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 industry, labor, food, 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, we find that shortages are associated with persistently high inflation and lower economic activity. A structural VAR model reveals that, compared to a traditional supply shock, surprise movements in shortages produce less inflation relative to their GDP impact, suggesting that shortages are associated with constraints on price adjustment that limit inflation but magnify the decline in real activity. We also show that post-pandemic shortages and inflation were primarily driven by supply forces, with demand factors playing a less important role.

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

JEL CLASSIFICATION: C32, C55, E31, N10.

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1 Introduction

Shortages——defined as the inability of supply to meet demand at prevailing prices——have been a recurring feature of economic life throughout the 20th and early 21st centuries. From widespread disruptions during major wars to the acute shortages of goods and labor during the COVID-19 pandemic, these episodes have strained supply chains, hindered production, and placed significant burdens on households and businesses. Despite their importance, there has been limited research on the long-run trends and patterns of shortages across different sectors, as well as on their economic effects. This paper addresses this gap by providing a comprehensive analysis of shortages over a 125-year period and demonstrating their persistent effects on inflation and economic activity.

In the first part of this paper, we construct a monthly shortage index based on newspaper articles spanning from 1900 through the present (Section 2). This index——covering industry, labor, food and energy shortages—is derived from approximately 25 million articles from six major U.S. newspapers, providing a novel, long-term perspective on global supply disruptions. The index captures historical events effectively, showing significant spikes during periods of economic turmoil such as the World Wars and the 1970s oil crises, and reaching its highest level in 40 years during the COVID-19 pandemic.

Although developed using U.S. news sources, our index captures shortages on a global scale. We demonstrate this by constructing sub-indexes for six major advanced economies—Canada, France, Germany, Great Britain, Japan, and the United States. These indexes spike around common global events, but also reflect country-specific variation, capturing both differential exposure to global shocks and idiosyncratic episodes, such as the Suez Crisis in 1956 or the 2011 tsunami in Japan. In Section 3, we validate our index through narrative investigation, AI-based text analysis, and comparison to alternative measures of supply-side disruptions.

The second part of this paper shows that shortages are associated to higher inflation and lower economic activity in the United States. Using predictive regressions (Section 4), we estimate a negative correlation between shortages and future GDP and a positive relationship between shortages and future prices, particularly for durable consumption goods and private fixed investment. These results remain robust even when controlling for traditional indicators of inflation pressures such as commodity prices and wages, suggesting that our shortage index provides additional information not captured by conventional measures. An out-of-sample forecasting exercise reveals that a model incorporating the shortage index outperforms competing models at a 3-month horizon, highlighting the practical value of tracking shortages for inflation prediction.

To investigate how the relationship between shortages and activity varies over time, we estimate rolling regressions of future prices and future GDP on shortages. Throughout most historical periods, shortages have been associated with higher future inflation. The predictive power for future GDP growth is typically negative, with notable exceptions during World War II and the COVID-19 pandemic—periods when shortages coincided with strong demand pressures, suggesting that both supply and demand forces are important for understanding shortage dynamics.

The varying impact of shortages and their persistent impact on inflation motivate our structural vector autoregressive (VAR) model in Section 5. Unlike predictive regressions, a fully identified VAR provides a comprehensive and economically interpretable framework for understanding joint movements in GDP, inflation, and shortages. The model also includes commodity prices and short-term interest rates, allowing us to identify "traditional" demand and supply shocks, commodity price shocks, monetary policy shocks, and shortage shocks.[1] Our identification strategy is as follows: demand and supply shocks are identified based on the slope of economy-wide demand and supply curves and can affect prices, activity, and shortages contemporaneously, thus allowing shortages to react on impact in response to standard demand and supply shocks, for instance because price adjustment is not instantaneous. Shortage shocks, by contrast, are assumed to affect prices and activity with one-quarter lag—reflecting that while newspapers may immediately report on shortages, their broader economic impact typically may materialize more gradually. This approach conservatively attributes immediate movements in activity and prices to traditional shocks, while preserving a distinct role for episodes of acute shortages.

We interpret shortages shocks as unexpected disruptions that require two concurrent conditions to materialize. First, there must be supply constraints stemming from events such as extreme weather, natural disasters, geopolitical conflicts, labor strikes, or production failures. Second, unusual market frictions must impede normal price adjustment processes. These frictions include hoarding behavior, regulatory interventions, social norms against price

[1] The inclusion of commodity prices is also motivated by a large and growing literature that attributes a role to energy shocks in driving post-pandemic inflation dynamics (Baumeister, 2023; Dao et al., 2024).

increases, or coordination failures. Together, these two conditions result in quantity rationing that persists beyond what traditional market clearing would predict, and differentiate shortages shocks from traditional adverse supply shocks.[2]

The VAR results reveal several key insights. First, while traditional economic forces contribute to the identified movements in the shortage index, exogenous shortage shocks remain the dominant driving force behind these fluctuations. Second, shortage shocks have significant and persistent effects on GDP and inflation, showcasing the shortage index's value as a leading indicator of activity and prices. Third, compared to traditional contractionary supply shocks, shortage shocks produce less inflation relative to their impact on economic activity—suggesting that shortages often involve constraints on price adjustment that limit inflation but magnify the decline in real activity.

