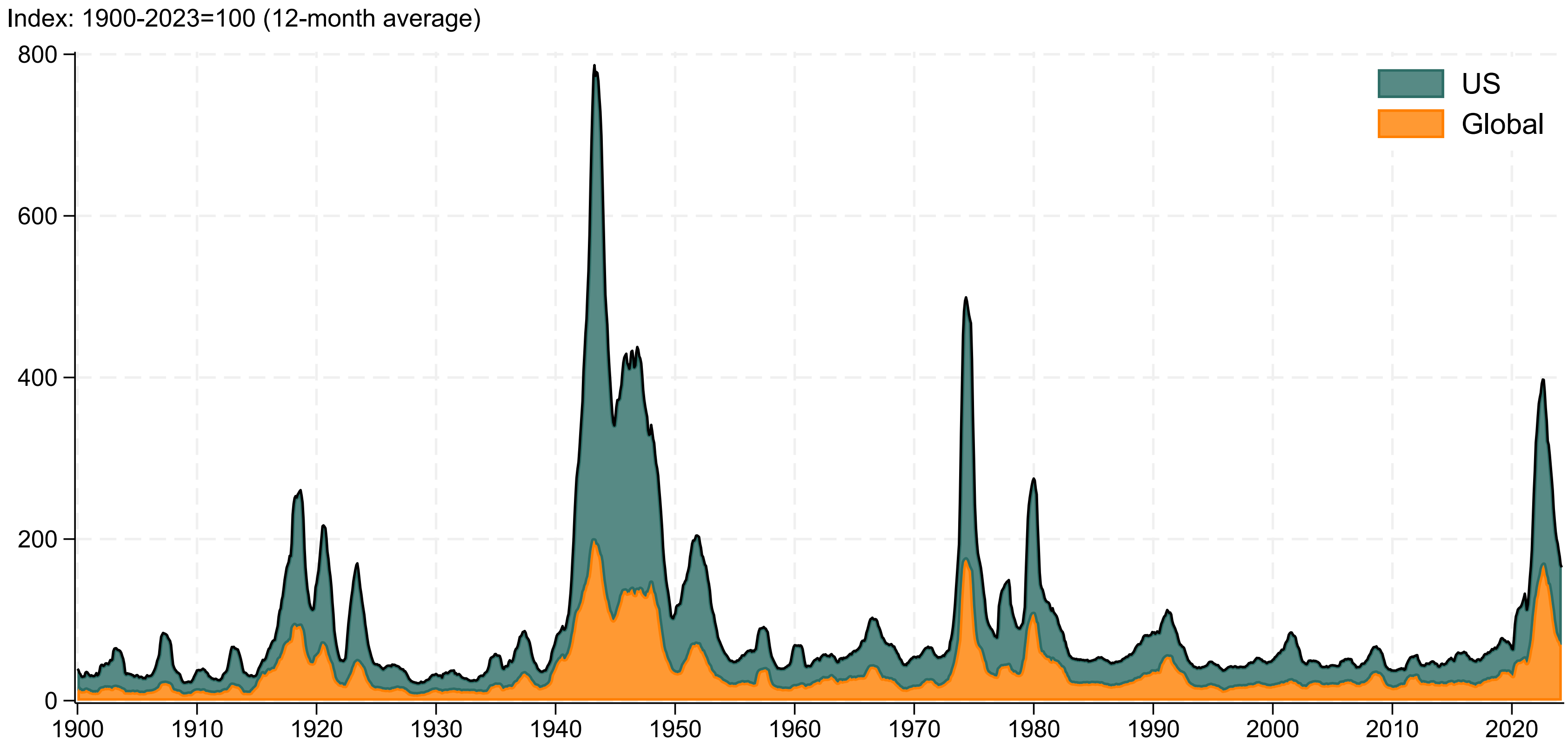
Note: The figure shows the Shortage Index from 1900 through 2024. Last observation is March 2024.

