Measuring Shortages Since 1900*

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Abstract

This paper introduces a monthly shortage index spanning 1900 to the present, constructed from 25 million newspaper articles. The index captures shortages across labor, materials, goods, and energy, and spikes during economic crises and wars. We validate the index and show that it provides information beyond traditional macroeconomic indicators. Using predictive regressions and structural VAR models, we find that shortages are associated with persistently higher inflation and lower economic activity. Our analysis reveals that post-pandemic inflation was driven by supply shocks—with demand shocks playing a quantitatively relevant, albeit secondary, role.

KEYWORDS: Shortages; Inflation; Textual Analysis; Predictive Regressions; Structural VAR Model.

JEL CLASSIFICATION: C43, E32, N11, N12.

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1 Introduction

Shortages—defined as the temporary inability of supply to meet demand at the current price level—have been a recurring feature of economic life throughout the 20th and early 21st centuries. Recent events, such as the widespread shortages of goods and labor during the COVID pandemic, have demonstrated that shortages can have profound impacts on consumers and businesses, and have the potential to hamper overall economic performance. Yet, despite their importance, there has been limited research on the long-run trends and patterns of shortages across different sectors.

In the first part of this paper, we construct a monthly shortage index based on newspaper articles spanning from 1900 to the present (Section 2). The shortage index measures the intensity of shortages of labor, materials, goods, and energy. To construct the index, we use news articles from six major U.S. newspapers, amounting to about 20,000 articles per month—approximately 25 million articles over the entire sample. The index covers a wide swath of historical events and is significantly higher during periods of increased economic turmoil, such as the World Wars and the 1970s oil crises. It spikes considerably during the COVID-19 pandemic, reaching its highest level in the last 40 years.

Although the index is developed using U.S. news sources, its interpretation is intended to be global. In addition, we create country-specific indexes for the United States and five advanced economies: Canada, France, Great Britain, Germany, and Japan. We validate that our index is plausible and captures real-world shortage events through a narrative investigation, an AI-based text analysis, and a comparison to alternative measures of supply-side disruptions (Section 3).

In the second part of this paper, we show that shortages lead to persistently higher inflation and lower economic activity in the United States using predictive regressions, an out-of-sample forecasting exercise, and a structural vector autoregressive (VAR) model.

We start with a series of predictive regressions in which we estimate the effect of shortages on measures of inflation and real growth (Section 4). We find that shortages place downward pressure on GDP and upward pressure on prices, particularly in durable consumption and private fixed investment. Our results remain robust even when we include variables associated with inflation—such as commodity prices and wages—indicating that our shortage index provides additional information not captured by traditional indicators.

To quantify how the effects of shortages vary over time, we estimate our regressions on a rolling sample. We find that shortages have consistently contributed to higher inflation in history. The impact of shortages on economic growth is modest but negative over most of the sample, with two periods of higher growth associated with shortages: during World War II and the COVID-19 pandemic. We interpret these results as evidence that both supply and demand forces are relevant for analyzing shortages. Finally, we conduct a simple out-of-sample forecasting exercise—building on the approach of Stock and Watson (1999)—to examine the efficacy of the shortage index in forecasting inflation at shorter horizons. We find that a model incorporating shortages outperforms competing models that excludes the shortage measure.

To further investigate the interplay between shortages and the business cycle, we estimate a structural vector autoregressive (VAR) model (Section 5). In this model, we identify "traditional" demand and supply shocks, shocks to commodity prices, to monetary policy, as well as shocks to shortages, which capture atypical market adjustments in response to sudden shifts in economic conditions, regulatory interventions (such as mandated price ceilings or quantity rationing), and disruptions from weather or geopolitical events that impede the normal flow of goods. The advantage of a fully identified VAR over predictive regressions is that it provides a comprehensive and economically interpretable framework for understanding movements in GDP, inflation, and shortages.

Our results reveal that not all shortages are created equal. Movements in the shortage index are driven primarily by exogenous shortage shocks, with other demand and supply shocks playing some role in history. In the 1950s, shortages were largely driven by the Korean War, pent-up demand after World War II, and the rapid economic recovery accompanying the transition from wartime to peacetime economies. In contrast, the oil embargo by OPEC producers in the 1970s triggered an unusual surge in shortages beyond the direct effect of commodity price shocks. During the COVID pandemic, shortages emerged as a confluence of demand, supply, and shortage shocks, resulting in a persistent increase in inflation.

Counterfactual simulations reveal that, according to the model, the rise in inflation that started in 2020 is predominantly driven by supply forces—a combination of traditional supply shocks, shocks to commodity prices and to shortages—with demand forces playing a secondary but quantitatively relevant role. Supply shocks in 2020 and 2021 had a cumulative effect of raising inflation by 6 percentage points and reducing GDP growth by nearly 2 percentage points. Demand shocks exerted downward pressure on both inflation and GDP growth in

2020, whereas in 2021 they contributed to a rebound in these variables. In the absence of countervailing shocks in 2022 and 2023—in part capturing the tightening in the stance of monetary policy—we would have observed a more prolonged period of elevated inflation and subdued economic activity.

A growing literature has examined the drivers of pandemic inflation, and there is no consensus in apportioning inflationary effects to demand and supply developments. While Giannone and Primiceri (2024) and Bergholt et al. (2024) find that demand factors primarily drove the pandemic-era inflation rise, Bańbura et al. (2023) and Ascari et al. (2024) ascribe the bulk of the pandemic inflation surge in the euro area to supply shocks. Comin et al. (2024) develop an open economy New Keynesian model to evaluate how binding capacity constraints and associated shocks shape inflation. They find that capacity constraints explain half of the increase in inflation during 2021-2022.

Relative to these papers, our results underscore the dominant role of supply shocks—with demand shocks playing a quantitatively relevant, albeit secondary, role. The differences with Giannone and Primiceri (2024) are reconciled by our estimate of the slope of the aggregate demand curve, which is steeper than assumed in their paper, thereby allowing supply shocks to exert a more sustained impact on inflation. Importantly, a robustness exercise shows that imposing a flat demand curve in our structural VAR model significantly worsens the fit to the data.[1] In terms of timing, our analysis broadly aligns with Shapiro (2024) and DiGiovanni et al. (2023), who find that supply and shortages sparked inflation in 2020 and 2021, with strong aggregate demand exerting additional inflationary pressures in 2022.

A key paper in this literature is Bernanke and Blanchard (2025), who focus on the role of labor markets finding that most of the inflation surge was the result of shocks to prices—reflecting a mix of supply-side shocks, strong aggregate demand, and sectoral shocks—given wages. Using Google Trends-based measure of shortages starting in 2004, Bernanke and Blanchard (2025) report that shortages have a strong but short-lived effect on inflation. In contrast, our analysis, using data over a longer period of time, indicates a more prolonged inflationary response to shortage shocks.

Our approach builds on previous work that uses news-based measures to track economic phenomena, such as the Economic Policy Uncertainty Index (Baker, Bloom, and Davis, 2016)

[1] Giannone and Primiceri (2024) estimate their model on data from 1997 through 2019, while we estimate our models on data from 1950 through 2023, a longer sample encompassing periods of large demand and supply shocks.

and the Geopolitical Risk Index (Caldara and Iacoviello, 2022). However, to our knowledge, this is the first attempt to create a comprehensive global shortage index and country-specific indexes spanning over a century. By examining the evolution of the index alongside other economic indicators, we gain insights into the causes and consequences of shortages and can inform policy responses.

Several studies have also employed news sources to construct indicators of shortages. As early as 1997, Lamont (1997) developed a hand-coded news-based indicator of shortages using Wall Street Journal headlines. This work was followed by additional efforts to measure shortages or related concepts via news-based indices (e.g., Chen and Houle, 2023 for Canada and Burriel et al., 2023 for several advanced economies). There are several accurate indicators of supply disruptions constructed using alternative methodologies. For instance, (Benigno et al., 2022) measure supply chain pressures using data on factors such as transportation costs and manufacturing indicators. Bai et al. (2024) construct an index that measures the state of global supply chains starting in 2017 using high-frequency maritime satellite data to track port congestion. Liu et al. (2024)) construct a firm-level index of supply chain disruptions in the U.S. using granular shipment-level data on seaborne imports from 2013 to 2023. Pitschner (2022) and Bernanke and Blanchard (2025) have examined the intersection of shortages and inflation during the COVID-19 pandemic.

Many papers in this brief review identify energy prices and energy shocks as potential drivers of inflation. For example, Dao et al. (2024) find that energy shocks significantly contributed to the rise in headline inflation across 21 countries, with demand forces also being quantitatively significant in the United States. These findings motivate our inclusion of a commodity price index in our regression models, both to quantify commodity shocks and to ensure that our shortage shocks remain distinct from traditional commodity shocks.[2]

Thus, our contributions to the existing literature are threefold. First, we develop the first comprehensive shortage index covering over 125 years, offering a unique long-run perspective on shortage dynamics compared to existing indicators. Second, we show that our detailed indexes capture events in different markets (energy, labor, materials, and food) at both global and country-specific levels, thereby providing valuable insights for historical and cross-country analysis. Third, our empirical analysis demonstrates that shortages have persistent effects on

[2] Baumeister (2023) shows that the COVID-19 pandemic and the Russian invasion of Ukraine have reshaped the global oil market by altering the supply side in major oil-producing countries. These events generated significant oil price fluctuations that have contributed to the recent surge in inflation.

inflation and economic activity, which has important implications for both policymakers and researchers seeking to understand and mitigate the impacts of supply disruptions.

The remainder of the paper is structured as follows. Section 2 discusses the construction of the index and its evolution over time. Section 3 validates the index. Sections 4 and 5 examine the relationship between the shortage index and U.S. economic outcomes using predictive regressions, forecasting analysis, and a structural VAR model. Section 6 concludes.

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 that measures the intensity of shortages in materials, goods, labor, and energy in the United States. It is constructed from a sample of approximately 20,000 news articles per month, spanning from 1900 through the end of 2023—about 25 million articles in total. These articles are published in major U.S. newspapers: 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 articles that discuss shortages in energy, food, industry or labor markets—the set $\mathcal{S}$ visualized in the top panel of Figure 1—normalized by the total number of articles, denoted as the set $\mathcal{A}$. A higher index value indicates more intense shortages. Below, we outline the steps used to create the search query, reported in Table 1, for isolating set $\mathcal{S}$.

First, we construct a broader set of articles, $\mathcal{B}$, the pink area in Figure 1. Articles in this set must mention at least one shortage term—namely 'shortage', 'scarcity', 'bottleneck', or 'rationing'—in conjunction with an economics-related term, such as 'economy', 'market', or 'commerce'. The shortage terms used are those most frequently linked to economically relevant constraints on production or on the availability of goods to consumers.[3] Including an economics term reduces false positives—articles mentioning shortages unrelated to economic phenomena.

[3] Potential synonyms of shortage, such as 'lack' or 'paucity' or 'insufficiency' were excluded, as they have a broader range of meanings and are less likely to be specifically associated with economic shortages.

Next, we draw a random sample of about 3,300 articles from the set $\mathcal{B}$ and extract the 1,000 most frequent collocates, words appearing within five words of the shortage terms. From these collocates, we select those indicative of shortages in specific sectors. The most common collocates, excluding stopwords, include 'oil', 'water', 'war', 'time', 'coal', 'days', 'food', 'cars', 'people', 'government', 'million', 'labor', 'state', 'home', 'steel', and 'fuel'. Generic words like 'time', 'days', 'people', and 'government', which convey little information about shortages, are subsequently removed. The remaining collocates are grouped into four topics: food, industry, labor, and energy.[4]

Using the lists of shortage terms, economics terms, and topic-specific terms, we construct the search query shown in Table 1. An article is included in the shortage index (set $\mathcal{S}$ in Figure 1) if it meets two conditions: (1) a shortage term must appear within five words (*N/5*) of a topic-specific term, and (2) the article must contain at least one economics term. If an article meets the first condition for multiple topic-specific categories, it is counted once for each—so the total number of shortage articles is the sum across categories. This method gives greater weight to articles discussing multiple types of shortages, enhancing the index's informational content. Section 3 documents that requiring proximity between shortage and topic-specific terms is crucial for reducing false positives and improving search accuracy.

Our article classification into four topics is further supported by an ex-post Latent Dirichlet Allocation (LDA) analysis on a sample of articles meeting our inclusion criteria. LDA, a widely used unsupervised machine learning technique for topic modeling, identifies hidden topics by analyzing word co-occurrences. The analysis uses two inputs: a text corpus consisting of a random sample of 13,623 newspaper abstracts that mention shortages (about 4% of the approximately 330,000 articles from 1900 to 2023) and the number of topics (set to four).[5] The output of the LDA analysis is a set of topic distributions—one for each abstract. Specifically, for each article, LDA provides a probability vector indicating the degree to which each of the four topics is present. These probabilities allow us to validate the topic classification used in our searches and enable us to track trends in topic prevalence over time.

The LDA results are presented in the bottom panel of Figure 1. The word clouds display the most frequent terms for each topic, which we interpret as follows: Topic 1 corresponds to energy;

[4] Exploratory work identified additional categories (housing, health, and education shortages), but these were excluded as they either reflect long-standing social issues or contribute minimally to evolution of the overall index.

[5] Standard pre-processing was applied, including the removal of stopwords, numbers, and word stemming.

Topic 2 to water, food, and agricultural products; Topic 3 to goods and industrial products (e.g., coal, steel, railroads, cars); and Topic 4 to the labor market. These findings validate our selection of topics for the index, confirming that they capture the primary dimensions of economic shortages reflected in the news. We discuss the evolution of topics over time in the next section.

2.2 Shortages In History

We now present the shortage index, highlight its spikes, and discuss the historical context of these events. Figure 2 shows the monthly shortage index from 1900 through 2023. The index is computed as the monthly share of articles discussing economic shortages ($\mathcal{S}/\mathcal{A}$), scaled so that its average over 1900–2023 is 100. Figure 3 presents a breakdown of the index by topic. Table 2 lists the thirty largest spikes in the index, along with descriptions of the key events associated with each episode.[6]

The index varies considerably over time, with the most significant spikes linked to events related to the four classification topics—energy, food, industry, and labor. Geopolitical events—especially wars—are strongly associated with severe shortages. For instance, the index rises sharply during World War I and again during World War II, peaking at over 1,000 (ten times the sample mean) in January 1943, with spikes recorded across all shortage categories. Other events, such as the Suez Crisis and the Iraqi invasion of Kuwait in 1990, also coincide with substantial spikes. Many of these spikes are linked to energy shortages, often resulting from wars and instability in the Middle East. The oil shocks of the 1970s—the only other instance when the index exceeded 1,000—further illustrate this pattern. Labor shortages—particularly those caused by strikes—were historically significant, especially in the early part of the sample. For example, coal-related strikes in 1903, 1919, and 1922 produced notable spikes. However, strike-related shortages have become less frequent in recent decades as labor markets evolved and other factors gained prominence.

More recently, the index increased several times during the COVID-19 pandemic. The first spike corresponds to shortages in medical equipment and healthcare workers at the pandemic's onset. A larger spike occurred at the beginning of 2022, driven by global supply bottlenecks

[6] We calculate spikes by first extracting the residuals from a regression of the shortage index, h_t, on its values two months before and two months after. The largest residuals are our candidate spikes. We then discard any spike if it is not a local maximum within the 13-month window $[t-6, t+6]$, ensuring that we capture true local peaks. The table reports the thirty largest residuals.

as economies reopened after prolonged mobility restrictions in 2020 and 2021. As shown in Figure 3, this second spike primarily reflected shortages of labor and industry components.

The stacked bar chart at the bottom of Figure 3 visualizes the probabilistic topic mixture calculated with the LDA algorithm for each abstract—13,623 bars in total—sorted by year. Each year's news coverage reflects varying degrees of focus on different shortage topics, confirming the taxonomy of shortages from the analysis of the sub-indexes. In the early part of the sample, discussions are primarily centered around industry-related shortages, with food and water shortages receiving some attention. Energy shortages become particularly prominent during the 1970s, largely due to events like the oil crisis, which significantly impacted the global economy. In the more recent period, following the COVID-19 pandemic, labor shortages have increasingly dominated the news, reflecting the widespread disruptions in workforce availability and supply chains that have persisted post-pandemic.