Historical decompositions from our model provide new perspectives on major economic episodes. Shortages in the 1950s were largely driven by the Korean War, post-WWII pent-up demand, and the rapid economic transition from wartime to peacetime. The 1970s oil embargo triggered shortages beyond what could be explained by commodity price shocks alone. During the COVID-19 pandemic, shortages emerged from a confluence of demand, supply, and shortage-specific shocks. Counterfactual simulations reveal that, according to the model, the rise in shortages and inflation that started in 2020 was predominantly driven by supply forces—a combination of traditional supply shocks, shocks to commodity prices, and shocks to shortages—with demand forces playing a somewhat secondary role. The reversal of adverse supply shocks and negative demand shocks in 2022 and 2023—capturing the tightening of monetary policy and more favorable supply conditions—led to a faster-than-expected decline in inflation.[3]

Our approach builds on previous work combining newspaper sources and textual analysis to measure economic phenomena, such as the Economic Policy Uncertainty Index (Baker, Bloom, and Davis, 2016) and the Geopolitical Risk Index (Caldara and Iacoviello, 2022). While other researchers have developed news-based shortage indicators for shorter periods

[2] The combination of supply disruptions with market frictions that impede price adjustment can potentially result in larger quantity reductions relative to price increases, distinguishing shortages shocks from conventional supply shocks where prices bear relatively more of the adjustment burden.

[3] Our analysis of the post-pandemic drivers of inflation relates to a large and growing literature. Giannone and Primiceri (2024) and Bergholt et al. (2024) find that the pandemic-era rise in inflation was mostly driven by demand factors. By contrast, Ascari et al. (2024), Comin et al. (2024), Shapiro (2024) and Di Giovanni et al. (2023) find a relatively larger role for supply factors.

(Lamont, 1997; Chen and Houle, 2023; Burriel et al., 2023) or constructed alternative supply disruption measures using transportation and shipping data (Benigno et al., 2022; Bai et al., 2024; Liu et al., 2024), our contribution is distinct in three ways.[4] First, we develop the first comprehensive shortage index covering more than 125 years, offering a unique long-term perspective unavailable in existing indicators. Second, our disaggregated indexes capture events in different markets at both global and country-specific levels, providing valuable insights for historical and cross-country analysis. Third, our empirical analysis sheds light on causes and consequences of shortages, and demonstrates that shortages have more persistent effects on inflation than previously recognized. Unlike Bernanke and Blanchard (2023), who use Google searches for the term "shortage" as a proxy for supply disruptions and find only short-lived inflationary effects from shortages, our longer-term analysis reveals significantly more prolonged inflationary responses—underscoring the importance of examining supply disruptions across extended time horizons.

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

[4] Goldfarb (2013) provides a valuable taxonomy of shortages that aligns well with our framework. Goldfarb identifies six distinct shortage types: (1) demand deadline shortages (e.g. Christmas toys), (2) dynamic shortages from supply/demand lags (labor shortages), (3) below-market pricing by suppliers (concert tickets), (4) government-regulated prices (parking), (5) capacity choice under demand variance (airline seats), and (6) sudden supply shocks (natural disasters). These types stem from key underlying causes—planning errors, non-market-clearing pricing, supply constraints, and reaction lags—that correspond well with our idea that news about shortages are likely to occurs when the combination of supply constraints and market frictions impedes price adjustment.

approximately 20,000 news articles per month, spanning from 1900 through present—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.[5] Including an economics-related term reduces the occurrence of false positives—articles mentioning shortages unrelated to economic phenomena, such as shortages of empathy or goodwill.

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'. Subsequently, generic words like 'time', 'days', 'people' and 'government', which convey little information about shortages, are removed. The remaining collocates are grouped into four topics: food, industry, labor, and energy.[6]

Using the lists of shortage terms, economic 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 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

[5] 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.

[6] 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.

articles discussing multiple types of shortages, enhancing the index's informational content. Section 3 documents that the requirement of proximity between shortage and topic-specific terms is crucial to 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).[7] 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 allow 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; 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 the topics capture the primary dimensions of economic shortages reflected in the news. In the next section, we discuss the evolution of topics over time.

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 2024. The index is calculated as the monthly share of articles discussing economic shortages (number of articles in $\mathcal{S}$ divided by the number of articles in $\mathcal{A}$), scaled so that its average is 100 between 1900 and 2019. 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.[8]

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

[8] 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.

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. Adverse geopolitical events—especially wars—are strongly associated with severe shortages. For instance, the index rises sharply during World War I and 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.[9] Many of these spikes are linked to energy shortages, often resulting from wars and instability in the Middle East, such as during the oil shocks of the 1970s. 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 spiked on several occasions the COVID-19 pandemic. The first spike corresponds to shortages in medical equipment and healthcare workers at the pandemic's onset. A second, larger spike occurred at the beginning of 2022, driven by global supply bottlenecks 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, 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 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 persisted post-pandemic.

[9] Federle et al. (2024) show that wars are associated with supply disruptions both domestically and abroad.

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 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 7.6 times more frequently than expected under independence. Other events show weaker associations, but still co-occur between twice and three times more 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.

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 U.K. following the Suez Crisis, concerns about shortages in Germany around the time of the construction of the Berlin Wall in 1961, or shortages in the aftermath of the 2011 tsunami in Japan.[10] In sum, the 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.