Figure 4: Decomposition by Category



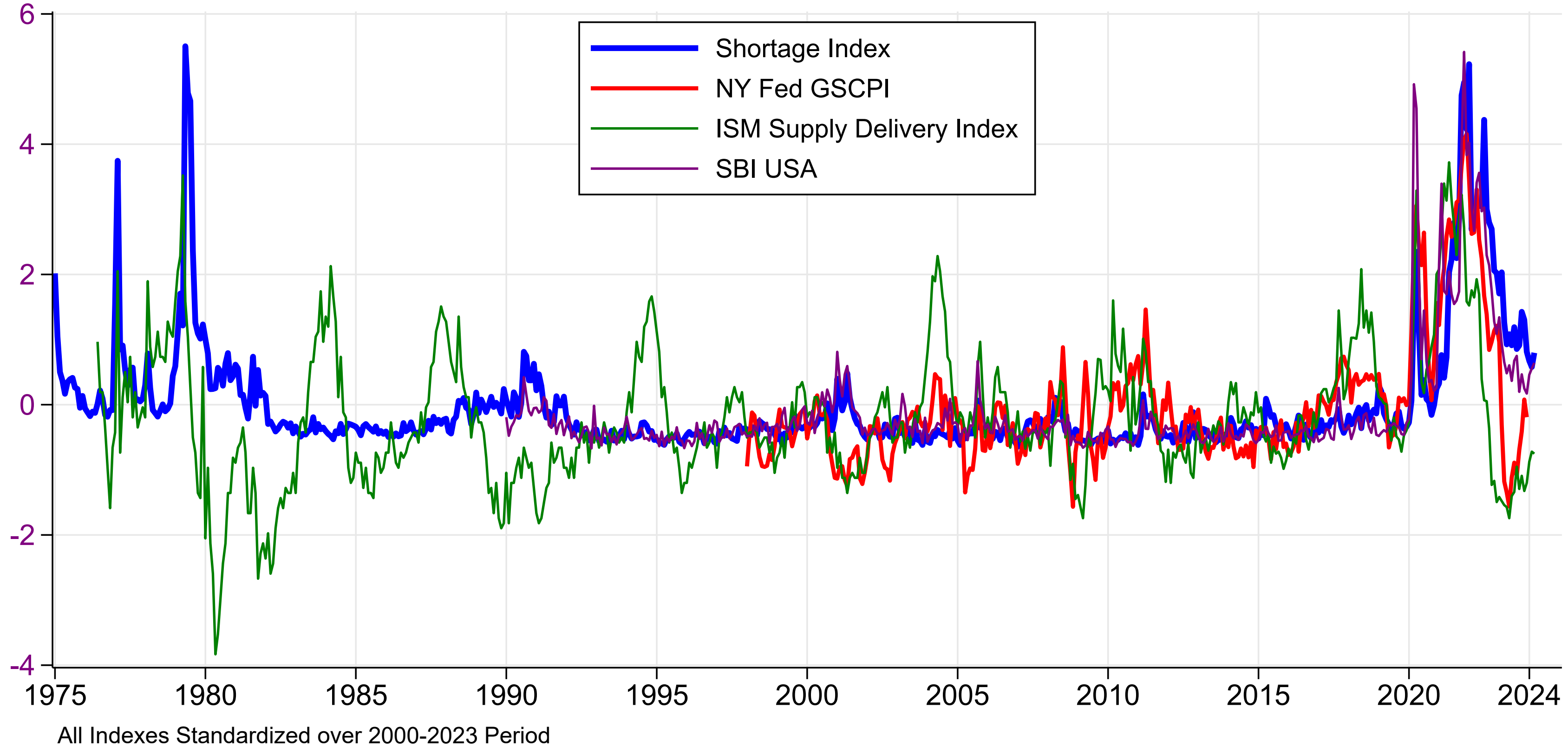
Note: The figure breaks down the shortage index into the four main categories used to construct the index.