2.3 Key Drivers of Shortages and Breakdown by Country

To determine whether shortages tend to occur alongside particular phenomena, we examine their co-occurrence in the news with other economic events—specifically, labor strikes, natural disasters, adverse geopolitical events, pandemics, and policy-induced price controls. Figure 4 compares the actual joint probability of these events being mentioned with shortages to the probability expected under independence. The lift ratio, defined as the ratio of the observed joint probability to the product of the individual probabilities, serves as a measure of association. A lift ratio greater than one indicates that these events co-occur more frequently than would be expected by chance.

The results indicate that price controls have the strongest association with shortages, co-occurring 7.8 times more frequently than expected under independence. In contrast, labor strikes show the weakest association, co-occurring nearly twice as often as expected. These patterns suggest that shortages are not randomly distributed across different economic disruptions but instead cluster with certain events, with price controls exhibiting the strongest association.

Finally, Figure 5 breaks down the shortage index by country. Specifically, we "slice" the main index by counting the number of articles that satisfy the shortage search query and mention either the name of a country or one of its major cities.

The country-specific shortage indexes reveal both similarities and differences. As expected, they all tend to spike around global events; however, there are notable differences as well. Countries are differentially exposed to global shortages in terms of timing—for instance European countries experienced earlier and more prolonged shortages during the two world wars than North American countries—and intensity, as evidenced by France and Germany during World War I and by Japan in the late 1970s.

The figure also reveals some country-specific episodes of shortages. For instance, it shows oil and energy shortages in France and the UK following the Suez Canal crisis, concerns about shortages in Germany around the time of the Berlin Wall's erection in 1961, and in the aftermath of the 2011 tsunami in Japan.[7]

These country-specific indexes offer valuable insights for comparative and cross-country research. Their ability to capture country variation in shortage events also provides additional evidence that our methodology accurately measures shortages, reinforcing the robustness of our search-query-based approach.

3 Assessing the Accuracy of the Shortage Index

We perform two exercises to assess the index's accuracy. First, we confirm that the newspaper articles in the index mention actual shortage-related concerns. Second, we evaluate whether the index aligns with alternative measures or proxies for shortages during the overlapping periods. A key advantage of our index is its long historical coverage—from 1900 through 2023—compared to existing measures that span only shorter, more recent time frames.

3.1 Validation of the Shortage Index

We verify that our index accurately measures shortages—minimizing both Type-I and Type-II errors—by sampling the abstracts of 872 articles from the shortage set $\mathcal{S}$.[8] By design, each article contains at least one economics-related term along with a reference to scarcities,

[7] In line with our measurement, the Suez Canal crisis did not create energy shortages in Germany because its energy supply was less reliant on Middle Eastern sources compared to France and the UK.

[8] Our search query for calculating the index is based on six U.S. newspapers listed in Section 2. Due to technical reasons, abstracts have not been available for these newspapers since 2015. For the period 2015–2023, we sampled abstracts from a broader set of newspapers, including some based in the U.K., Canada, and Australia. A detailed list of the 872 abstracts and their sources used for validation is available upon request. Abstracts are typically short portions of text, often containing the opening sentences or the first paragraph of the article.

shortages, or bottlenecks near a topic word (energy, food, industry, or labor). For each article, we extract the first snippet that references shortages. These snippets are centered on the shortage word and are limited to 110 characters—a length chosen to balance brevity, computational as well as cognitive load, inspired by Twitter's original 140-character limit. For example, two snippets from our sample include:

- "Although demand remains strong... the resulting supply shortage of German manufacturing goods could also..." (2021)
- "...men interested in the industries affected by the shortage of steel are anxious to see the strike settled." (1901)

We then used the Claude AI assistant (Anthropic, 2024) to determine whether each snippet mentioned current or prospective shortages, rationing, scarcity, or bottlenecks related to goods, labor, materials, food, or water. Claude returned a table of results, coding snippets as 1 (shortage mentioned), 0 (shortage not mentioned), or 99 (unsure). Additionally, Claude provided a brief explanation for each coding decision.

Before initiating classification, we provided Claude with examples—listed in the Appendix—of how to code the snippets, ensuring that the training sample included false positives (e.g., mentions of the lack or end of shortages). Although AI-based validation is not foolproof, we found that Claude performed comparably to a human evaluator, even extrapolating contextual cues (such as linking a sentence to a particular country or individual). For example, when processing the sentence "economy may be slowing but Lowe is banking on labour shortages gradually leading to an increase...", Claude classified it as 1 and noted that the Reserve Bank [of Australia] [was] expecting labour shortages to lead to wage growth.

The audit results are presented in Table 3. Out of 872 articles in the set $\mathcal{S}$, only 6.3 percent were classified by Claude as false positives. For example, Claude coded the snippet "...says that while there is not necessarily a shortage of people wanting to work in management" as 0, explaining that "No shortage of people wanting to work in management". Additional examples are provided in the Appendix.

We then repeated the audit for a sample of 298 articles outside the set $\mathcal{S}$. Among these, only one article mentioned shortages that were not captured by our search query ("recycling of newsprint was held back by a shortage of deinking plants"). Notably, our search query deliberately excluded the word "plants" because preliminary tests revealed that its inclusion produced numerous false positives.[9]

Finally, we confirm that restricting the search to include shortage words near terms related to goods, labor, food, or energy significantly improves accuracy. In a broader set of articles—where the presence of shortage words near these key terms is allowed but not required—84.2 percent mention economically relevant shortages. This yields a Type I error rate of 15.8 percent, considerably higher than that achieved with our preferred search query. False positives in the broader set include articles referencing non-economic shortages, such as shortages of political campaign funds, a lack of quality baseball photos, legislative bottlenecks, and even shortages of sunshine.

3.2 Comparison with Other Indicators of Supply Constraints

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

Figure 6 plots our shortage index alongside the New York Fed Global Supply Chain Pressure (GSCPI) Index (Benigno et al., 2022), the Supplier Delivery Index (SDI), and the Supply Bottlenecks Index (SBI) for the U.S. (developed by Burriel et al. (2023)). The GSCPI, published by the Federal Reserve Bank of New York, measures global supply chain conditions using data on both manufacturing and transportation costs. The SDI, published by the Institute of Supply Management (ISM), is based on a monthly survey that asks firms whether they are experiencing longer or shorter wait times compared to the previous month; the SDI value represents the share of respondents reporting longer wait times, plus half the share reporting no change. The SBI uses a text-based newspaper search to quantify supply chain issues. To facilitate the comparison, we standardize each variable to have a mean of 0 and a variance of 1 over the overlapping period.

Figure 6 shows that our index shares similar features with these three indicators. Over the full period of the GSCPI, the correlation between our index and the GSCPI is 0.73. Both measures increased sharply at the onset of COVID-19 in early 2020, and again at the beginning of 2022 as supply chain bottlenecks intensified. The correlation between our index and the SDI is 0.25; nonetheless, both measures spiked around the 1979 oil crisis and during COVID-19. One possible explanation is that both events caused significant transportation delays—whether

[9] For example, see 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."

due to rising fuel costs or supply bottlenecks—that contributed to manufacturing shortages. Finally, our index has a high correlation of 0.90 with the U.S. SBI, indicating strong alignment between these measures over the common sample.

Thus, while all indicators provide useful insights into shortages and broader supply constraints, a key advantage of our index is its long historical coverage. Its availability from 1900 through 2023 makes it particularly valuable for historical research on long-term trends and cyclical patterns in shortages.

3.3 Validation of Categorical Shortage Indexes

The categorical shortage subindexes are correlated, yet each contains unique information about different aspects of shortages. We show this result in Table A.1, which reports the coefficients from regressions where selected price and wage measures are regressed on the four categorical shortage indexes for industrial products, labor, energy and food. The dependent variables in these regressions are prices indexes that are more likely to be impact by shortages in these four categories: the 3-month ahead log difference of the Producer Price Index (PPI) for processed goods for intermediate demand, the Consumer Price Index (CPI) for energy, CPI for food, and the 12-month ahead log change in average hourly earnings (total private). Each regression includes three lags of the monthly changes in the dependent variable and one lag of the log change in industrial production.[10]

When the four categorical indexes are included one at a time, we find that the industrial products/materials shortage index predicts PPI materials inflation, the labor shortage index predicts earnings growth, and the energy and food shortage indexes predict CPI energy inflation and CPI food inflation, respectively. In other words, each index forecasts the prices (and earnings) of products most likely to be affected by that specific shortage. When all four indexes are included simultaneously, these results largely hold, with one exception: the food shortage index no longer predicts CPI food inflation. In addition, energy shortages also predict PPI materials inflation and (weakly) earnings growth.

[10] We use the 12-month change for earnings because earnings adjust more slowly than commodity prices or materials. Our results are similar when using the 6-month change in earnings.

4 Shortages as Predictors of Inflation and Activity

In this section, we investigate the predictive power of our shortage index for key macroeconomic outcomes. We first analyze how shortages relate to near-term inflation and economic activity using a predictive regression framework. Our results indicate that higher levels of shortages are associated with prolonged periods of elevated inflation and a deceleration in economic activity. We then extend our analysis to a real-time forecasting exercise, demonstrating that incorporating the shortage index improves out-of-sample forecasts of headline inflation. Together, these findings underscore the importance of supply-side disruptions in shaping macroeconomic dynamics and validate our search-query-based approach. As a simple illustration of this key result, Figure 7 shows that, for a sample starting in 1940, periods of elevated shortages coincide with higher U.S. inflation—a finding that is robust across various econometric methodologies.

4.1 Predictive Regressions: Shortages, Inflation, and Activity

We formally explore the relationship between shortages, inflation, and economic activity using the following predictive regression:

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

where

$$\Delta Y_{t+h} = \frac{400}{h} \ln\left(\frac{Y_{t+h}}{Y_t}\right)$$

represents the annualized log change of a variable of interest Y_t between period t and forecast horizon h, and $SHORTAGE_t$ denotes the level of the shortage index. The vector $\mathbf{X}_t$ contains 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 expenditures, and private fixed investment. Inflation for each category is measured using the associated price deflator. For GDP and its price deflator, we extend the sample back to 1900 using data from Ramey and Zubairy (2018). Data on total population also come from Ramey and Zubairy (2018), extended through 2023 using the POP series from FRED.

For each price and economic activity indicator, we estimate equation (1) by OLS, with standard errors calculated following Newey and West (1987). As control variables, we include quarterly changes of the dependent variable and the corresponding economic indicator or price deflator, both contemporaneously and with three lags. For example, the regression for real GDP growth includes contemporaneous and lagged values of both real GDP growth and inflation (measured by the log change in the GDP deflator).

Figure A.2 presents the results for four-quarter-ahead regressions, while Figures **??** and **??** report results for the one- and eight-quarter horizons, respectively. For ease of comparison, we report standardized estimates of the coefficient β. A standardized coefficient represents the change in standard deviation units in the dependent variable following a one-standard-deviation change in the explanatory variable.

The blue bars of Figure A.2 report estimates for the full sample. An increase in shortages is associated with a rise in inflation (left panel) and a decline in economic activity (right panel)—the typical effects of supply-side disruptions. The inflationary effects of shortages are fairly evenly distributed across GDP components, with prices in the services consumption category being the least affected. While durable goods consumption and private fixed investment decline, there is no statistically significant effect on the consumption of non-durable goods or services. In terms of magnitudes, the standardized coefficients imply that a one-standard-deviation increase in the shortage index raises durable goods inflation by 0.75 percentage points (equivalent to 0.25 standard deviations) and reduces durable goods consumption growth by 1.75 percentage points (or -0.25 standard deviations). Similarly, the GDP coefficients indicate that a one-standard-deviation increase in the shortage index is associated with a 0.5 percentage point rise in inflation (as measured by the GDP deflator) and a 0.3 percentage point decline in real GDP growth.

The orange and green bars of Figure A.2 reveal notable time variation in the relationship between shortages, inflation, and economic growth. When we split the sample at 2013:Q4, we observe that in the pre-COVID sample (1950–2013), the effects of shortages on both inflation and activity are precisely estimated and widespread across sectors—except for private consumption of services. In contrast, in the sample beginning in 2015, which includes the COVID-19 pandemic, the inflationary impact of shortages becomes substantially larger, albeit less precisely estimated, while the coefficient on economic activity turns positive yet remains statistically insignificant. These findings suggest that demand factors may have played a more prominent role in driving shortages during and after the COVID-19 pandemic compared to the pre-COVID period.

A further concern is whether the shortage index contains information beyond that captured by other macroeconomic variables. In Figure **??**, we address this issue by augmenting our baseline regression with additional controls, including oil prices, commodity prices, wage growth, and inflation expectations. We focus on the robustness of the estimates for 4-quarter ahead GDP deflator inflation and GDP growth. The top row of Figure **??** reproduces the estimated effects of shortages on inflation and growth from the baseline regressions, while subsequent rows report the effects of shortages from regressions that include each of the additional controls. Although the inclusion of these controls slightly attenuates the coefficients on shortages, they generally remain statistically significant. When partitioning the sample into pre- and post-COVID periods, the pre-COVID estimates remain stable and highly significant, while the post-COVID results are largely consistent with the baseline. Overall, these findings suggest that our shortage index contains additional information beyond that captured by traditional macroeconomic indicators.

To further assess the robustness of our findings, we estimate equation (1) on a rolling sample using a 30-year window, focusing on real GDP growth and inflation (measured by the GDP deflator). Figure 9 shows that shortages have consistently exerted inflationary effects since World War II, except during the 10-year period preceding the pandemic, when the effect becomes negligible and imprecisely estimated. Moreover, shortages have had statistically significant adverse effects on economic activity from the 1970s until the COVID-19 pandemic, except during periods—such as the pandemic and World War II—when high demand helped sustain economic activity despite shortages.

4.2 Forecasting Inflation

Building on the work of Stock and Watson (1999), we also examine the efficacy of the shortage index in forecasting inflation at shorter horizons. Specifically, we try and see whether our shortage measure can improve 3-month ahead forecasts of annual inflation. To this end, we estimate the following specification:

$$\pi_{t+3} = c + \beta\pi_t + \gamma x_t + \delta h_t, \tag{2}$$

where π_{t+3} is the three-month ahead, 12-month percent change in the headline CPI index, π_t is current 12-month CPI inflation, x_t is a vector of economic variables (including unemployment and the 12-month change in oil prices), and h_t is the shortage index. To keep the specification as simple as possible, we only include the current value each variable. However, to reduce the influence of extreme swings in the variables during the pandemic, we smooth each series using 12-month lagged moving averages. The exercise is a full-blown real-time forecasting exercise, as three-month-ahead inflation forecasts are made using only data available up to each forecast date. use a 30-year rolling window, and implement a series of real-time rolling forecasts from 1990:M1 to 2024:M9 (the last observation for inflation is 2024:M12).

The choice of the forecasting framework is motivated by the findings of Ang et al. (2007), who compare alternative inflation forecasting methods and show that while survey-based and atheoretical models often yield the best predictions for inflation, economic models that build on the Phillips curve can still perform well while maintaining a structural grounding. In particular, we select a specification that delivers good out-of-sample performance while maintaining interpretability and coherence with macroeconomic fundamentals.

Our primary finding is that a model incorporating inflation expectations, unemployment, oil prices, and the shortage index outperforms a competing model that excludes the shortage measure. For the whole forecasting window covering the 1990–2024 period, the root mean square error (RMSE) of the forecast without shortages is 0.92—7 percent higher than the RMSE of 0.86 for the model that includes shortages. In the 2020–2024 period, the RMSE is 1.31 for the model without shortages compared to 1.04 for the model including shortages, an improvement of about 20 percent in the RMSE. As illustrated in Figure 10, the model with shortages predicts a sharper rise in inflation between 2021 and 2022, thereby reducing forecast errors. [11]

In summary, our results from both the predictive regressions and the out-of-sample forecasting exercise strongly suggest that shortages have significant effects on inflation and economic activity.