[10] In line with our measurement, the Suez Crisis did not create major energy shortages in Germany because its energy supply was less reliant on Middle Eastern sources compared to France and the U.K.

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 proxies for shortages during the overlapping periods. A key advantage of our index is its long historical coverage—from 1900 through present—compared to existing measures that span only shorter, more recent time frames.

3.1 Validation of the Shortage Index

Audit of the Overall 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 $\mathcal{S}$.[11] By design, each article contains at least one economics-related term along with a reference to shortages, scarcities, or bottlenecks near a topic word (energy, food, industry, or labor). For each article, we extract the first snippet of text 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. For example, a snippet from our sample includes:

> "...Ford motor company said today that still lingering steel shortages would force a closing next week of eighteen..." (New York Times, 1952)

We then use the Claude AI assistant (Anthropic, 2024) to determine whether each snippet mentioned current or prospective shortages, rationing, scarcity, or bottlenecks related to industry, 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.,

[11] The abstracts must also satisfy the conditions to belong in the set $\mathcal{S}$. Our search query is based on six U.S. newspapers listed in Section 2 and uses the ProQuest Newspapers Databases. Abstracts are only available for the six newspapers until 2014. For the period 2015–2023, we sampled abstracts from a broader set of newspapers, including U.K., Canadian, and Australian newspapers. Abstracts in ProQuest are typically short portions of text, often containing the opening sentences or the initial paragraphs of the article. A list of the 872 abstracts is available upon request.

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 snippet "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.[12]

The audit results are summarized 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 there was "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 shortage of manufacturing plants that were not captured by our search query ("recycling of newsprint was held back by a shortage of de-inking plants"). Notably, our search query deliberately excluded the word "plants" because preliminary tests revealed that its inclusion produced numerous false positives.[13]

As a last check, we confirmed that restricting the search to include shortage words near key terms related to industry, 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 of articles 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 shortages of sunshine.

Validation of Categorical Shortage Indexes

The categorical shortage sub-indexes are correlated, yet each contains unique information about different aspects of shortages. We show this result in the Appendix, where we reports estimates from regressions where selected price and wage measures are each regressed on

[12] The excerpt quoted is from March 2019, when Philip Lowe was the Governor of the Reserve Bank of Australia.

[13] 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."

the four categorical shortage indexes for industrial products, labor, energy and food. We find that the industry 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 subindex forecasts the prices (and earnings) of products most likely to be affected by that specific shortage, thus providing further support to the idea that our index and its disaggregated components contains useful informational content.

3.2 Comparison with Other Indicators 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 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 alignment between these measures over the common sample, although most of the correlation is driven by the sharp rise in shortages after 2020 (the correlation drops to 0.61 when the sample is cut in December 2019).

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 present (other indexes only start in 1980s or later) makes it particularly valuable for historical research on long-term trends and cyclical patterns in shortages.

4 Shortages as Predictors of Inflation and Activity

In this section, we investigate the predictive power of our shortage index for key macroeconomic outcomes in the United States. We first analyze how shortages relate to 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.

4.1 Predictive Regressions: Shortages, Inflation, and Activity

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

$$\Delta Y_{t+h} = \alpha + \beta\, SHORTAGE_t + \sum_{i=0}^{p} \boldsymbol{\gamma}_i' \mathbf{X}_{t-i} + \varepsilon_{t+h} \tag{1}$$

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 shortage index. The vector $\mathbf{X}$ contains control variables. We use quarterly data from 1950 through 2023 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 7 presents the results for four-quarter-ahead regressions (the Appendix reports results for the one- and eight-quarter horizons). For ease of comparison, we report standardized estimates of the coefficient β. In the full sample, higher shortages are associated with a rise in inflation and a decline in economic activity—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 investment decline, there is no statistically significant effect on nondurable and services consumption. Quantitatively, the standardized coefficients imply that a one-standard-deviation increase in the shortage index is associated with a rise in inflation (as measured by changes in the GDP deflator) of 0.41 percentage point, and a decline in GDP growth of 0.32 percentage point.

Figure 7 also documents time variation in the relationship between shortages, inflation, and economic growth. When we split the sample into two periods, pre- and post-2000s, shortages exhibit a positive correlation with future sectoral inflation throughout, but their link with future economic activity shifts from negative in the earlier period to positive (and statistically insignificant) in the latter. The positive correlation between shortages and activity during the more recent period, which includes the COVID-19 pandemic, suggests demand factors may have been more prominent drivers of shortages relative to the pre-2000 period, an issue that we return to in Section 5.

A further concern is whether the shortage index contains information beyond that captured by other macroeconomic variables. We address this issue by augmenting our baseline regression with additional controls, including oil prices, commodity prices, wage growth, and inflation expectations. The inclusion of these controls only slightly attenuates the effect of shortages on inflation and activity, but the coefficients remain in large part statistically significant (see the Appendix for details). These findings suggest that our shortage index contains additional information beyond that captured by traditional macroeconomic indicators.