Figure 5: U.S. vs. Global Shortages



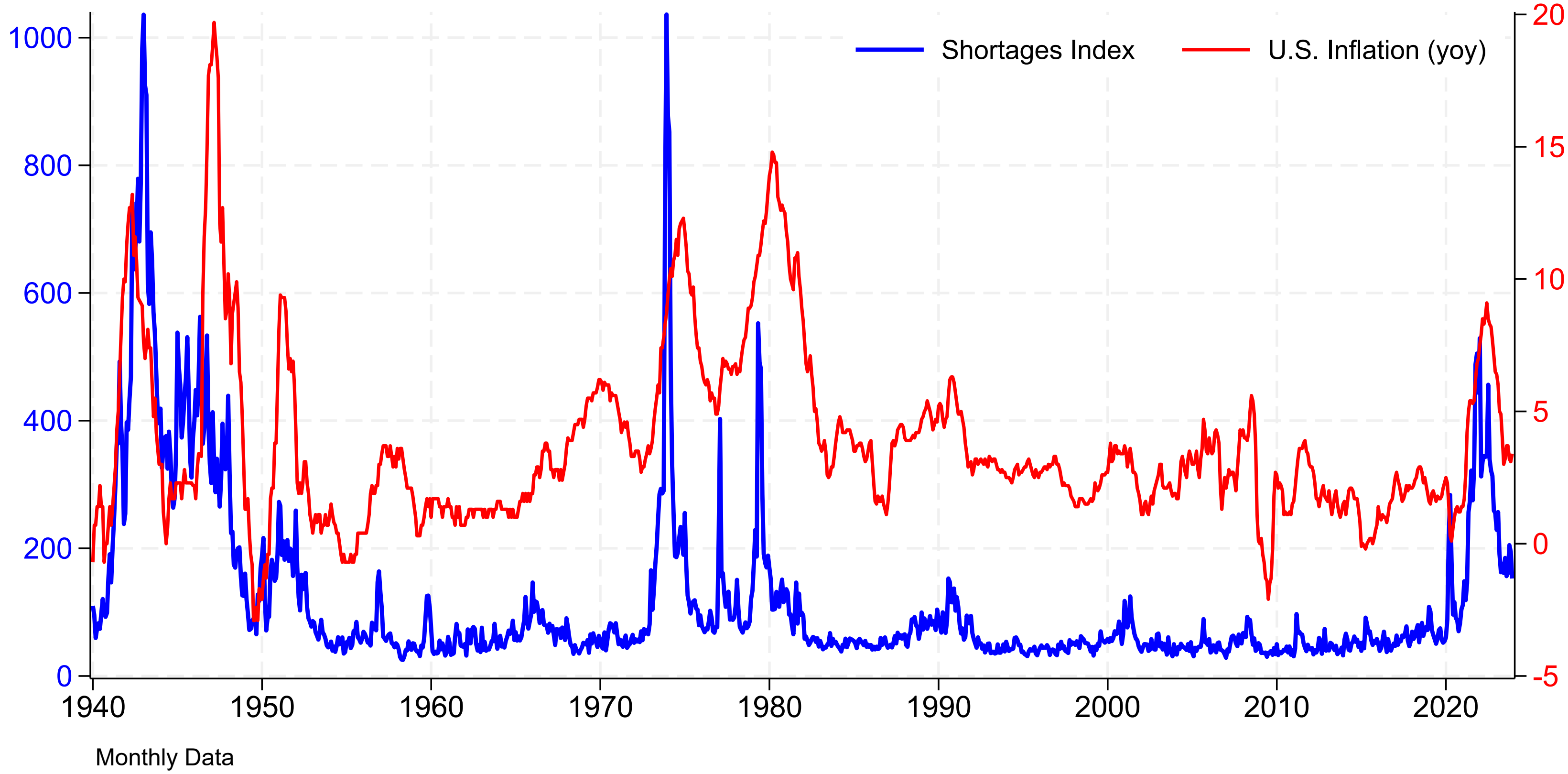
Note: The figure breaks down shortages into a US and a global component.