[11] The shortage index also improves the forecast for core inflation (CPI All Items Less Food and Energy). In the full 1990–2024 period, the root mean square error (RMSE) of the forecast with shortages is 0.40—lower than the RMSE of 0.44 for the model that excludes shortages. In the 2020–2024 period, the RMSE is 0.83 for the model with shortages compared to 0.77 for the model without shortages.

5 Shortages: A VAR Analysis

In this section, we present a structural VAR model of the U.S. economy that incorporates shortages. Compared to the predictive regressions discussed earlier, a full structural model offers a more comprehensive explanation of how movements in shortages interact with broader economic activity. An additional advantage of the VAR approach is its ability to capture time-varying reduced-form effects of shortages on economic activity as the relative importance of different factors shifts over time.

5.1 The Model

Our model includes five quarterly indicators: economic activity, inflation, commodity prices, shortages, and the short-term interest rate. These are summarized by the vector

$$\mathbf{X}_t = (y_t, \pi_t, c_t, h_t, r_t)' \tag{3}$$

where **Economic activity** (y_t) is measured as the four-quarter percent change in real GDP; **Inflation** (π_t) is measured as the four-quarter percent change in the headline CPI index; **Commodity prices** (c_t) are measured as the four-quarter percent change in the Reuters–CRB Spot Commodity Price Index for raw industrials and foodstuffs; **Shortages** (h_t) are expressed in levels (standardized); **Short-term interest rate** (r_t) is the annualized 3-month Treasury bill rate. All series are demeaned.

The VAR representation is given by:

$$\mathbf{A}\mathbf{X}_t = \sum_{j=1}^{p} \mathbf{B}_j \mathbf{X}_{t-j} + \mathbf{C}\mathbf{u}_t, \tag{4}$$

where $\mathbf{u}_t = (u^S, u^D, u^C, u^H, u^R)'$ is the vector of structural shocks with zero mean and a diagonal covariance matrix $E\left[\mathbf{u}_t\mathbf{u}_t'\right] = \mathbf{\Sigma}_u$. Without loss of generality, we normalize one entry per row of $\mathbf{A}$ to 1.

The structural relationships among variables, with $\mathbf{z}_{t-1} = (\mathbf{X}_{t-1}', \mathbf{X}_{t-2}', \ldots, \mathbf{X}_{t-p}')'$ denoting lagged variables, are described by the following equations:

Aggregate Supply (Inverse):

$$\pi_t = u_t^S + \kappa\, y_t + [\mathbf{b}^S]'\mathbf{z}_{t-1}, \tag{5}$$

where inflation is positively related to output ($\kappa > 0$) and subject to adverse supply shocks u^S.

Aggregate Demand:

$$y_t = u_t^D - \delta\, \pi_t + [\mathbf{b}^D]'\mathbf{z}_{t-1}, \tag{6}$$

where demand is negatively related to inflation ($\delta > 0$) and driven by demand shocks u^D.

Commodity Prices:

$$c_t = u_t^C + \chi_D\, u_t^D + \chi_S\, u_t^S + [\mathbf{b}^C]'\mathbf{z}_{t-1}, \tag{7}$$

capturing responses to both demand and supply shocks along with commodity-specific disturbances.

Monetary Policy Rule:

$$r_t = u_t^R + \alpha_H\, h_t + \alpha_Y\, y_t + \alpha_\pi\, \pi_t + \alpha_C\, c_t + [\mathbf{b}^R]'\mathbf{z}_{t-1}, \tag{8}$$

where u^R represents monetary policy shocks.

Shortages:

$$h_t = u_t^H + \theta_D\, u_t^D + \theta_S\, u_t^S + \theta_C\, u_t^C + [\mathbf{b}^H]'\mathbf{z}_{t-1}, \tag{9}$$

where shortages are assumed to reflect standard business cycle fluctuations, commodity shocks, as well as an exogenous component u^H capturing newsworthy unexpected disruptions in the flow of goods, services, and factors of production that cause demand to temporarily exceed supply. Examples of exogenous shortages shocks include abrupt demand reallocation across sectors may create bottlenecks that necessitate temporary rationing, regulatory shocks (e.g., price ceilings or quantity rationing), panic buying under constrained supply conditions, or disruptions caused by extreme weather or geopolitical events.

Note that the timing assumptions in the model imply that exogenous shocks to shortages affect economic activity, prices, and commodity prices only with a delay of at least one quarter. In addition, our assumption that shortages reflect, within the quarter, movements in economic conditions caused by traditional demand and supply shocks differentiates our analysis from the work of Burriel et al. (2023), who order shortages first in a monthly VAR from 1990 through 2020; and from the work of Bernanke and Blanchard (2025), who use a quarterly VAR from 1990 through 2023 assuming that shortages affect inflation within the quarter.

5.2 Priors and Estimation

Following Baumeister and Hamilton (2019), we treat identification and estimation of this structural VAR as a Bayesian exercise, imposing prior restrictions directly on the parameters in the matrices $\mathbf{A}$, $\mathbf{B}_j$, and $\mathbf{C}$. These priors help identify the structural shocks and their dynamic effects. For example, assuming a flat within-quarter Phillips curve—through a prior distribution centered at $\kappa = 0$ with zero variance—renders the impact matrix $\mathbf{D} = \mathbf{A}^{-1}\mathbf{C}$ lower triangular, providing a recursive VAR interpretation with the ordering $(y_t, \pi_t, c_t, h_t, r_t)$.

We estimate the model with $p = 2$ lags, setting most cross-partial terms beyond the first lag to zero to avoid overfitting. Table A.2 in the Appendix provides details of the prior distributions for all model parameters, along with their posterior mean, standard deviation, and 80 percent credible intervals. Key prior assumptions include:

- **Supply and Demand:** The priors for κ and δ in equations (5) and (6) follow inverse gamma distributions with a mean of 0.2 and a standard deviation of 1. At these values, a 1% increase in activity driven by demand shocks raises inflation by 0.2 percentage points, and a 1% supply-driven increase in inflation reduces GDP growth by 0.2 percentage points. These assumptions are consistent with estimates from DSGE models, for instance Smets and Wouters (2007).

- **Commodity Prices:** The priors for χ_S and χ_D are drawn from an inverse gamma distribution with mean equal to 2 and standard deviation equal to 5. Thus, the prior imposes that commodity prices rise and react strongly—but with a very generous range of possible outcomes—to both expansionary demand shocks and contractionary supply shocks.

- **Shortages:** The parameters θ_S, θ_D, and θ_C have inverse gamma priors with a mean of 0.2 and a standard deviation of 1. These priors assume that expansionary demand shocks increase shortages, contractionary supply shocks decrease shortages, and commodity price shocks increase shortages.

- **Monetary Policy:** The priors assume that there is a systematic positive response of interest rates to inflation and GDP, with a short-run response coefficients of 0.1; the long-run response is assumed to be larger due to the autoregressive parameters in the rule itself, as captured by the coefficients $\rho_{1,RR}$ and $\rho_{2,RR}$.

- **Lagged Coefficients:** For the lag coefficients in $\mathbf{B}_j$, we set the prior means so that the variables exhibit first- and second-order autocorrelations of 0.65 and 0.10, respectively, with most lagged indirect effects set to zero (except for specific responses of inflation and activity to interest rate shocks).

Priors for key parameters are depicted in red in Figure 11. The prior densities are intentionally wide to allow the data to update both the location and spread of these distributions. Figure A.3 shows that the prior-induced impulse responses have much wider confidence intervals than the corresponding posterior intervals, indicating that the data are informative about the model parameters.

5.3 Results

We estimate the model on quarterly data from 1950:Q1 through 2023:Q4 using Dynare. The first 20 observations serve as a training sample, and we draw 20,000 posterior samples using a Random Walk Metropolis-Hastings algorithm.

Parameter Estimates

Figure 11 shows the prior distributions and the estimated posterior distributions for some of the key parameters of the model. The location and spread of all posterior distributions is substantially updated compared to the priors, revealing that the data and the structure of the model are informative about the structural parameters.

The posterior median for the parameter δ in the demand equation is around 0.1, which implies that a supply shock that increases inflation by 1 percentage point leads to a decrease in GDP growth of about 0.1 percentage point. The posterior mean for the parameter κ is around 0.1—which implies that a demand shock that raises GDP growth by 1 percentage point leads on impact to an increase in inflation of around 0.1 percentage point. All told, the posterior distributions reveal a “flatter” supply curve and a “steeper” demand curve than assumed by the prior distribution.

The top right panel of Figure 11 illustrates one of the underlying forces driving the inflationary effects of shortages in our model. After controlling for current and lagged movements in all other variables, the posterior density measuring the effect of shortages in period t on inflation in period $t+1$—as captured by the parameter $\rho_{1,PH}$—is positive, indicating a high likelihood of lagged shortages having a positive effect on inflation.

Estimates for θ_D, θ_S and θ_C are consistent with the notion that shortages respond to the business cycle and to movements in commodity prices, albeit to a smaller degree than assumed by the priors. The posterior estimate for both parameters is positive but relatively small.

The last row of Figure 11 describes the estimated response of interest rates to inflation and output, which is positive. Additionally, the parameter estimates suggest a relatively modest response of interest rates to increases in shortages.

Impulse Responses

Figure 12 reports the impulse responses to the estimated shocks in the model. The solid line depicts the posterior mean, while the shaded areas represent the 80 percent posterior credible sets. All shocks are one standard deviation in size.

Panel (a) shows that an exogenous increase in shortages leads to a slow, persistent decline in GDP alongside a rise in inflation. Inflation peaks about two years after the shock and remains elevated. There is also an initial, modest decline in interest rates followed by a tightening in the monetary policy stance.

Panels (b) and (c) illustrate that shortages can also respond endogenously: an expansion in aggregate demand or a contraction in aggregate supply tends to increase shortages. Similarly, panel (d) shows that commodity price shocks, such as those observed in the 1970s and 1980s, also drive up shortages. Thus, we find bidirectional causality: exogenous shortage shocks can trigger business cycle fluctuations, while demand and supply shocks can in turn generate movements in shortages.

Comparing shocks scaled to one standard deviation, an important finding is that, for a given decline in activity, the inflationary response is smaller under a shortage shock than under a traditional contractionary supply shock. In other words, while news about shortages signals higher inflation, the associated economic slowdown is more subdued. Notably, unlike typical supply shocks that tend to push up interest rates, shortage shocks exert only limited upward pressure on rates.

The Effects of Shortages throughout History

Figure 13 presents the historical decomposition of the model. In the early 1950s, shortages were largely driven by the Korean War and by demand shocks associated with the rapid transition from wartime to peacetime economies after World War II. In the 1970s, the oil embargo by OPEC producers caused a significant rise in shortages beyond what commodity price shocks alone would predict.

Historical decompositions over a long sample can obscure the role of shortage shocks, particularly since large shortage episodes have been relatively infrequent since the 1950s. To better highlight their impact in recent years, Figure 14 zooms in on the COVID and post-COVID period that began in 2020. To generate this figure, we plot variables in deviation from 2019Q4, thereby largely removing the lingering effects of earlier shocks and focusing on those that started in 2020.

Figure 14 reveals that the COVID and post-COVID years can be separated into three distinct periods. The first period, running from 2020:Q1 through 2021:Q1, is characterized by shortage shocks driven by both tight labor markets and supply chain disruptions, alongside depressed aggregate demand. In the second period, from 2021:Q2 through 2022:Q3, shortage shocks continue to stem from tight labor markets and supply chain strains; however, this phase occurs in a context of strong aggregate demand and rising commodity prices, leading to a step-up in upward pressure on inflation. The third period, from 2022:Q4 through the end of 2023, is marked by a reduction in shortages, although they remain above their pre-pandemic levels. Importantly, as the estimated effect of shortage shocks on inflation is delayed and long-lived, past shortages continue to be a prominent driver of inflation well into 2023.

Most of the discussion in policy and research about the drivers of inflation and economic activity since 2020 has been framed in terms of demand and supply forces. We connect to this debate by presenting in Figure 15 counterfactual paths for shortages, inflation, and GDP growth under alternative historical realizations of demand-side and supply-side forces. In our model, we define supply-side forces as the sum of supply, commodity, and shortages shocks, while demand-side forces are the sum of demand and monetary policy shocks. Each line in the figure represents a counterfactual path that assumes (i) no shocks are active through 2019 and (ii) shocks become active from 2020Q1 through the end of the specified date. For instance, the green lines labeled 2019 correspond to a scenario with no shocks in history; the purple lines labeled 20Q4 assume that shocks are active from 2020Q1 through 2020Q4; the yellow lines labeled 21Q4 assume that shocks are active from 2020Q1 through 2021Q4.

Figure 15 illustrates that, according to the model, the rise in inflation is predominantly driven by supply forces, with demand forces playing a secondary but quantitatively relevant role as well. Supply shocks in 2020 and 2021 had a cumulative effect of raising inflation by 6 percentage points and reducing GDP growth by nearly 2 percentage points. Demand shocks exerted downward pressure on both inflation and GDP growth in 2020, whereas in 2021 they contributed to a rebound in these variables. In the absence of countervailing shocks in 2022 and 2023—in part capturing the tightening in the stance of monetary policy—we would have observed a more prolonged period of elevated inflation and subdued economic activity.

Our results differ from those of Giannone and Primiceri (2024), who found that demand factors predominantly drove the pandemic-related rise in inflation in the euro area and the United States. Giannone and Primiceri (2024) emphasize that a key element of their findings is a flat aggregate demand (AD) curve; when the AD curve is flat, supply shocks can only exert modest inflationary pressures, and a large increase in inflation must be driven primarily by demand shocks. In contrast, our estimates for the United States suggest a steeper AD curve, implying a larger role for supply shocks in driving inflation. It is important to note that our calculations indicate that demand shocks in 2021 could account for a 2-percentage-point increase in inflation by the end of 2023 relative to a no-shock scenario—a sizeable effect. We examine the implications of a flatter demand curve in our model in the robustness exercises presented next.

Robustness

Figure 16 illustrates the response of inflation to a shortage shock and the role of shortages and other shocks in explaining the post-2020 fluctuations in inflation under the baseline model and three alternative specifications. The contribution of shortages remains substantial across specifications, except when we impose the strong assumption of a flat demand curve (panel b), fixing the slope of the short-run inverse demand curve at $\delta = 4$. Notably, a flatter demand curve assigns a larger role to demand shocks in accounting for the higher inflation observed in 2022. However, the fit of this model to the data is worse than for the baseline model as measured by the marginal likelihood of the models (-2243.7 for the baseline model against -2608.1 for the alternative model). Assuming a steeper supply curve (panel c) only marginally reduces the role of supply shocks in explaining the post-pandemic inflation surge. Finally, the results remain unchanged when activity is measured using the CBO output gap instead of 4-quarter GDP growth (panel d). These findings complement our comparison with Giannone and Primiceri (2024), confirming that a flatter AD curve than in our baseline estimates increases the role of demand shocks in driving inflation.

6 Conclusions

This paper introduces a novel monthly, newspaper-based shortage index covering the period from 1900 to the present. The index captures the intensity of shortages across sectors—labor, materials, goods, and energy—and exhibits pronounced spikes during periods of economic turmoil, such as the World Wars, the oil crises of the 1970s, and the COVID-19 pandemic. We construct country-specific indexes for the United States and five major advanced economies. Validation exercises confirm that the index accurately measures shortages and correlates strongly with other indicators of supply constraints. Its extensive historical coverage makes it a valuable tool for understanding long-run economic dynamics.

Predictive regressions demonstrate that, throughout history, increases in the shortage index are associated with persistently higher inflation and lower economic activity. These effects are particularly pronounced for durable goods consumption and private investment. Furthermore, the relationship between inflation and shortages appears to be much stronger during the COVID-19 pandemic.

Structural VAR analysis further decomposes shortage movements into components arising from traditional business cycle shocks and exogenous innovations. Our results indicate that shortages cannot be explained solely by conventional demand, supply, commodity, and monetary shocks; surprise shortage innovations contribute importantly to inflation. Historically, while the 1950s saw shortages driven mainly by demand factors, the 1970s witnessed unusual shortage shocks from the OPEC oil embargo, and the COVID-19 period reflects a mix of supply, demand, and exogenous factors that led to a sustained inflationary impact.