To 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 8 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 adverse effects on economic activity except during periods—such as the pandemic and World War II—when elevated demand alongside binding supply constraints may have temporarily sustained output levels while intensifying 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 assess whether our index can improve 3-month ahead forecasts of annual inflation. To this end, we use monthly data to estimate the following specification:

$$\pi_{t+3}^{12} = c + \beta\pi_t^{12} + \boldsymbol{\gamma}'\mathbf{x}_t + \delta h_t, \tag{2}$$

where π_{t+3}^{12} is the 12-month percent change in the headline CPI index three months ahead, π_t^{12} is current 12-month CPI inflation, $\mathbf{x}_t$ 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 shortages and each series in $\mathbf{x}_t$ 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. We 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 competing models that exclude the shortage measure. For the whole forecasting window covering the 1990–2024 period, the root mean square error (RMSE) of the forecast with shortages is 0.86—7 percent lower than the RMSE of 0.92 of the model that excludes shortages, and 8 percent lower than a simple autoregressive model that only uses current inflation. In the 2020–2024 period, the RMSE of the model including shortages is 1.04, an improvement of about 20 percent relative to the model without shortages, which has an RMSE of 1.31. As illustrated in Figure 9, the forecasting model that includes shortages predicts a sharper rise in inflation between 2021 and 2022, thereby reducing forecast errors.[14]

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

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. The VAR approach has the additional benefit of capturing how the relationship between shortages and economic activity may evolve over time as different economic shocks become more or less dominant. This time-varying relationship is the expected outcome when the composition of shocks underlying movements in shortages changes and each shock is associated with distinct patterns of economic responses.[15]

5.1 The Model

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

[14] 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.

[15] A more comprehensive approach to quantifying time-varying relationships between shortages, economic activity, and inflation would involve estimating a VAR model with time-varying parameters or other forms of nonlinearities. For instance, periods of intense shortages might coincide with—or even induce—changes in the structural parameters of the model, giving rise to nonlinear dynamics. We leave these issues for future research.

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

where activity (y_t) is the four-quarter percent change in U.S. real GDP; inflation (π_t) is the four-quarter percent change in the U.S. headline CPI index; shortages (h_t) are expressed in levels (standardized); commodity prices (c_t) are measured by the four-quarter percent change in the Reuters–CRB Spot Commodity Price Index for raw industrials and foodstuffs; and the short-term interest rate (r_t) is the annualized 3-month Treasury bill rate. All series are demeaned. The sample runs from 1950:Q1 through 2023:Q4.

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 $\mathbf{u}_t = (u^S, u^D, u^H, u^C, u^R)'$ 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:

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

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

$$h_t = u_t^H + \theta_D\ u_t^D + \theta_S\ u_t^S + [\mathbf{b}^H]'\mathbf{z}_{t-1}, \tag{7}$$

$$c_t = u_t^C + \chi_D\ u_t^D + \chi_S\ u_t^S + \chi_H\ u_t^H + [\mathbf{b}^C]'\mathbf{z}_{t-1}, \tag{8}$$

$$r_t = u_t^R + \alpha_\pi\ \pi_t + \alpha_Y\ y_t + \alpha_H\ h_t + \alpha_C\ c_t + [\mathbf{b}^R]'\mathbf{z}_{t-1}, \tag{9}$$

Equation (5) represents the economy-wide aggregate supply equation, where inflation is positively related to activity ($\kappa > 0$) and subject to adverse supply shocks u_t^S. Equation (6) describes aggregate demand, which is negatively related to inflation ($\delta > 0$) and driven by demand shocks u_t^D. Equation (7) models shortages, which are assumed to respond to demand and supply shocks as well as to an exogenous component u_t^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 instances where supply disruptions, such as extreme weather events, production failures, or geopolitical disruptions, co-occur alongside market frictions, such as sudden hoarding behavior, emergency regulatory interventions, rapid adoption of social norms against price increases, or coordination failures, resulting in persistent quantity rationing beyond what traditional market clearing would predict. Equation (8) describes the behavior of commodity prices, that respond to demand, supply and shortages shocks along with commodity-market specific disturbances (u_t^C). Finally, equation (9) describes the monetary policy rule, where u_t^R denotes monetary policy shocks.

Our model incorporates specific timing assumptions regarding shortages and their economic impacts. In particular, exogenous shortage shocks affect GDP and inflation with at least a one-quarter delay, while they can influence commodity prices and interest rates within the same quarter. This timing structure reflects how news about shortages tends to immediately impact fast-moving variables like commodity prices and interest rates, before affecting broader economic measures such as inflation and economic activity. Our approach distinctly treats shortages as contemporaneously responsive to economic conditions caused by traditional demand and supply shocks. This differentiates our analysis from both Burriel et al. (2023), who order shortages first in a monthly VAR using data from 1990 through 2020, and Bernanke and Blanchard (2023), who employ a quarterly VAR from 1990 through 2023 using the assumption that shortages affect inflation within the same 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, if one were to assume a flat within-quarter Phillips curve—through a prior distribution centered at $\kappa = 0$ with zero variance—, the impact matrix $\mathbf{D} = \mathbf{A}^{-1}\mathbf{C}$ would become lower triangular, providing a recursive VAR interpretation with the ordering $(y_t, \pi_t, h_t, c_t, r_t)$.