Figure 6: Comparison to Other Shortage Measures



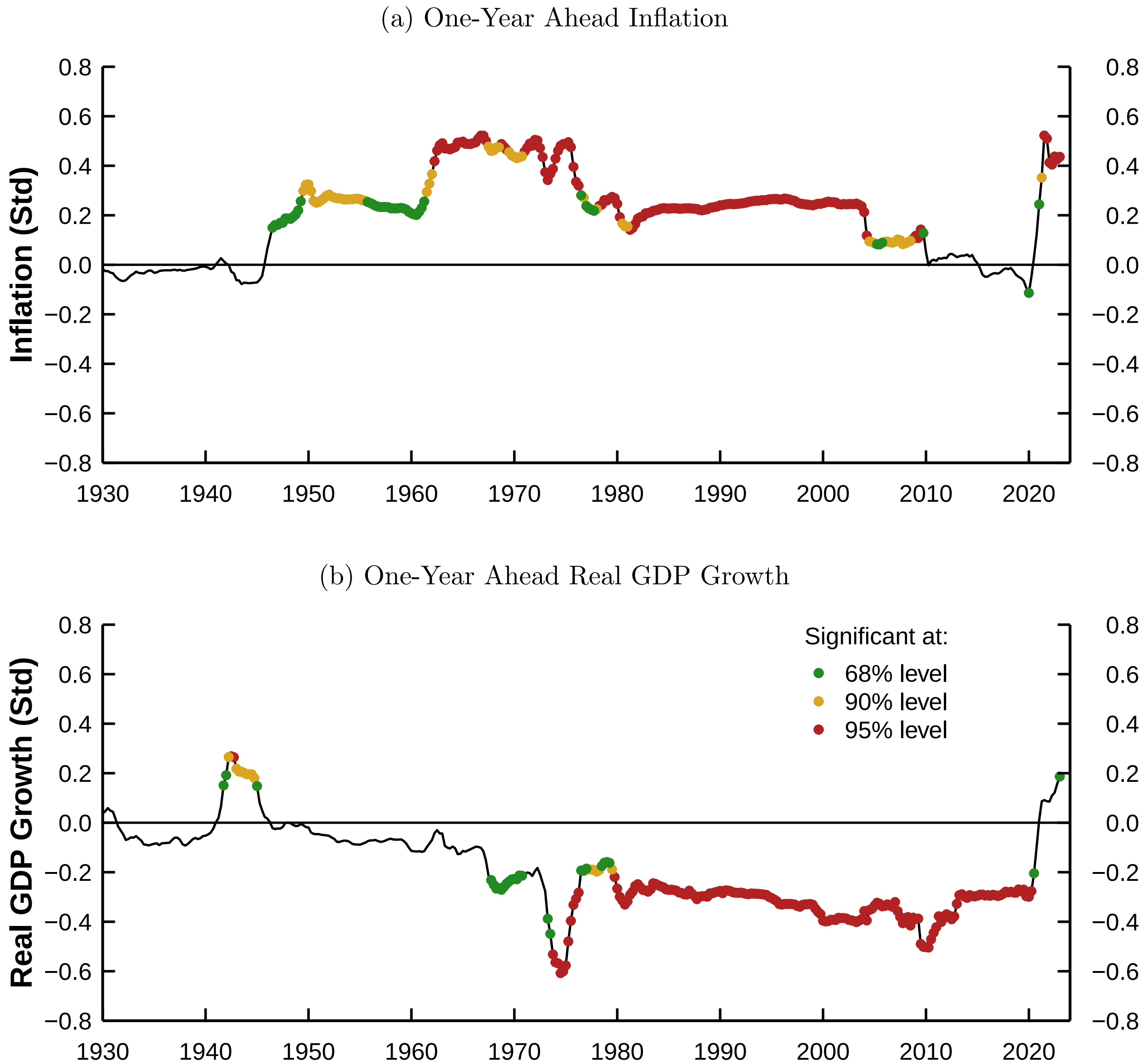
Note: The figure compares the shortage index for the period 1975-2024 to alternative measures of shortages. The ISM Supply Deliver Index is computed as the share of respondents reporting longer delivery times plus half the share of respondents reporting no change in delivery times. The SBI USA index is from Burriel et al. (2023).

Figure 7: Shortages and U.S. Inflation



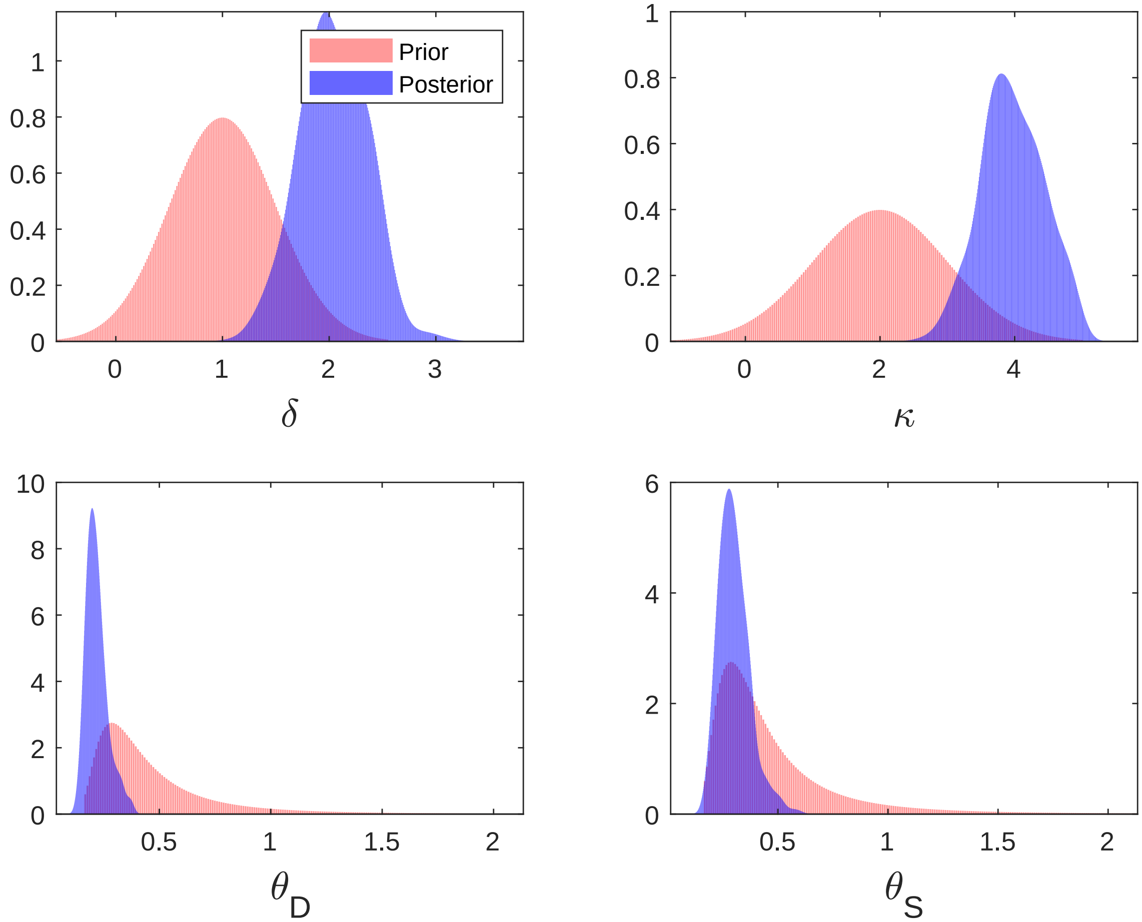
Note: The figures shows over time shortages and U.S. inflation.