Overall, our shortage index provides a comprehensive long-run perspective on the prevalence, drivers, and consequences of shortages in the U.S. over the past century. These findings underscore the complex interplay between various forces behind shortages and highlight their significant role in boosting inflation, offering valuable insights for policymakers and researchers.

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Table 1: Search Query for the Construction of the Shortage Index

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". "AND" and "OR" are logical operators, N/5 denotes a proximity operator requiring words appearing within five words from each other.

Table 2: Largest Shortage Spikes, 1900-2023

Month	**Index**	**Surprise (st.dev.)**	**Event**
Jan-1903	174	2.84	Nationwide coal shortages
Dec-1906	191	2.58	Shortage of coal and freight cars in Midwest
Nov-1916	235	2.54	Nationwide coal shortages
Jan-1918	578	7.63	Fuel and coal shortages
Dec-1919	300	2.75	Fuel and coal shortages due to war, strikes
Jul-1920	317	2.32	Freight car shortage affects coal and steel transportation
Aug-1922	281	3.24	Coal shortage due to strikes
Aug-1930	93	1.28	Drought leads to food and water shortages
Jul-1934	134	1.70	Strike by Teamsters unions in the West Coast
Sep-1939	152	1.81	Steel shortage due to the beginning of WW2
Aug-1941	516	3.30	War-related energy, materials and labor shortages
Jan-1943	1085	4.87	War-related oil, labor and food shortages
Jan-1945	563	4.17	War-related widespread shortages
Aug-1945	556	3.46	Labor shortages at the end of war
May-1946	589	4.31	Strikes by coal workers and fuel shortages
Jan-1948	460	4.01	Metal, fuel and food shortages
Feb-1950	226	2.30	Coal shortages amid strikes
Jan-1951	286	2.44	Labor shortages due to demand from defense industries
Jan-1952	271	2.87	Nationwide and worldwide shortages
Dec-1956	172	1.80	Oil shortages due to Suez crisis
Dec-1973	1085	11.28	Gasoline shortages due to 1973 oil crisis
Jan-1975	267	2.02	Concerns about gasoline rationing
Feb-1977	422	6.81	Carter's appeal on energy conservation
Feb-1978	158	1.59	Concerns about energy shortages
May-1979	579	4.81	Concerns about energy shortages
Aug-1981	153	1.18	Gasoline shortages due to 1979 oil crisis
Aug-1990	160	1.47	Concerns about energy shortages
Apr-2020	297	4.58	Medical shortages due to COVID-19 pandemic
Jan-2022	554	2.69	Labor shortages
Oct-2023	213	1.20	UAW strike and food shortages in Gaza

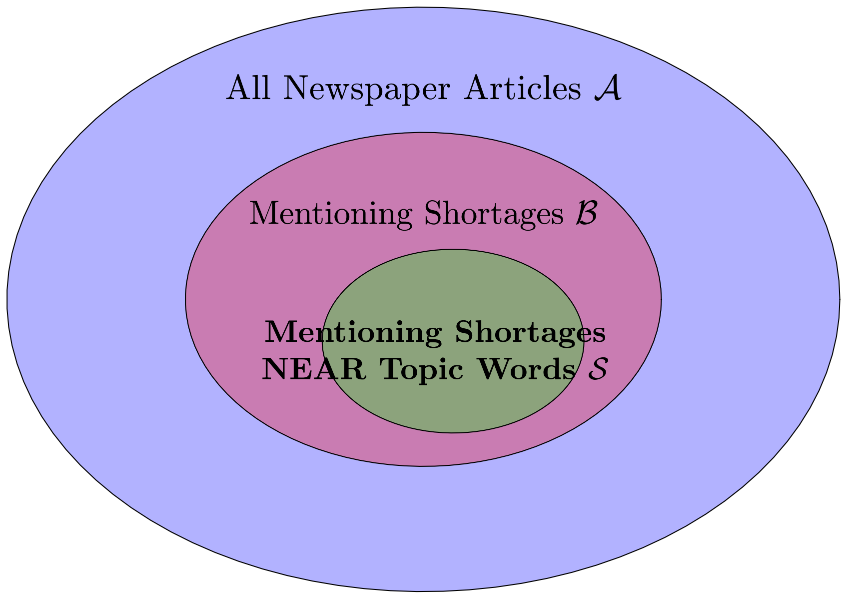
Note: The table lists the 30 largest spikes in the shortage index. For this table, the spikes are identified using the residuals of an autoregression and a condition on local maxima described in footnote 6.

Table 3: Validation of the Shortage Index

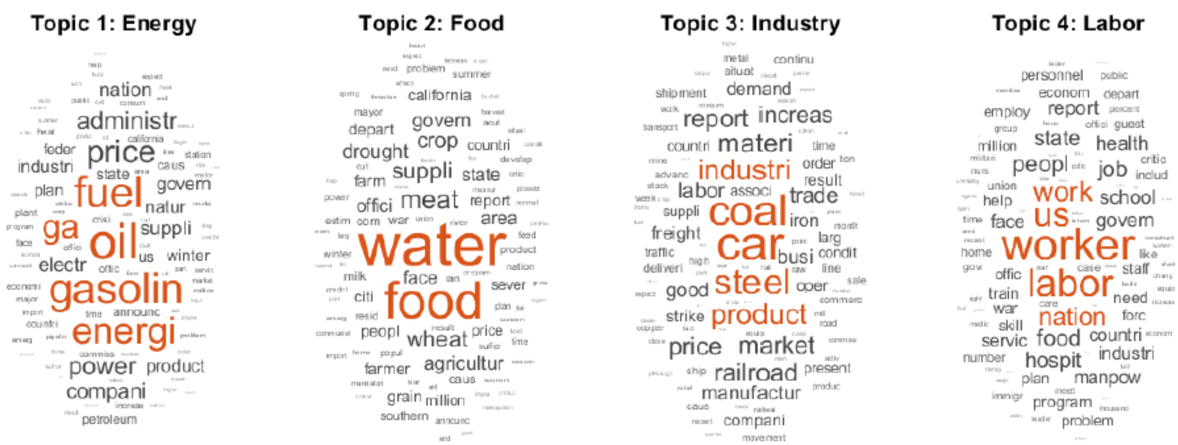
Set	**Share of Total Newspaper Articles in Set**	**Validation Sample**	**Articles Mentioning Actual Shortages**	**Type I Error**	**Type II Error**
Shortages AND Topic Words $\mathcal{S}$	1.58%	872	817	6.30%	–
Not Shortages ($\mathcal{A} \setminus \mathcal{S}$)	98.42%	298	1	–	0.33%
All Shortages ($\mathcal{B}$)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

Note: Validation of the Shortage Index using a sample of newspaper articles used to construct the index (denoted by the set Shortages AND Topic Words $\mathcal{S}$) and excluded from the construction of the index (denoted by the set $\mathcal{A} \setminus \mathcal{S}$. See main text for additional details.

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



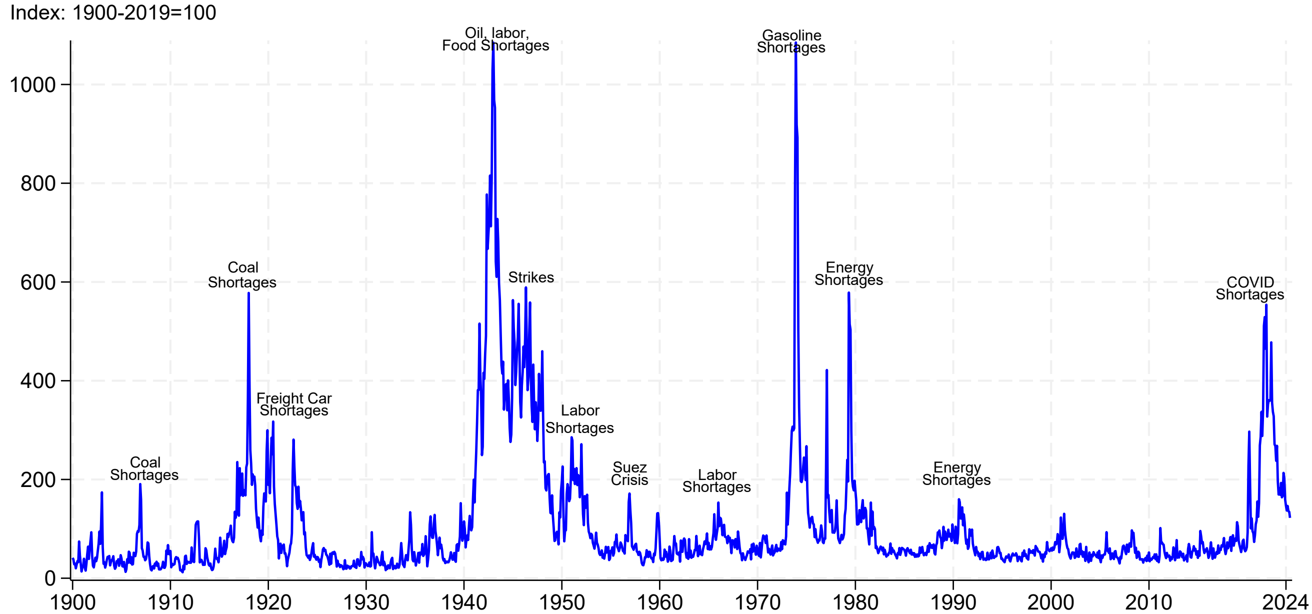
(a) Grouping of Newspaper Articles



(b) Word Clouds and Topic Classification of Articles

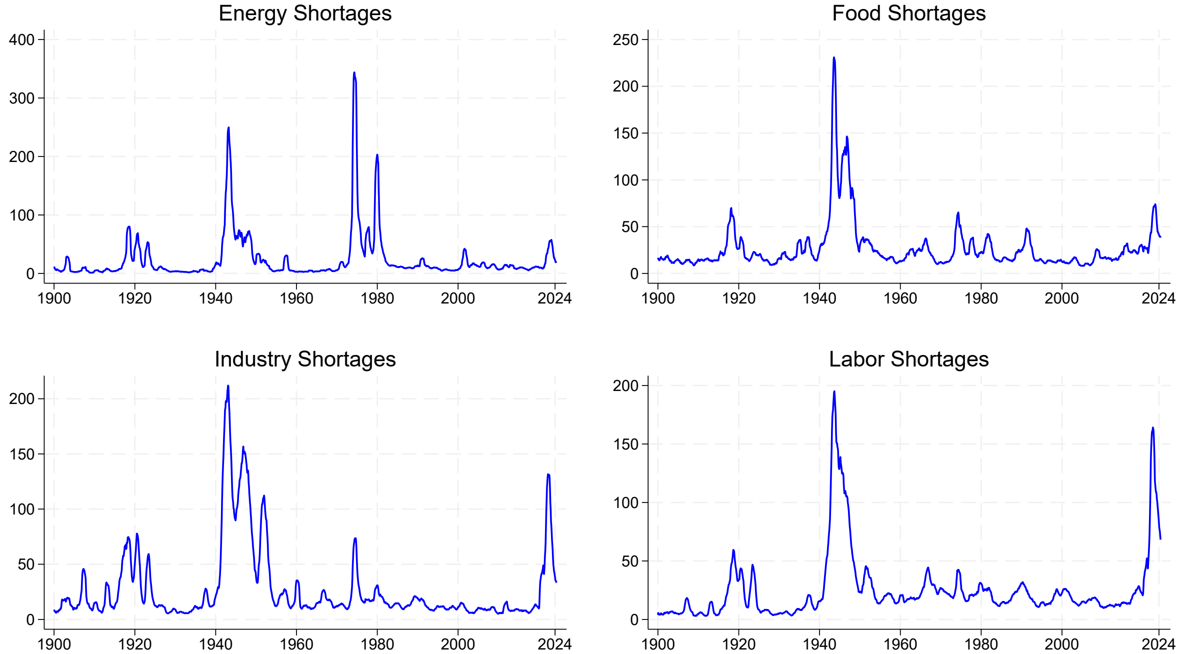
Note: The top panel shows a diagram representing the set of articles used in the construction of the index. The bottom panel shows word clouds associated with the four most influential topics chosen by LDA analysis on a large set of articles.

Figure 2: The Shortage Index

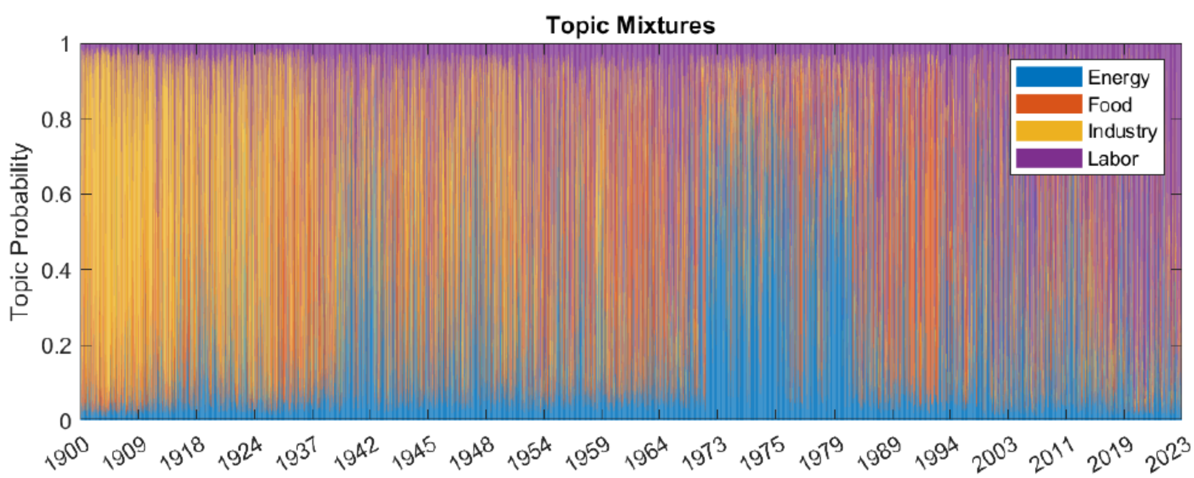


Note: The figure shows the shortage index from January 1900 through June 2024.

Figure 3: Decomposition of the Shortage Index by Category



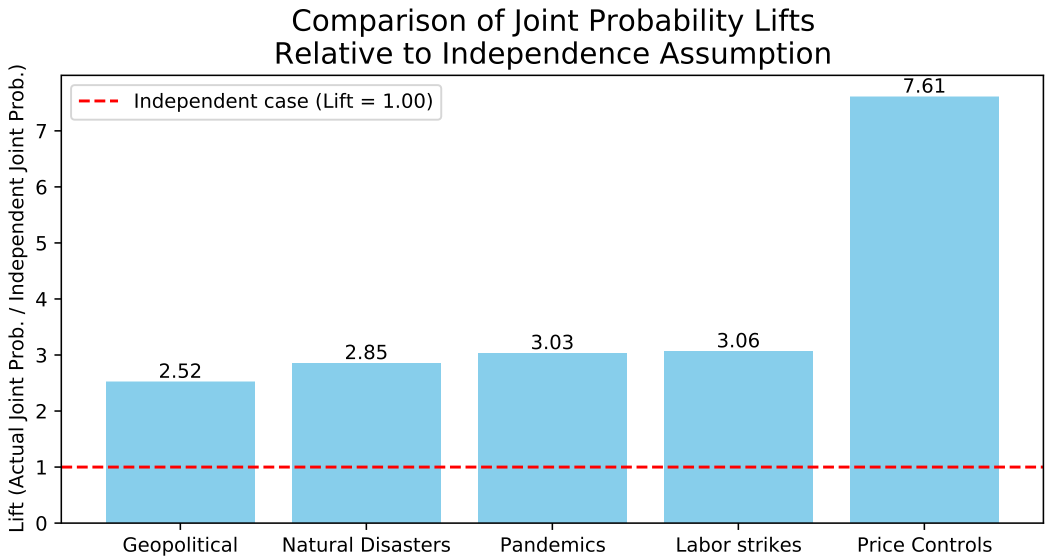
(a) Decomposition of the Shortage Index by Category



(b) Topic Classification for the Index

Note: The top panel shows shortage indexes by category, scaled so that the sum of the four indexes adds up to the total index shown in Figure 2. The bottom panel shows the evolution over time of the topic classification by an LDA algorithm for a large sample of articles used in the construction of the index. Data are from January 1900 through June 2024.