We estimate the model with $p = 2$ lags, setting most cross-partial terms beyond the first lag to zero to avoid overfitting. The Appendix describes 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 broadly consistent both with estimates from DSGE models—see for instance Smets and Wouters (2007)—and with structural VAR models of the U.S. economy—see for instance Baumeister and Hamilton (2018).

- **Commodity Prices:** The priors for χ_S, χ_D and χ_H 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 in response to expansionary demand shocks, contractionary supply shocks, and shortages shocks—but with a generous range of possible outcomes.

- **Shortages:** The parameters θ_S and θ_D have inverse gamma priors with a mean of 0.2 and a standard deviation of 1. These priors assume that positive demand shocks and contractionary supply shocks lead to higher shortages.

- **Monetary Policy:** The priors assume that there is a systematic positive response of interest rates to inflation and GDP, with 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).

- **Standard Deviation of Shocks:** We calibrate the prior means for the standard deviations of the five structural shocks using a simple moment-matching exercise. Following Justiniano and Primiceri (2008), we try to generate plausible volatilities of the five variables in the VAR. The calibration of the prior also targets three additional moments: (i) shortage shocks should account for approximately 50 percent of the variance in the shortage index; (ii) commodity price shocks should account for approximately 50 percent of the variance in commodity prices; and (iii) demand-related shocks (traditional demand

and monetary policy shocks) and supply-related shocks (traditional supply, shortage, and commodity price shocks) should each account for about 50 percent of the variance of inflation. The objective is to balance the contribution of demand and supply factors to inflation as well as the contribution of shortage and non-shortage shocks to fluctuations in the shortage index.[16] All prior standard deviations are relatively diffuse.

Priors for key parameters are shown in Figure 10. All prior densities are intentionally wide to allow the data to update both the location and spread of these distributions. The Appendix 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 using the algorithms in Dynare (Adjemian et al., 2011). 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 10 shows the prior distributions and the estimated posterior distributions for the key parameters of the model. The location and spread of all posterior distributions are substantially updated compared to the priors, revealing that the data and the structure of the model are informative about the structural parameters.

The posterior mean for δ in the demand equation is 0.12, 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 κ is around 0.12—a demand shock that raises GDP growth by 1 percentage point leads on impact to an rise in inflation of around 0.1 percentage point. All told, the posterior distributions reveal a "flatter" supply curve—lower sensitivity of inflation to shifts in demand—and a "steeper" demand curve—higher sensitivity of inflation to shifts in supply—than assumed by the prior distributions.

The top right panel of Figure 10 illustrates one of the underlying forces driving the inflationary effects of shortages in our model. After controlling for current and lagged movements

[16] We use a standard minimum distance procedure, by minimizing the Euclidean distance between VAR-implied moments on the one hand, and empirical and additional target moments on the other.

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 $\rho_{1,\pi H}$—shows that most of its probability mass lies in the positive region. This indicates a high likelihood that lagged shortages have a positive effect on inflation.

Estimates for θ_D and θ_S are consistent with the notion that shortages respond to the business cycle, albeit to a smaller degree than assumed by the priors. The posterior estimate for both parameters is positive but relatively small. This finding echoes results from the variance decomposition: the share of the forecast error variance of shortages accounted for by shortages shocks is 66.8 at the posterior mean, higher than its prior value that was calibrated at 51 percent. Finally, The last row of Figure 10 describes the estimated response of interest rates to inflation and output, which is positive. Additionally, the parameter estimates suggest a relatively modest, negative response of interest rates to increases in shortages.

Impulse Responses

Figure 11 reports the impulse responses to the estimated shocks in the model.

An exogenous increase in shortages leads to persistent rise in inflation alongside a slow, persistent decline in GDP. Quantitatively, a one-standard deviation shock to shortages leads to a material rise in inflation after one year of about 0.2 percentage points.[17] As shortages return towards the baseline, inflation keeps rising and peaks about two years after the shock, remaining elevated thereafter. Commodity prices rise significantly. There is an initial, modest decline in interest rates that is quickly followed by an overall tightening in the monetary policy stance. Shortages also respond endogenously to other shocks: an expansion in aggregate demand or a contraction in aggregate supply tend to increase shortages. Similarly, commodity price shocks, such as those observed in the 1970s and 1980s, also drive up shortages.[18] Finally, an interest rate shock leads to a reduction in shortages, alongside lower inflation, commodity prices, and GDP. All told, we find bidirectional causality: exogenous shortage shocks trigger business cycle fluctuations, and traditional macroeconomic shocks generate movements in

[17] At the posterior mean, the share of the unconditional variance of inflation accounted for by shortage shocks is 6.3 percent, compared to 1.4 percent at the prior mean. As shown later, this share is substantially larger in the post-pandemic period.

[18] Our identification strategy assumes that shortages respond within the quarter to shocks to commodity prices, while commodity prices respond to shortage shocks only with a one-quarter lag. This timing restriction helps explain two key patterns in our impulse responses: commodity prices respond little to exogenous shortage shocks, while shortages jump on impact following commodity price shocks.

shortages.