Figure 8: Effect of Shortages on Inflation and Real GDP Growth (30-Year Window)



Note: The solid black line shows the time-varying estimated effect of shortages on inflation (top panel) and real GDP growth (bottom panel). The estimates are based on regressions using rolling 30-year windows. In each regression, the dependent variable is the 4-quarter ahead difference in log real GDP per capita or the 4-quarter ahead difference in log GDP deflator. On the right-hand side, the main explanatory variable is our shortage index. As controls, we include the one-quarter change in both log real GDP per capita and log GDP deflator, in quarter t plus three lags, and allow for up to three quarters of autocorrelation.

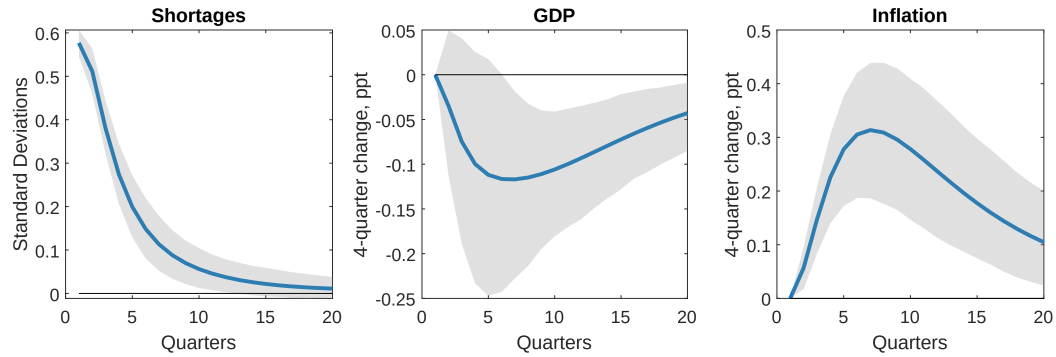
Figure 9: Priors and Posteriors



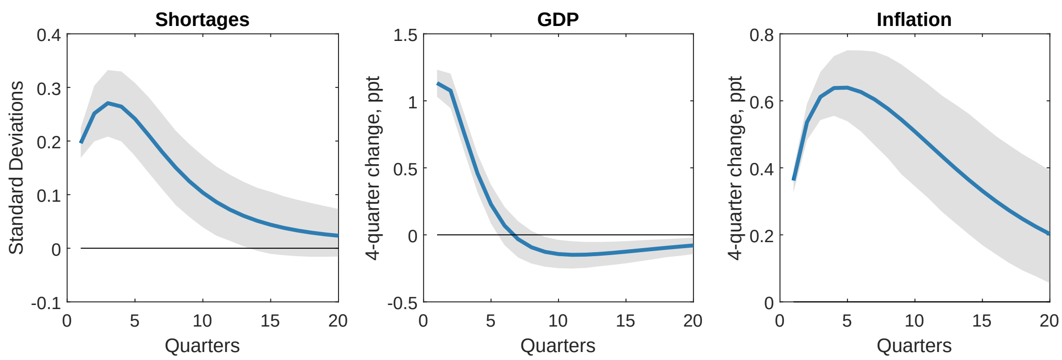
Note: Prior and posterior distributions of the parameters of the VAR model.