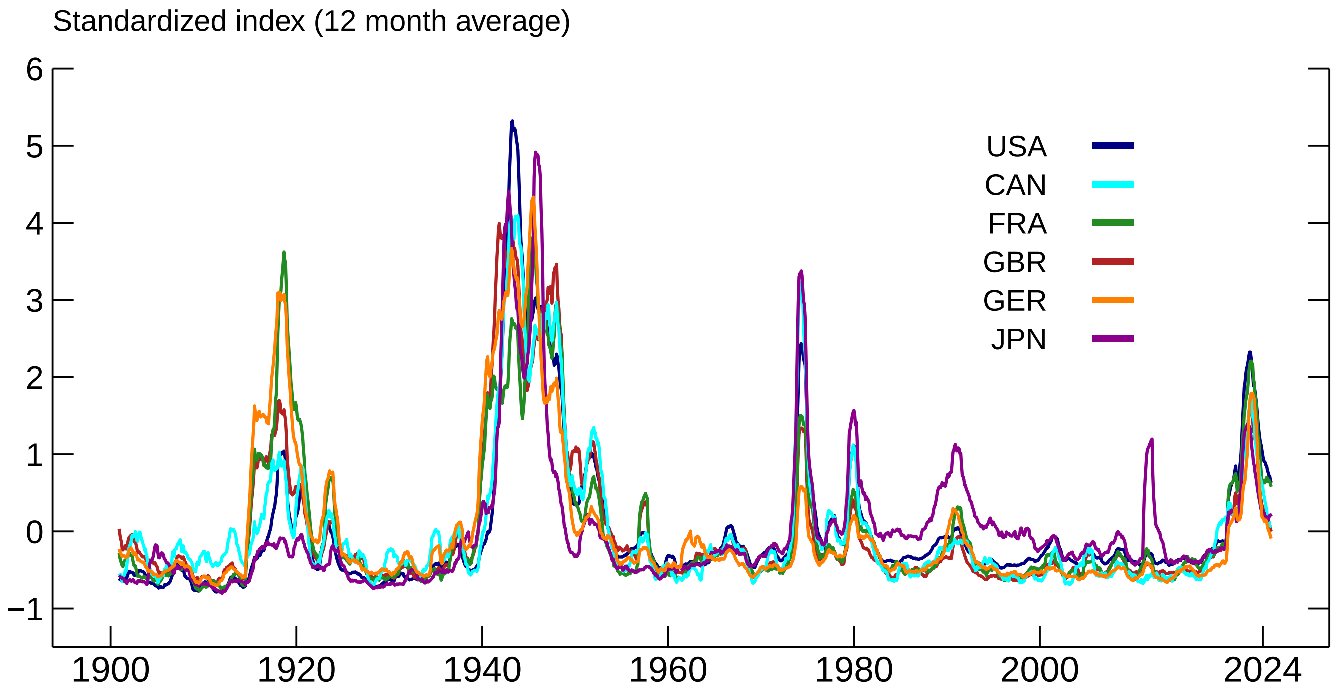
Figure 4: Phenomena Associated With Shortages



Category	***P(Shortage)***	***P(Category)***	***P(Joint)***	***P(Indep.)***
Geopolitical	1.27%	2.63%	0.084%	0.033%
Natural Disasters	1.27%	2.85%	0.103%	0.036%
Pandemics	1.27%	1.23%	0.047%	0.016%
Labor strikes	1.27%	2.69%	0.104%	0.034%
Price Controls	1.27%	0.80%	0.077%	0.010%

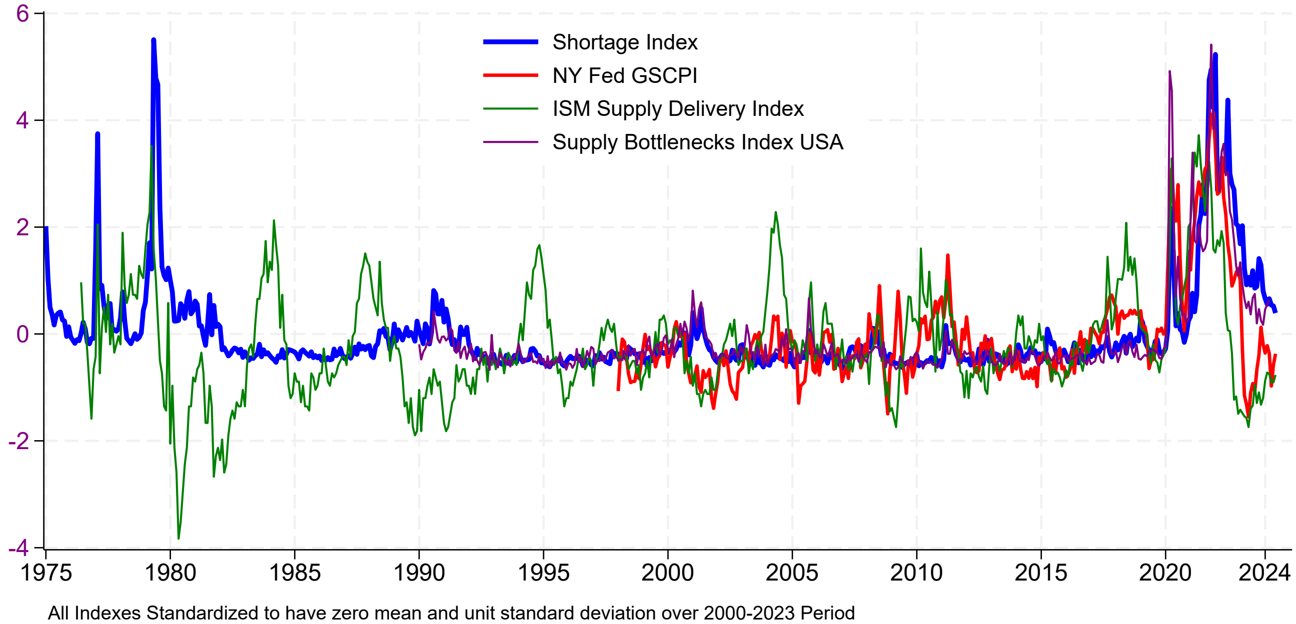
Note: The figure plots lift ratios, calculated as the ratio between the realized joint probability of events in five categories being mentioned in newspaper articles alongside shortages, and the probability that would be expected if these events and shortages were independent. The higher the lift ratio, the stronger the association between events and shortages. In the table, *P(Shortage)* is the frequency of news articles mentioning shortages; *P(Category)* is frequency of news articles mentioning the specific category in each row; *P(Joint)* is frequency of news articles mentioning both shortages and the specific category in each row; *P(Indep.)* is the hypothetical joint probability under the independence assumption.

Figure 5: Shortage Index across Countries



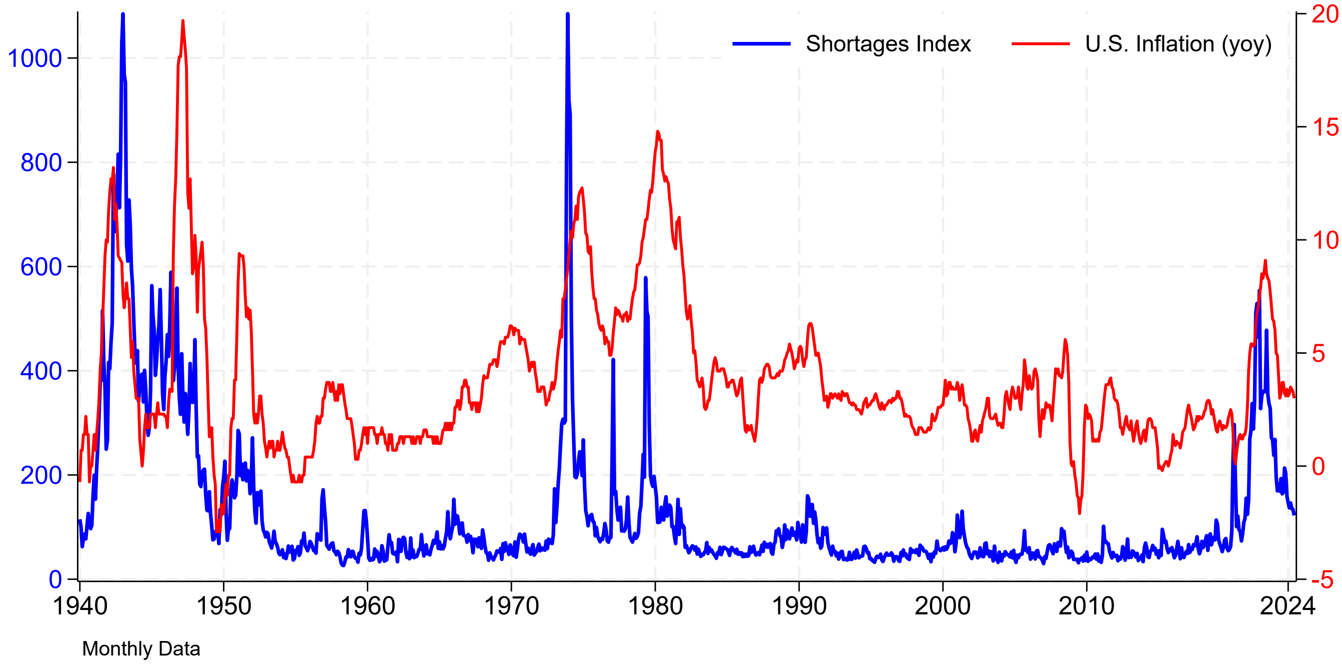
Note: The figure shows the shortage index for six major economies: the United States, Canada, France, Germany, Great Britain, and Japan. The country indexes are proportional to the share of newspaper articles mentioning shortages and the name of a foreign country and/or one of its major cities. Indexes are standardized to have mean zero and unit standard deviation over the period 1900-2023.

Figure 6: Comparison to Other Supply Constraints Measures



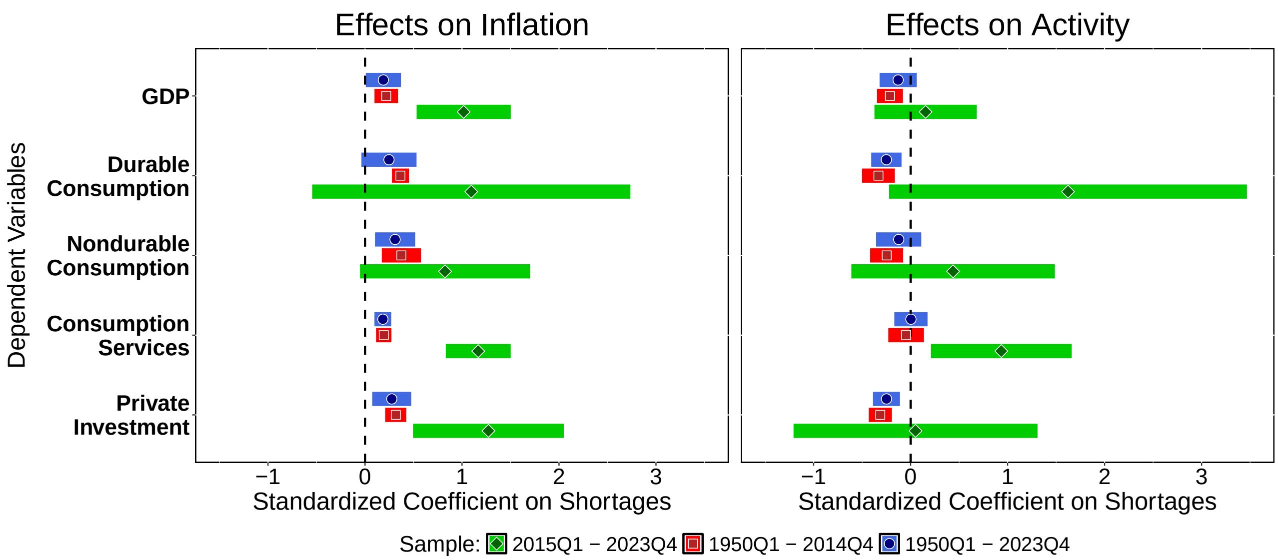
Note: The figure compares the shortage index to alternative measures of supply constraints from January 1975 through June 2024. The GSCPI is the New York Fed Global Supply Chain Pressure index (Benigno et al., 2022), measuring global supply chain conditions using data on both manufacturing and transportation costs. The ISM Supply Delivery 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 Supply Bottlenecks Index is the U.S. Supply Bottlenecks Index from Burriel et al. (2023).

Figure 7: Shortages and U.S. Inflation



Note: The figures compares the shortage index (left scale) with U.S. inflation (right scale), from January 1940 through June 2024.

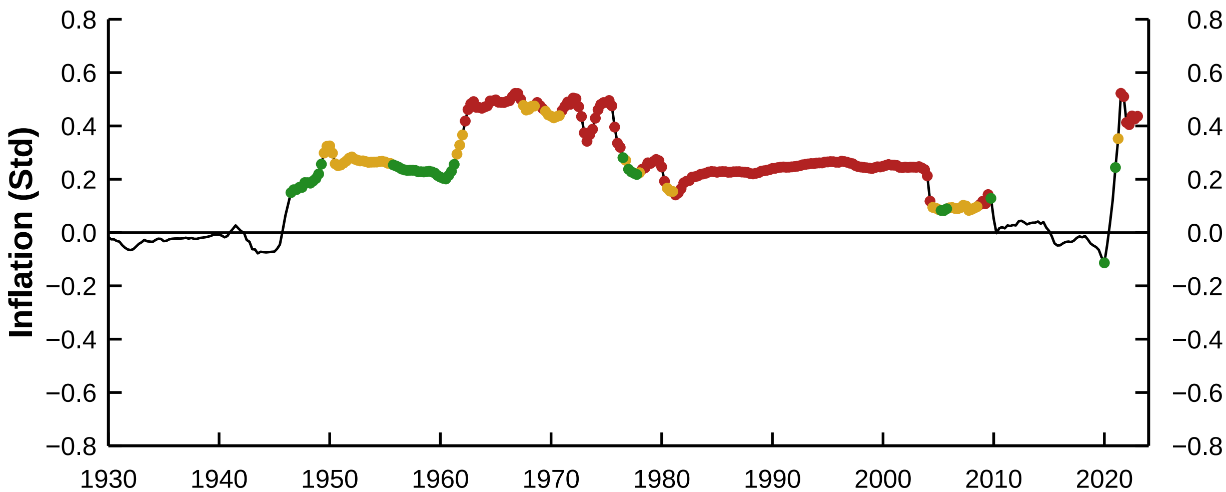
Figure 8: Effects of Shortages on Inflation and Economic Activity 1-Year Ahead



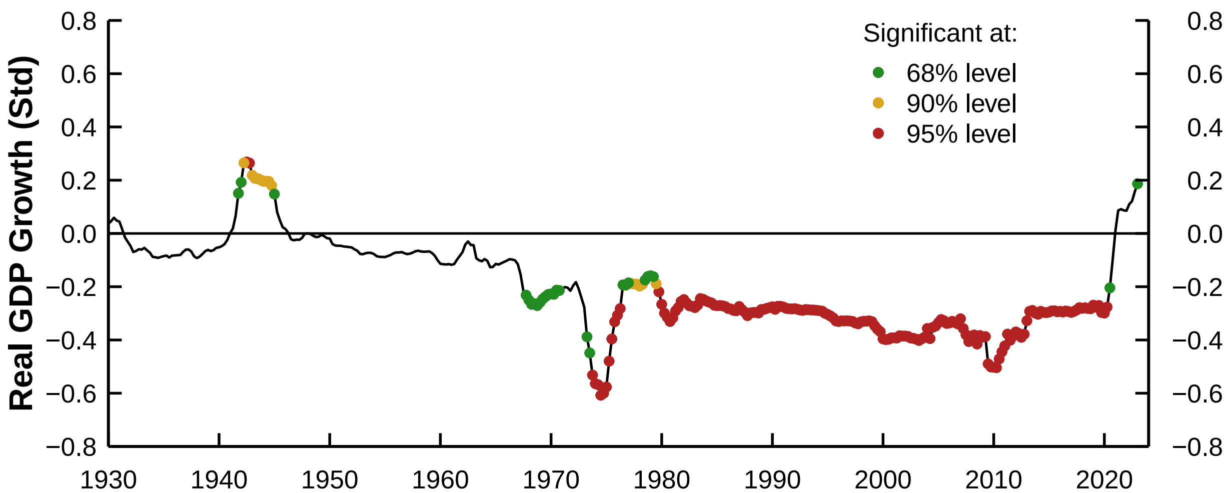
Note: The figure reports standardized coefficients of predictive regressions of inflation and economic activity on the shortage index estimated on quarterly data. The dependent variable for each regression is the log difference between $t + 4$ and t of the variable listed in each row (the price deflator for inflation and real quantities for growth). 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 runs from 1950Q1 to 2023Q4. We 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 95% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987).