We highlight two important insights from our impulse response analysis. First, a shock that leads to an immediate jump in shortages has significant and persistent effects on GDP and inflation, with the maximum effects occurring between one and two years after the shock. The size and timing of these effects highlight the value of the shortage index as a leading indicator for macroeconomic variables. Second, compared to the traditional contractionary supply shock identified in the model, a shortage shock produces a smaller effect on inflation relative to its impact on economic activity. For a one-percentage point rise in inflation, GDP growth bottoms out at 0.41 percent after a shortage shock, compared to a 0.26 percent decline after a supply shock. This observation suggests that, all else equal, a supply-driven rise in shortages is associated with more muted price pressures—for instance due to price controls, sluggish adjustment of prices, or other constraints—at the cost of a larger decline in economic activity.

The Effects of Shortages throughout History

Figure 12 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. Shortages were muted throughout the 1960s. In the 1970s, the oil embargo by OPEC producers caused a significant rise in shortages beyond what commodity price shocks alone would predict. This shortage shock contributed to higher inflation and, to a lesser higher, to slower economic activity. Shortages moved little in the 1990s and in the early part of the 21st century.

To better highlight the macroeconomic impact of shortages in recent years, Figure 13 zooms in on the pandemic and post-pandemic period that began in 2020. The figure reveals 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, along with depressed aggregate demand. Shortages are low because adverse shortage shocks are offset by depressed demand, and these two countervailing effects leave inflation close to baseline. In the second period, from 2021:Q2 through 2022:Q3, adverse shortage shocks continue to exert pressure on economic activity; these shocks occur in a context of stronger aggregate demand and rising commodity prices, leading to upward pressure on inflation. The third period, from 2022:Q4 through the end of 2023, is marked by a reduction in shortages, although shortages 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 contributor to inflation well into 2023. All told, the exercise illustrates that shortages shocks account for a non-negligible share of the post-pandemic rise in inflation in the United States.

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 14 counterfactual paths for shortages, inflation, and GDP growth under alternative historical realizations of demand-side and supply-side forces. For ease of exposition, we define supply-side forces as the sum of supply, commodity, and shortage shocks—these are the model shocks that move inflation and GDP in opposite directions—while demand-side forces are the sum of demand and monetary policy shocks—these are the model shocks that move inflation and GDP in the same direction.[19]

Figure 14 illustrates that, according to the model, the post-pandemic increase in inflation is predominantly driven by supply forces, with demand forces playing a secondary but quantitatively relevant role. Supply shocks in 2020 and 2021 had the cumulative effect of increasing inflation by 6 percentage points and reducing GDP growth by nearly 2 percentage points. Negative demand shocks exerted downward pressure on both inflation and GDP growth in 2020; the reversal of these shocks contributed to a rebound in both indicators in 2021. Additional shocks in 2022 and 2023—capturing the tightening of monetary policy and more favorable supply conditions—led to a faster-than-predicted decline in inflation, while leaving, on net, a smaller imprint on economic activity.[20]

Our results differ from those of Giannone and Primiceri (2024), who find—using VAR models identified through sign restrictions—that demand factors predominantly drove the post-pandemic rise in inflation in the euro area and the United States. These authors emphasize that a key element of their findings is a flat aggregate demand (AD) curve; When the AD curve is flat, supply shocks exert only modest inflationary pressures, and large inflation movements must be driven primarily by demand shocks. Our estimates for the United States point to a

[19] Each line in the figure represents a counterfactual path that assumes that: (i) no shocks are active through 2019, and (ii) shocks become active from 2020:Q1 through the end of the specified date.

[20] The results for the post-pandemic episode line up with the broader result of our estimated VAR that supply forces are relatively more important than demand forces in explaining the volatility of inflation throughout the sample. At the posterior mean, the share of the inflation forecast error variance that is accounted for by supply forces is 68.3 percent, higher than its value at the prior, which was calibrated to be near 50 percent.

steeper AD curve, implying a larger role for supply shocks in driving inflation.[21]

The Appendix contains robustness checks, showing results for alternative VAR models estimated under different specifications, including a flat slope of the demand curve, a steep slope of the supply curve, and a specification that replaces GDP growth with the CBO measure of the output gap. Both the flat demand curve and the steep supply curve model exhibit a worse fit (in terms of marginal likelihood) than the baseline model, leading us to prefer our baseline specification. The contribution of shortages to inflation remains substantial across specifications, except when the demand curve is assumed to be flat.

6 Conclusions

This paper introduces a novel monthly newspaper-based shortage index that covers the period from 1900 to the present. The index captures the intensity of shortages across sectors—industry, labor, food 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. 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-term economic dynamics.

Predictive regressions demonstrate that, throughout history, increases in the shortage index are associated with persistently higher inflation and lower economic activity. Furthermore, the relationship between inflation and shortages appears to be 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, the 1950s saw shortages driven mainly by demand factors, while the 1970s witnessed unusual

[21] Other papers have analyzed the post-pandemic inflation using time-series and quantitative models. Bergholt et al. (2024) find that demand factors primarily drove the pandemic-era inflation, Bańbura et al. (2023) and Ascari et al. (2024) attribute the bulk of pandemic inflation in the euro area to supply shocks. Comin et al. (2024) find that capacity constraints explain half of the increase in post-pandemic inflation. Our results underscore the dominant role of supply shocks, with demand shocks playing a smaller role. Our findings align with Shapiro (2024) and Di Giovanni et al. (2023), who find that an important role for supply factors and supply constraints in driving inflation in 2021 and 2022. Bernanke and Blanchard (2023) find that most of the post-pandemic inflation surge was the result of shocks to prices—reflecting a mix of supply-side shocks, strong aggregate demand, and sectoral shocks—given wages.

shortage shocks from the OPEC oil embargo. The COVID-19 period reflects a mix of supply and demand factors that led to a sustained inflationary impact, with supply shocks—including shocks to shortages—playing a predominant role.