Figure 10: Effects of Shortages on US Activity and Inflation in Estimated VAR Model

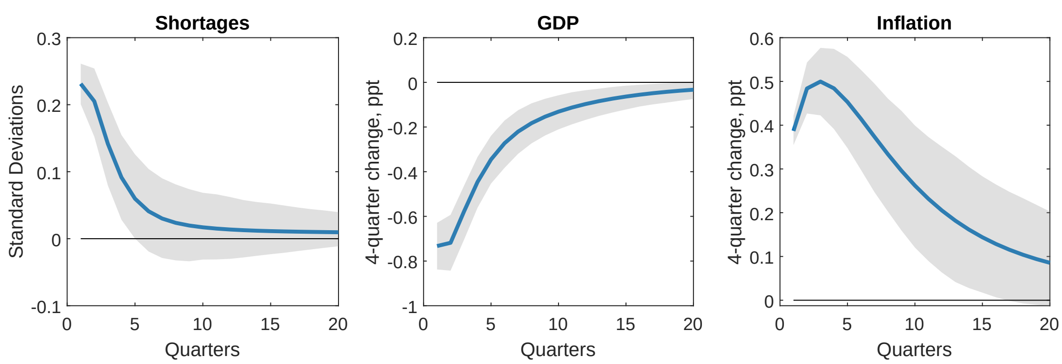
(a) Shock to Shortages