Figure 9: Effect of Shortages on Inflation and Real GDP Growth (30-Year Window)

(a) One-Year Ahead Inflation

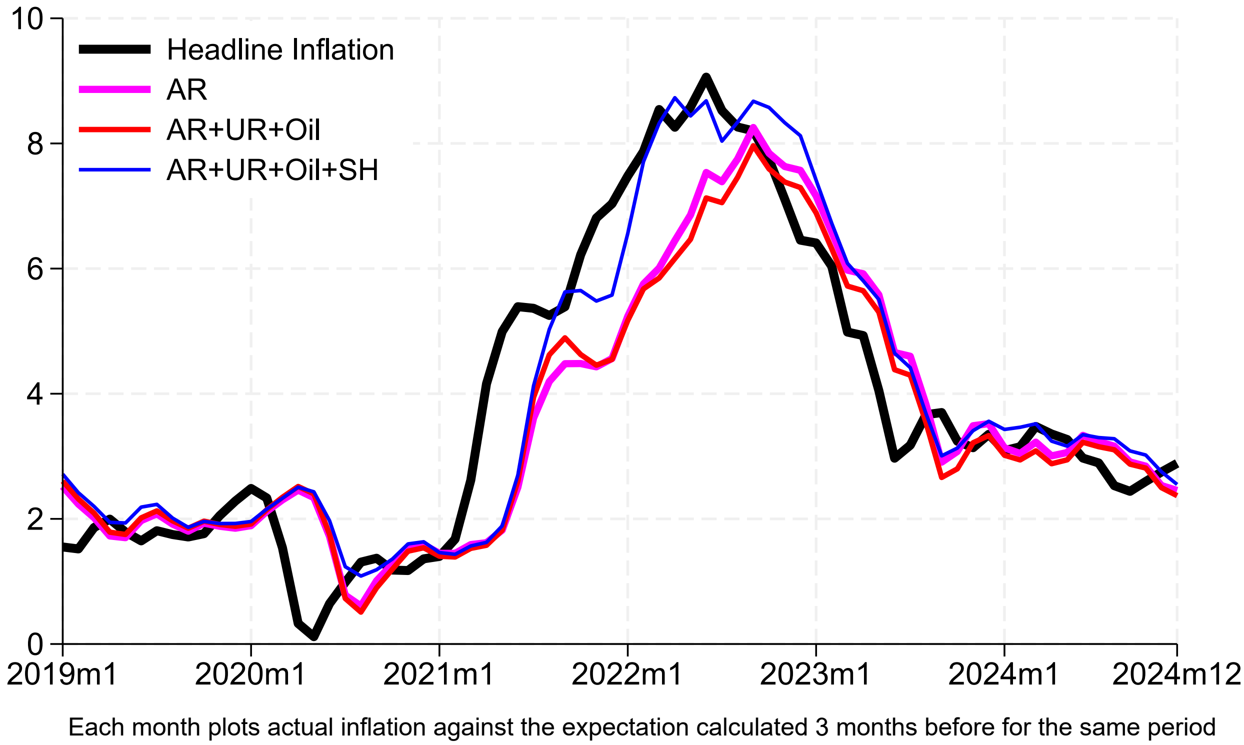


(b) One-Year Ahead Real GDP Growth



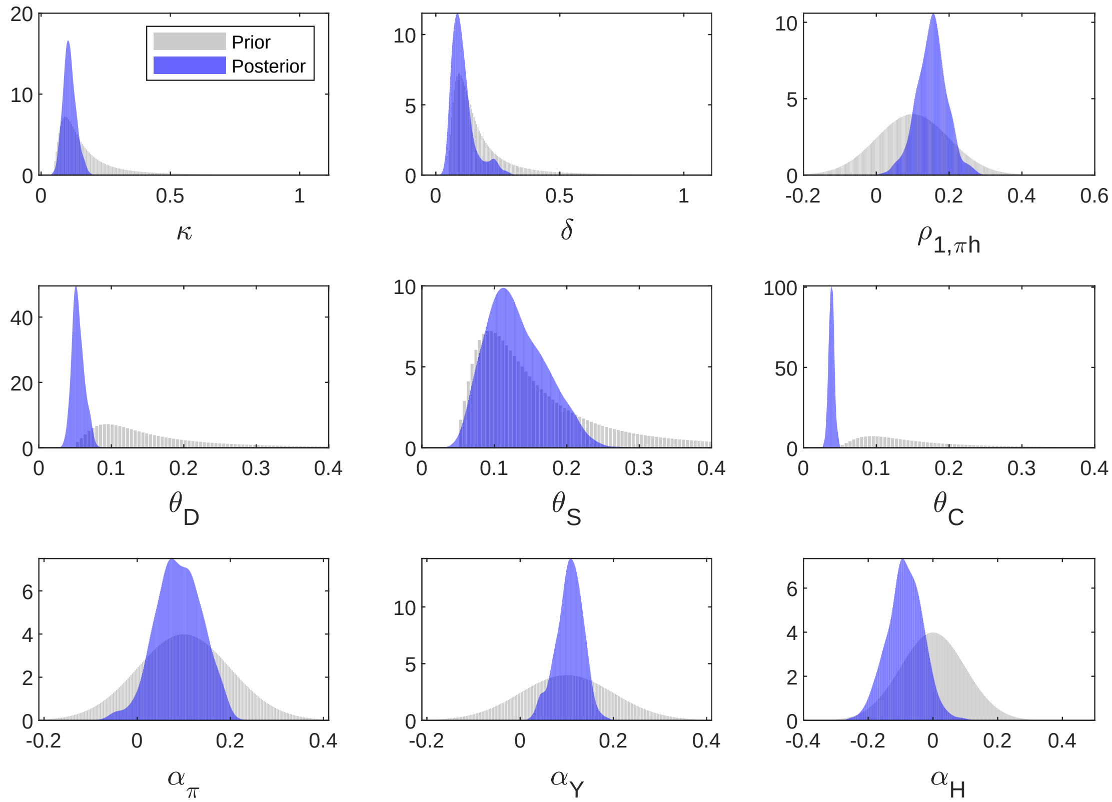
Note: The solid black line shows the time-varying estimated effect of shortages on inflation (top panel) and real GDP growth (bottom panel). The estimates are based on regressions using rolling 30-year windows. In each regression, the dependent variable is the 4-quarter ahead difference in log real GDP 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. Heteroskedasticity and autocorrelation consistent significance levels are computed according to Newey and West (1987).

Figure 10: Inflation and its Forecasts



Note: The figure plots realizations of annual, total CPI inflation with corresponding forecasts constructed 3 months earlier. The series are aligned so that the vertical distance between the plot of inflation and the forecast represents the forecast error. The model 'AR' predicts 3-month ahead inflation using current inflation only. The model 'AR+UR+Oil' adds to the prediction model the unemployment rate and the 12-month change in oil prices. The model 'AR+UR+Oil+SH' adds shortages.

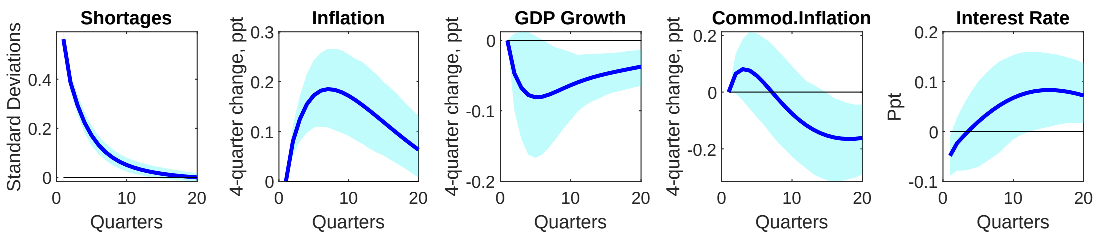
Figure 11: Prior and Posterior Densities of Structural VAR Parameters



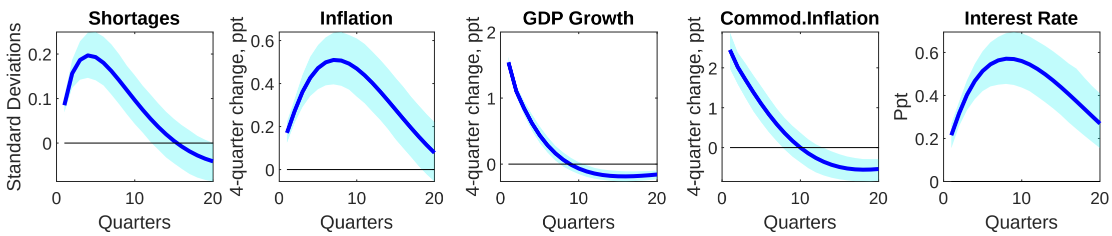
Note: Prior and posterior densities of selected parameters of the structural VAR model. See Section 5 for additional details and the appendix Table A.2 for the full list of prior and posterior moments of the model parameters.

Figure 12: Effects of Shortages on US Activity and Inflation in the Structural VAR Model