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 to policy makers and researchers.

Although our analysis relies on linear models to estimate the effects of shocks to the shortage index, future research could extend this framework to account for nonlinear dynamics using both data and theoretical models. Recent work has highlighted how supply chain disruptions and input bottlenecks can amplify shocks through production complementarities and rigidities (Bonadio et al., 2021; Baqaee and Farhi, 2022). Similarly, shortages in the form of binding capacity constraints and pricing frictions can lead to non-linear inflation responses (Guerrieri et al., 2022; Di Giovanni et al., 2023).

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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

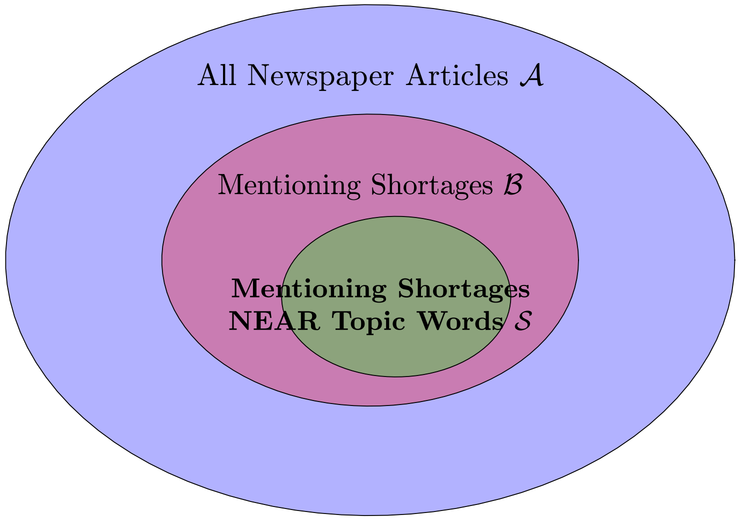
Note: The table lists the 30 largest spikes in the shortage index. For this table, the spikes are identified using the residuals of an autoregression and a condition on local maxima described in footnote 8.

Table 3: Validation of the Shortage Index

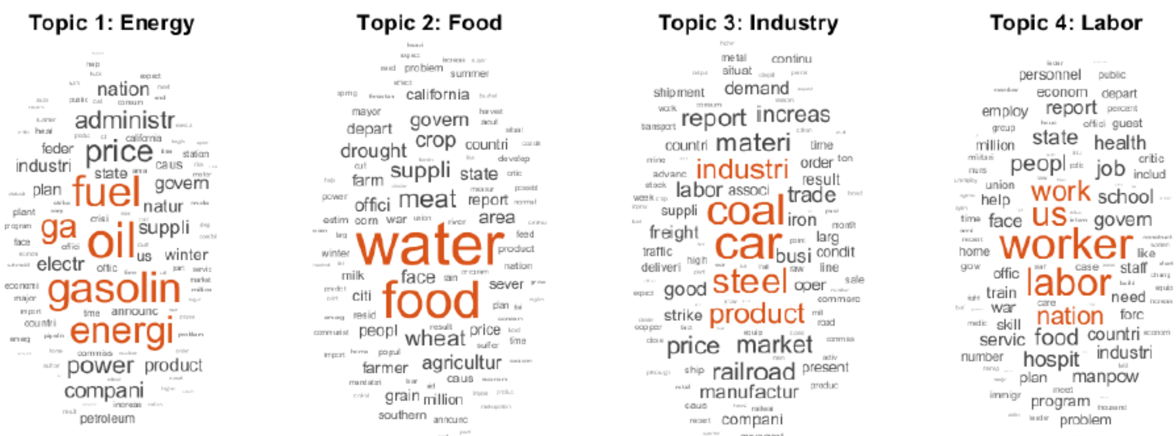
Set	Share of Total Newspaper Articles in Set	Validation Sample	Articles Mentioning Actual Shortages	Type I Error	Type II Error
Shortages NEAR Topic Words ($\mathcal{S}$)	1.58%	872	817	6.30%	–
Not Shortages ($\mathcal{A} \setminus \mathcal{S}$)	98.42%	298	1	–	0.33%
All Shortages ($\mathcal{B}$)	2.93%	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 NEAR Topic Words ($\mathcal{S}$), a sample of articles excluded from the construction of the index (denoted by the set $\mathcal{A} \setminus \mathcal{S}$), and a sample of articles mentioning All Shortages ($\mathcal{B}$).