(b) Shock to Demand

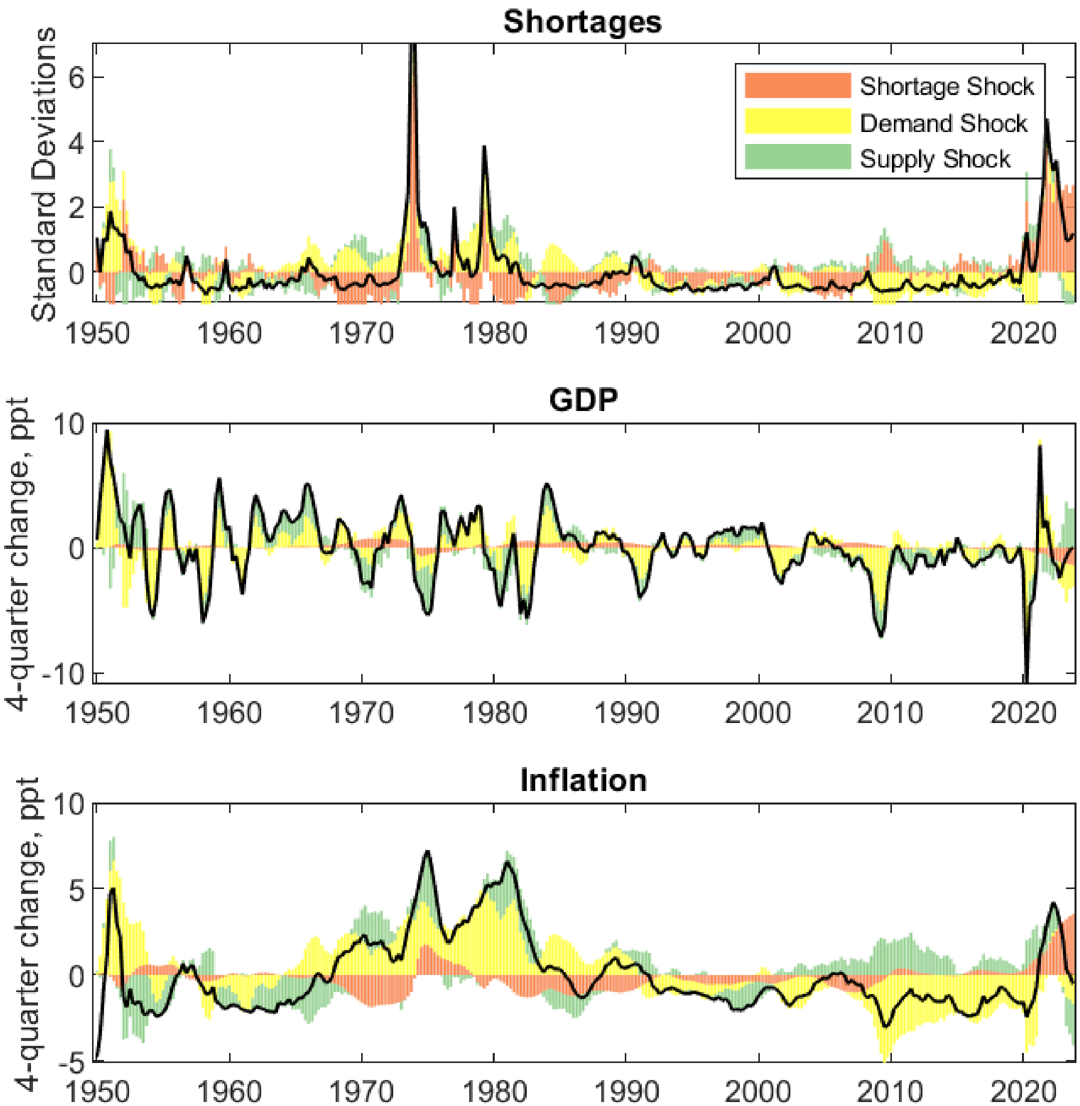


(c) Shock to Supply



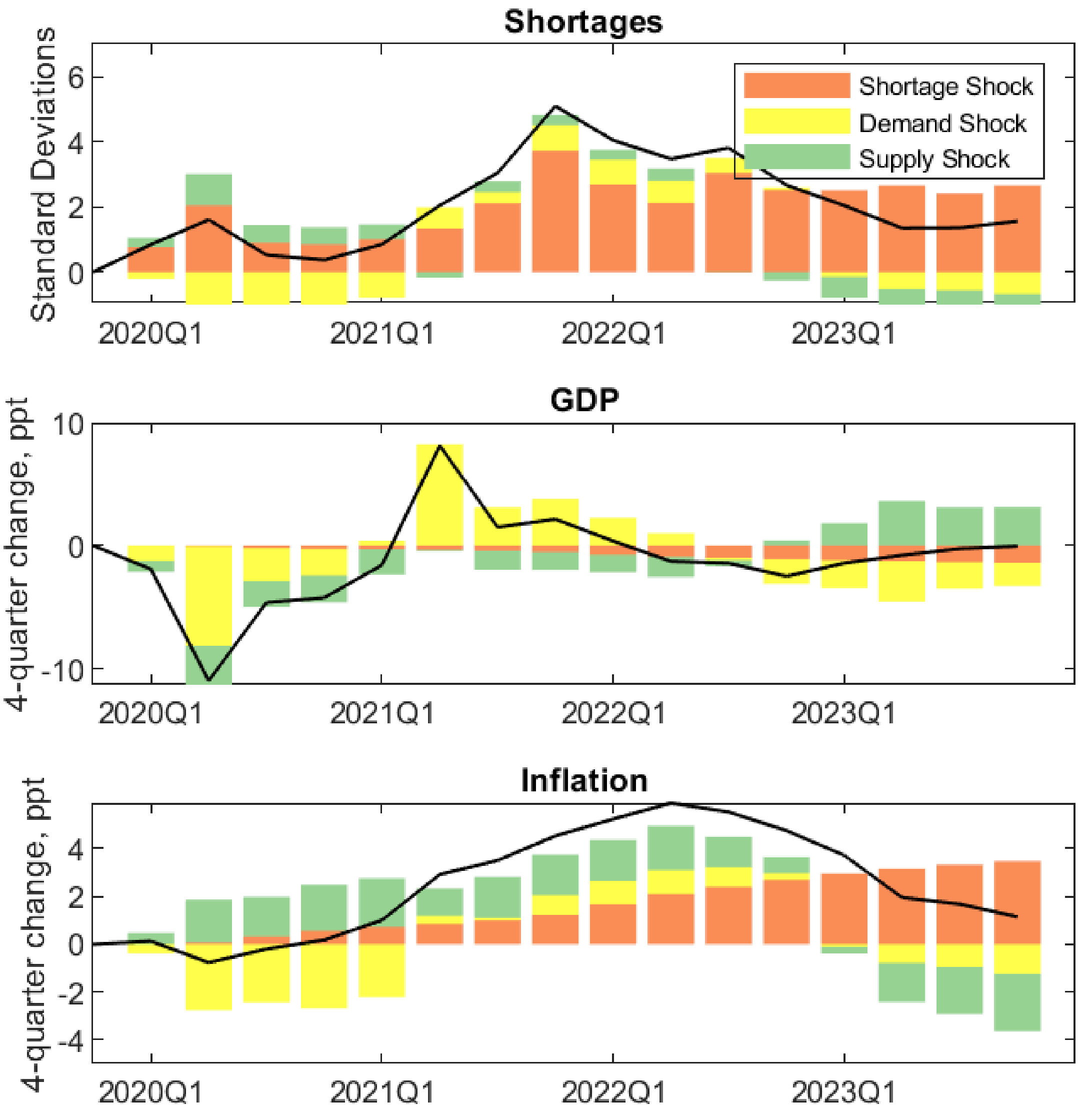
Note: Impulse Response in VAR.