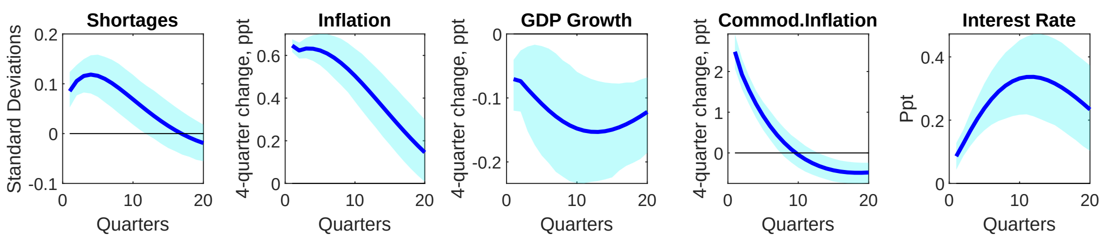
(a) Shock to Shortages



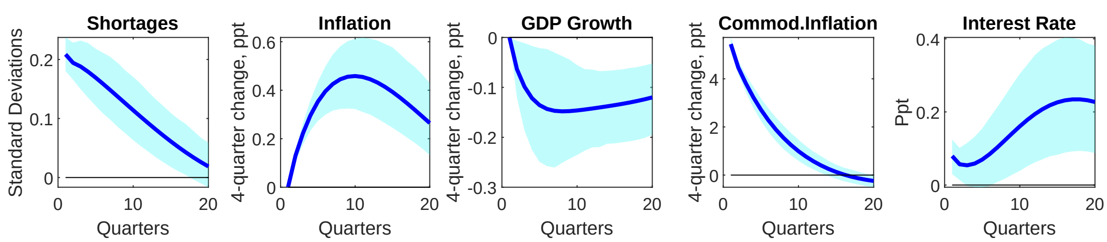
(b) Shock to Demand



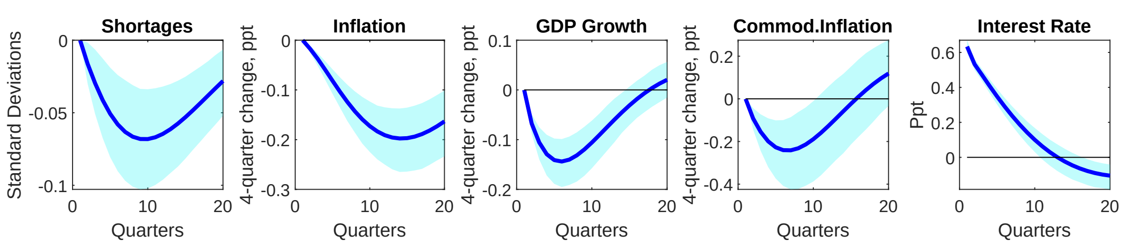
(c) Shock to Supply



(d) Shock to Commodity Prices

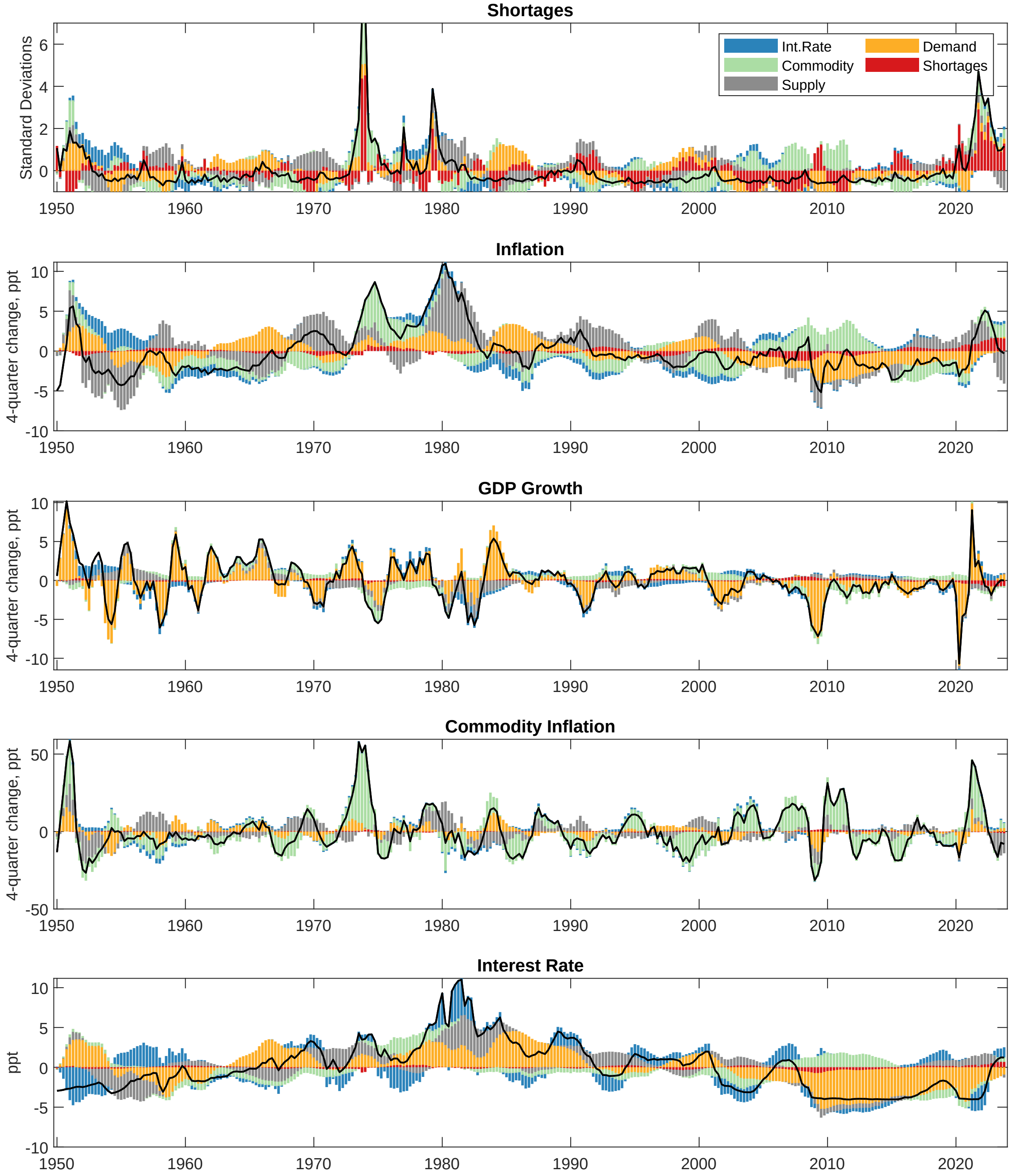


(e) Shock to Interest Rate



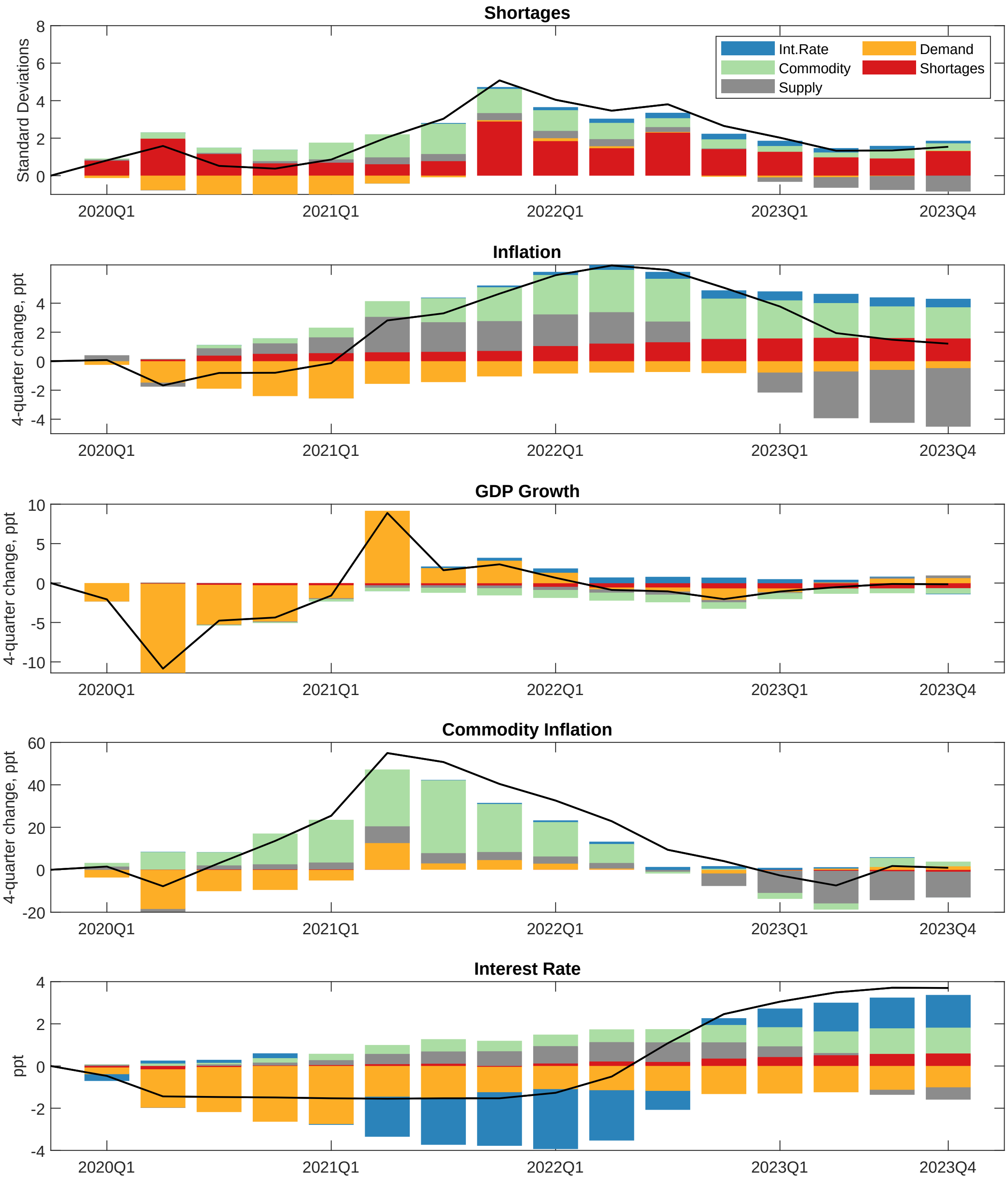
Note: Impulse responses to structural shocks of size one standard deviation estimated using the structural VAR model described in Section 5. Solid lines denote the responses at the posterior mean. Shaded areas denote 80 percent posterior credible sets.

Figure 13: Historical Decomposition from the structural VAR Model: Full Sample



Note: This figure displays the historical contributions of structural shocks to the evolution of the model's endogenous variables. All variables are expressed as deviations from their sample means.

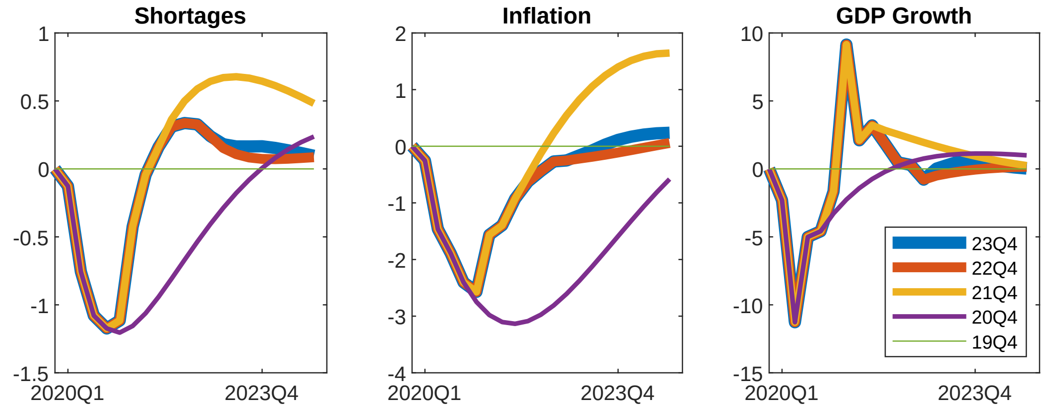
Figure 14: Historical Decomposition from the structural VAR Model: 2020-2023



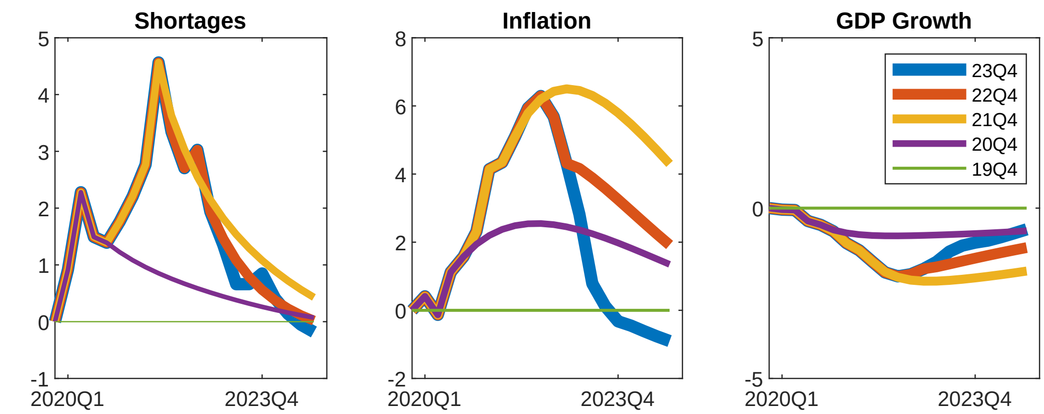
Note: This figure displays the contributions of structural shocks to the evolution of the model's endogenous variables since 2020. All variables are expressed in deviation from their 2019Q4 value.

Figure 15: Historical Contribution of Demand-side and Supply-side Forces: 2020-2024

(a) Demand-side shocks



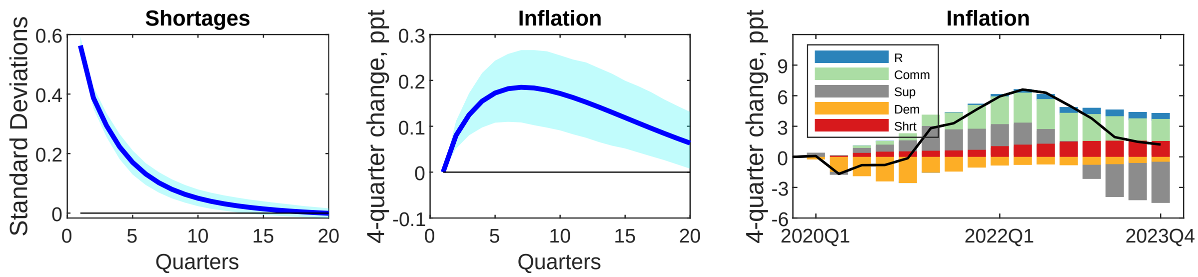
(b) Supply-side shocks



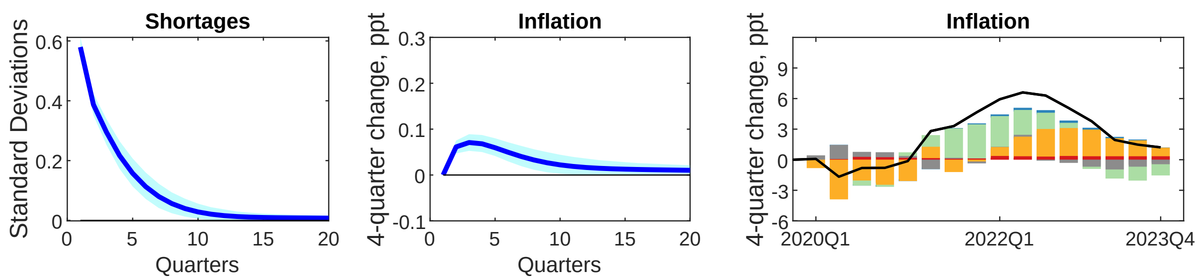
Note: The figure shows the contribution between 2019:Q4 and 2024:Q4 of demand-side forces (first row) and supply-side forces (second row) to shortages, inflation and GDP growth. Demand forces are the sum of demand and monetary shocks. Supply forces are the sum of shortage, commodity, and supply shocks. Variables are plotted in deviation from their 2019:Q4 value. Each line in the figure represents a counterfactual path that assumes (i) no shocks are active through 2019 and (ii) shocks become active from 2020Q1 through the end of the specified date. For instance, the green lines labeled 2019 correspond to a scenario with no shocks in history; the purple lines labeled 20Q4 assume that shocks are active from 2020Q1 through 2020Q4; the yellow lines labeled 21Q4 assume that shocks are active from 2020Q1 through 2021Q4.

Figure 16: Comparison of baseline VAR model with alternative versions

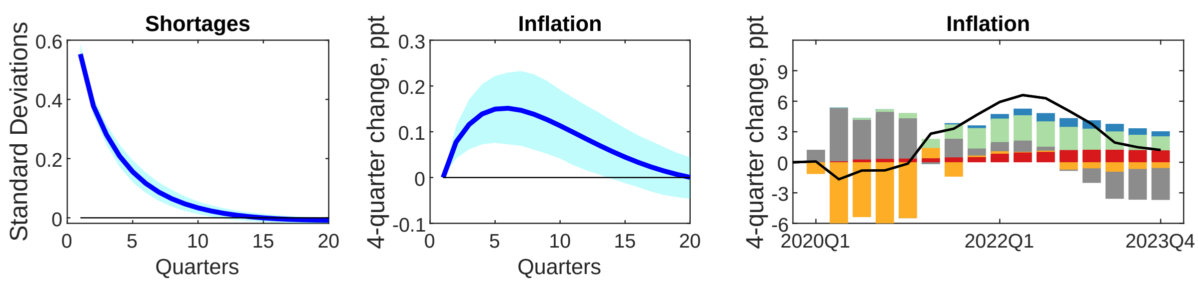
(a) Baseline Model



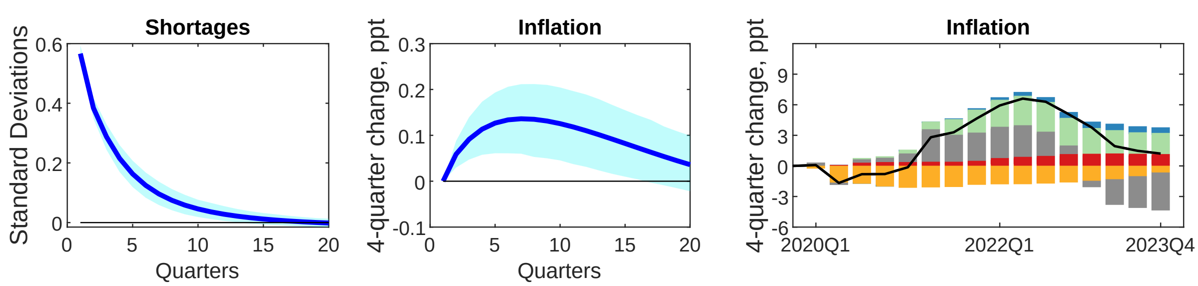
(b) Flatter Demand Curve ($\delta = 4$)



(c) Steeper Supply Curve ($\kappa = 1$)



(d) Using Output Gap instead of 4-quarter GDP growth



Note: Model (a) is the baseline model. Models (b) and (c) are estimated after fixing $\kappa = 1$ and $\delta = 4$, respectively. Model (d) replaces 4-quarter GDP growth with the output gap constructed using the CBO measure of the output GDP.