Figure 11: Historical Decomposition of Estimated VAR Model: Full Sample



Note: The figure decomposes movements in shortages, economic activity and inflation in the contribution of shortage shocks, demand shocks, and supply shocks. All variables are expressed in deviation from their sample mean.

Figure 12: Historical Decomposition of Estimated VAR Model: Shortages and Activity since 2020



Note: The figure decomposes movements in shortages, economic activity and inflation since 2020 in the contribution of shortage shocks, demand shocks, and supply shocks. All variables are expressed in deviation from their 2019Q4 value.

Appendix

A Appendix Tables

Table A.1: Predicted Effect of Shortages on Prices and Quantities (1-quarter ahead)

	(1) 1950Q1–2023Q4		(2) 1950Q1–2014Q4		(3) 2015Q1–2023Q4	
	Prices	Quantities	Prices	Quantities	Prices	Quantities
GDP	0.10**	-0.01	0.11***	-0.06	0.91***	-0.10
	(2.36)	(-0.18)	(3.22)	(-1.09)	(5.60)	(-0.45)
PCE Durables	0.12	-0.06	0.19***	-0.12**	0.07	1.21
	(1.58)	(-1.13)	(4.32)	(-2.13)	(0.15)	(1.28)
PCE Nondurables	0.28***	-0.06	0.31***	-0.09	0.52*	0.27
	(3.67)	(-0.71)	(3.83)	(-1.13)	(1.85)	(0.80)
PCE Services	0.13***	-0.02	0.14***	-0.06	0.71***	0.57**
	(4.35)	(-0.33)	(4.70)	(-0.91)	(4.77)	(2.14)
Investment	0.17***	-0.02	0.18***	-0.05	0.89***	-0.03
	(3.79)	(-0.38)	(5.13)	(-1.14)	(5.04)	(-0.07)
Obs.	295	295	260	260	35	35

Note: The table reports standardized coefficients of predictive regressions of economic activity and inflation on the shortage index. The dependent variable for each regression is the log difference between $t+1$ and t of the variable listed in each row and its associated price deflator. Each regression includes as controls the quarterly changes of the dependent variable and the associated economic indicator or price deflator, contemporaneously and with three lags. Data are quarterly. The full sample, reported in the first two columns, runs from 1950Q1 to 2023Q4. We also partition the sample into two periods: a "pre-Covid" period that runs from 1950Q1 to 2014Q4, and a "Covid" period which runs from 2015Q1 to 2023Q4. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses and computed according to Newey and West (1987). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Predicted Effect of Shortages on Prices and Quantities (8-quarters ahead)

	(1) 1950Q1–2023Q4		(2) 1950Q1–2014Q4		(3) 2015Q1–2023Q4	
	Prices	Quantities	Prices	Quantities	Prices	Quantities
GDP	0.17**	-0.08	0.15**	-0.12*	0.46	0.96
	(2.53)	(-1.14)	(2.54)	(-1.72)	(0.96)	(1.37)
PCE Durables	0.28***	-0.16**	0.32***	-0.21*	1.41	-0.29
	(3.06)	(-1.98)	(6.70)	(-1.94)	(1.31)	(-0.30)
PCE Nondurables	0.25***	-0.02	0.25***	-0.08	1.29***	0.12
	(2.74)	(-0.27)	(2.84)	(-1.04)	(3.24)	(0.36)
PCE Services	0.19***	-0.00	0.18***	0.01	1.13***	1.14**
	(3.52)	(-0.05)	(3.83)	(0.10)	(5.28)	(2.68)
Investment	0.26***	-0.19***	0.25***	-0.22***	0.76	0.44
	(4.42)	(-2.96)	(4.71)	(-3.63)	(1.52)	(0.72)
Obs.	288	288	260	260	28	28

Note: The table reports standardized coefficients of predictive regressions of economic activity and inflation on the shortage index. The dependent variable for each regression is the log difference between $t+4$ and t of the variable listed in each row and its associated price deflator. Each regression includes as controls the quarterly changes of the dependent variable and the associated economic indicator or price deflator, contemporaneously and with three lags. Data are quarterly. The full sample, reported in the first two columns, runs from 1950Q1 to 2023Q4. We also partition the sample into two periods: a "pre-Covid" period that runs from 1950Q1 to 2014Q4, and a "Covid" period which runs from 2015Q1 to 2023Q4. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses and computed according to Newey and West (1987). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$