Appendix

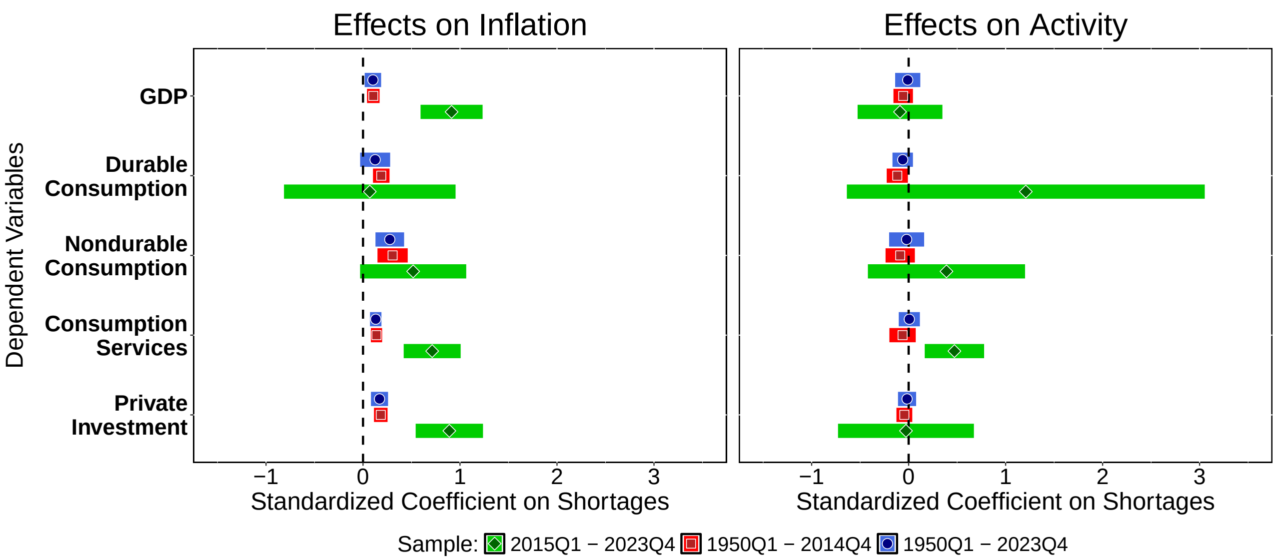
A Appendix Tables and Figures

Table A.1: Predictive Regressions with Categorical Shortage Indexes

	Wages		PPI Materials		CPI Energy		CPI Food	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor	0.17***	0.11***		-0.06		0.03		0.03
	(4.55)	(2.61)		(-1.03)		(0.61)		(0.47)
Industry		0.05	0.34***	0.23**		-0.00		0.15
		(0.71)	(5.63)	(2.00)		(-0.01)		(0.95)
Energy		0.12*		0.21***	0.30***	0.29***		0.07
		(1.90)		(2.63)	(5.24)	(3.68)		(.58)
Food		-0.06		-0.05		-0.02	0.15***	0.06
		(-1.26)		(-1.26)		(-0.32)	(3.01)	(1.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	668	668	672	672	672	672	672	672

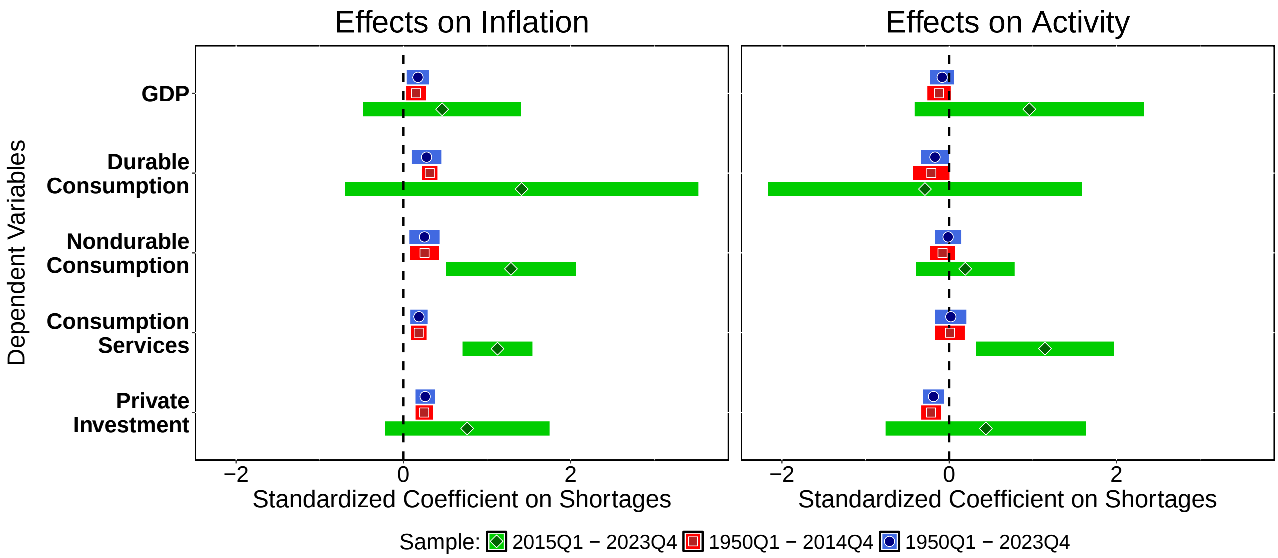
Note: The table reports standardized coefficients of predictive monthly regressions of selected prices and wages indicators on the categorical shortage indexes. The dependent variable for each regression is the 3-month log difference of the producer price index (PPI) for processed goods for intermediate demand, consumer price index (CPI) energy, CPI Food, and the 12-month log change in average hourly earnings (total private). Each regression includes as controls three lags of the monthly changes of the dependent variable and one lag of the log change in industrial production. The sample runs from 1964M1 through 2019m12. 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 A.1: Effects of Shortages on Inflation and Economic Activity 1 Quarter Ahead



Note: The figure reports standardized coefficients of predictive regressions of inflation and economic activity on the shortage index estimated on quarterly data. The dependent variable for each regression is the log difference between $t + 1$ and t of the variable listed in each row (the price deflator for inflation and real quantities for growth). 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 runs from 1950Q1 to 2023Q4. We 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 95% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987).

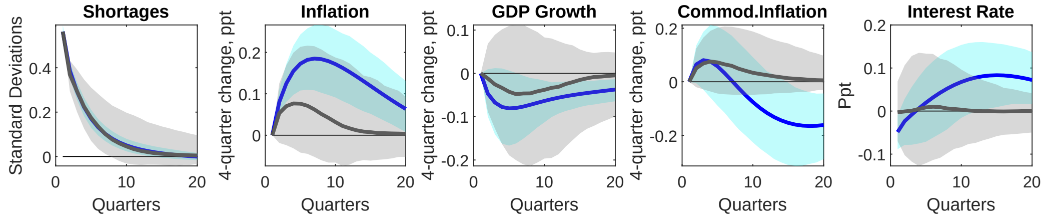
Figure A.2: Predicted Effects of Shortages on Inflation and Economic Activity 2-Year Ahead



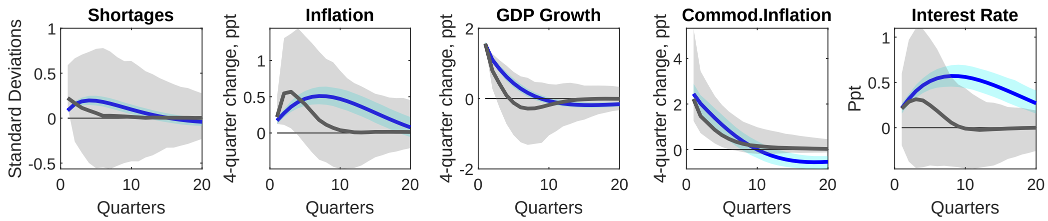
Note: The figure reports standardized coefficients of predictive regressions of inflation and economic activity on the shortage index estimated on quarterly data. The dependent variable for each regression is the log difference between $t + 8$ and t of the variable listed in each row (the price deflator for inflation and real quantities for growth). 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 runs from 1950Q1 to 2023Q4. We 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 95% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987).

Figure A.3: Effects of Shortages in the Estimated VAR Model: Prior vs Posterior

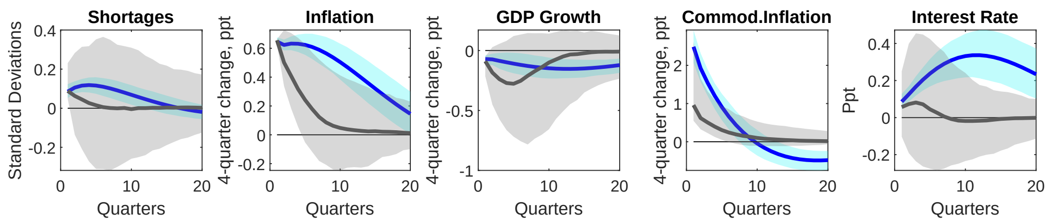
(a) Shock to Shortages



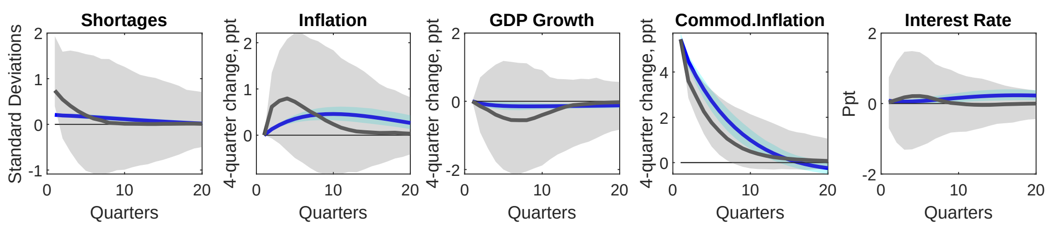
(b) Shock to Demand



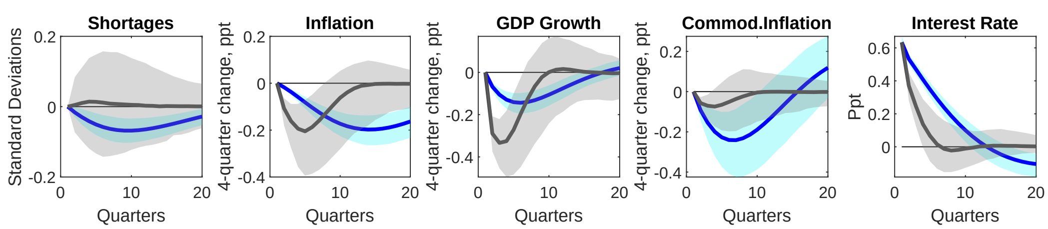
(c) Shock to Supply



(d) Shock to Commodity Prices



(e) Shock to Interest Rate



Note: Red lines and areas, prior; Blue lines and areas, posterior. Impulse Response in VAR to Estimated Shocks, Prior vs. Posterior. Posterior shocks are one-standard deviation in size. Solid lines denote the response at the mean. Shaded areas denote 80 percent confidence intervals. Impact of the shocks at the prior mean has been normalized to match the impact effect of the estimated shocks at the posterior mean.

Table A.2: VAR Model: Estimated Parameters

		Prior		Posterior			
Parameter	Type	**Mean**	St. Dev	**Mean**	St. Dev	10%	90%
σ_{ε_d}	Inv. Gamma	**1.00**	0.50	**1.56**	0.06	1.49	1.65
σ_{ε_s}	Inv. Gamma	**1.00**	0.50	**0.65**	0.02	0.62	0.68
σ_{ε_c}	Inv. Gamma	**1.00**	0.50	**5.44**	0.21	5.17	5.72
σ_{ε_h}	Inv. Gamma	**1.00**	0.50	**0.56**	0.02	0.53	0.59
σ_{ε_r}	Inv. Gamma	**1.00**	0.50	**0.63**	0.03	0.60	0.67
$\rho_{1,HH}$	Beta	**0.65**	0.10	**0.69**	0.04	0.63	0.73
$\rho_{1,YY}$	Beta	**0.65**	0.10	**0.75**	0.04	0.70	0.80
$\rho_{1,PP}$	Beta	**0.65**	0.10	**0.88**	0.03	0.84	0.92
$\rho_{1,CC}$	Beta	**0.65**	0.10	**0.82**	0.03	0.78	0.86
$\rho_{1,RR}$	Beta	**0.65**	0.10	**0.85**	0.03	0.82	0.89
$\rho_{1,PR}$	Beta	**0.10**	0.05	**0.02**	0.01	0.01	0.03
$\rho_{1,YR}$	Beta	**0.50**	0.10	**0.11**	0.03	0.08	0.14
δ	Inv. Gamma	**0.20**	1.00	**0.11**	0.05	0.06	0.17
κ	Inv. Gamma	**0.20**	1.00	**0.11**	0.02	0.08	0.14
θ_C	Inv. Gamma	**0.20**	1.00	**0.04**	0.00	0.03	0.04
θ_D	Inv. Gamma	**0.20**	1.00	**0.05**	0.01	0.04	0.07
θ_S	Inv. Gamma	**0.20**	1.00	**0.13**	0.04	0.08	0.19
α_C	Normal	**0.00**	0.10	**0.02**	0.01	0.01	0.03
α_Y	Normal	**0.10**	0.10	**0.11**	0.03	0.07	0.14
α_H	Normal	**0.00**	0.10	**-0.09**	0.06	-0.16	-0.02
α_P	Normal	**0.10**	0.10	**0.09**	0.05	0.03	0.15
χ_D	Inv. Gamma	**2.00**	5.00	**1.57**	0.21	1.31	1.85
χ_S	Inv. Gamma	**2.00**	5.00	**3.80**	0.50	3.15	4.46
$\rho_{1,HY}$	Normal	**0.00**	0.10	**0.05**	0.02	0.03	0.07
$\rho_{1,HP}$	Normal	**0.00**	0.10	**0.04**	0.02	0.02	0.07
$\rho_{1,HC}$	Normal	**0.00**	0.10	**0.01**	0.00	0.01	0.01
$\rho_{1,YH}$	Normal	**0.00**	0.10	**-0.07**	0.08	-0.17	0.03
$\rho_{1,YP}$	Normal	**0.00**	0.10	**0.11**	0.05	0.05	0.18
$\rho_{1,YC}$	Normal	**0.00**	0.10	**-0.00**	0.01	-0.02	0.01
$\rho_{1,PH}$	Normal	**0.10**	0.10	**0.15**	0.04	0.10	0.21
$\rho_{1,PY}$	Normal	**0.00**	0.10	**-0.04**	0.03	-0.07	-0.00
$\rho_{1,PC}$	Normal	**0.10**	0.10	**0.02**	0.00	0.01	0.02
$\rho_{1,CH}$	Normal	**0.10**	0.10	**0.10**	0.09	-0.02	0.23
$\rho_{1,CY}$	Normal	**0.00**	0.10	**0.04**	0.08	-0.07	0.14
$\rho_{1,CP}$	Normal	**0.00**	0.10	**-0.17**	0.09	-0.29	-0.05
$\rho_{1,RP}$	Normal	**0.00**	0.10	**0.03**	0.05	-0.04	0.09
$\rho_{1,RY}$	Normal	**0.00**	0.10	**0.00**	0.03	-0.03	0.04
$\rho_{1,RC}$	Normal	**0.00**	0.10	**-0.02**	0.01	-0.03	-0.01
$\rho_{1,RH}$	Normal	**0.00**	0.10	**0.09**	0.06	0.01	0.16
$\rho_{1,CR}$	Beta	**0.10**	0.05	**0.15**	0.06	0.07	0.23
$\rho_{1,HR}$	Normal	**0.00**	0.10	**0.03**	0.02	0.00	0.05
$\rho_{2,HH}$	Beta	**0.10**	0.05	**0.04**	0.02	0.02	0.07
$\rho_{2,YY}$	Beta	**0.10**	0.05	**0.05**	0.02	0.02	0.08
$\rho_{2,PP}$	Beta	**0.10**	0.05	**0.06**	0.03	0.03	0.10
$\rho_{2,CC}$	Beta	**0.10**	0.05	**0.03**	0.02	0.01	0.05
$\rho_{2,RR}$	Beta	**0.10**	0.05	**0.05**	0.02	0.02	0.08

Note: The table shows estimated parameters of the model described in Section 5. The coefficients describing lagged response of π, y, c, and h to interest rates are written with a negative sign in the model specification of the VAR model to impose a negative lagged impact of interest rates on each of these variables.

B Additional Details of Audit Conducted with Claude AI

We used Claude AI assistant to help with auditing the index. Claude was instructed to return a table of results, coding articles as 1 (shortage mentioned), 0 (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 each snippet's coding.

Before initiating the classification, we provided Claude with examples of how we would code the snippets and ensured that the training sample included false positives, such as mentions of the lack or end of shortages. 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 prospective shortages, rationing, scarcity, or bottlenecks related to goods, labor, materials, food, or water? Just return a table with yes=1, no=0, unsure=99, and a brief explanation. For instance:

- Article 1 mentions prospective shortages since it states that steel shortages will prevail in the near future, so it is coded as 1.
- Article 2 says steel shortages caused a plant closure, so it is coded as 1.
- Article 3 says the shortage of cars is crimping coal production, so it is coded as 1.
- Article 4 mentions the shortage of cars, so it is coded as 1.
- Article 10 mentions a shortage of workspace, so it is not related to a work shortage and is coded as 0.
- Article 329 says no shortage of cars has been experienced, so it is coded as 0."

Although using AI for validation is not foolproof, we found that Claude performed as well as, if not better than, a human classifier. For example, Claude demonstrated an ability to extrapolate the context of a particular sentence to a country or person. In one instance, the snippet "Economy may be slowing, but Lowe is banking on labor shortages gradually leading to an increase..." was classified as 1 by Claude, with the explanation: "Reserve Bank [of Australia] expecting labor shortages to lead to wage growth."

The results of the audit are in Table 3. Out of 872 articles belonging to the set $\mathcal{S}$, only 6.3 percent were deemed by Claude as false positives. 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. Of note, Claude classified only one snippet as "unsure," and we found it had good reason to do so: the snippet was sampled from a short article in the Chicago Tribune in 1929 that reported short snippets of information on miscellaneous news items, a common practice in early 20th-century journalism. The snippet mentioned "Food shortage in Batanes islands. (Neither do we.)..." and featured incomplete comparison, lack of context, grammatical mismatch, and ambiguous meaning.