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



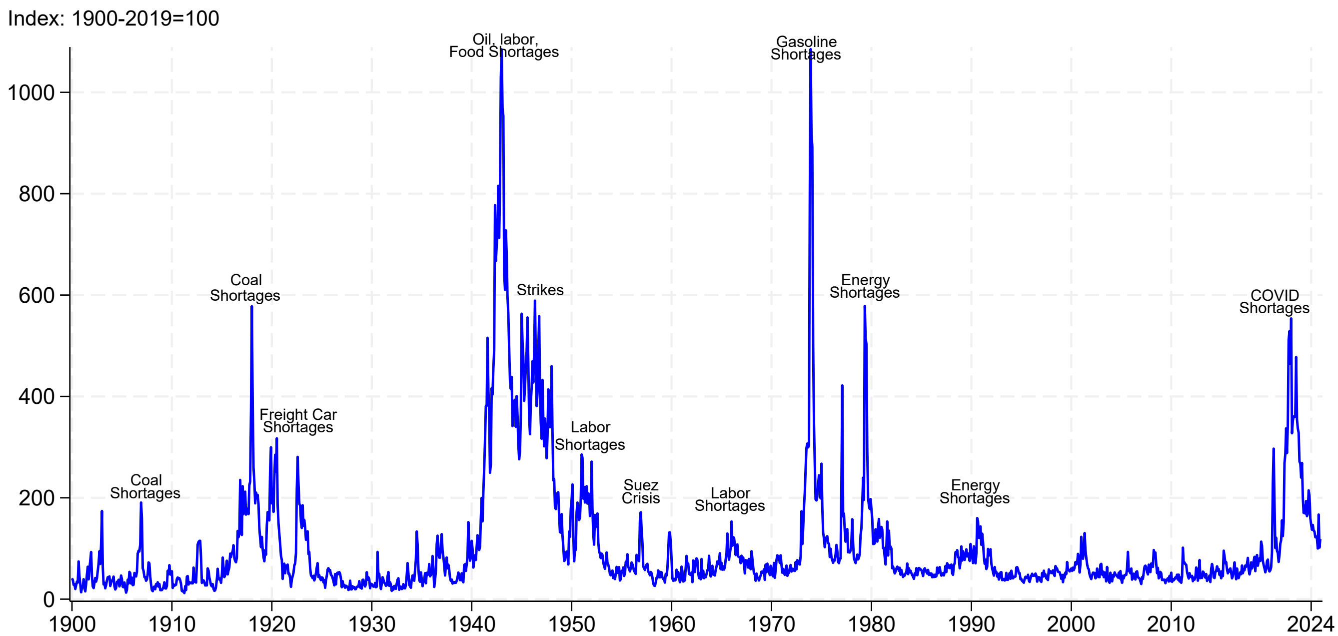
(a) Grouping of Newspaper Articles



(b) Word Clouds and Topic Classification of Articles

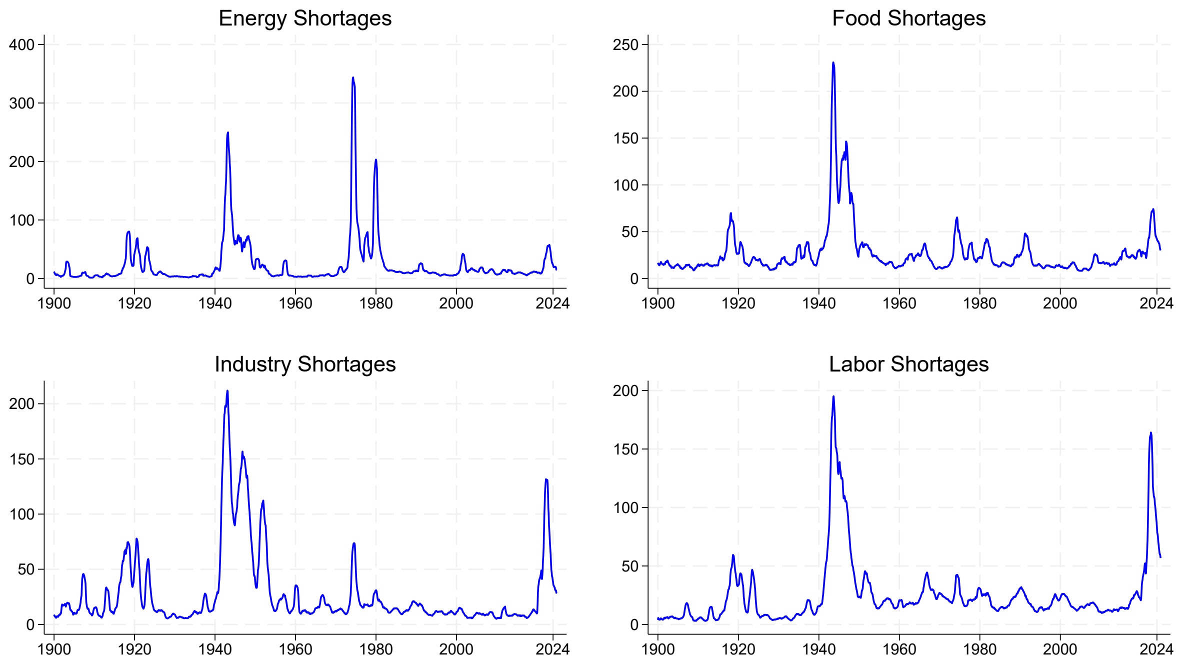
Note: The top panel shows a diagram representing the set of articles used in the construction of the index. The bottom panel shows word clouds associated with the four most influential topics chosen by LDA analysis on a large set of articles.

Figure 2: The Shortage Index

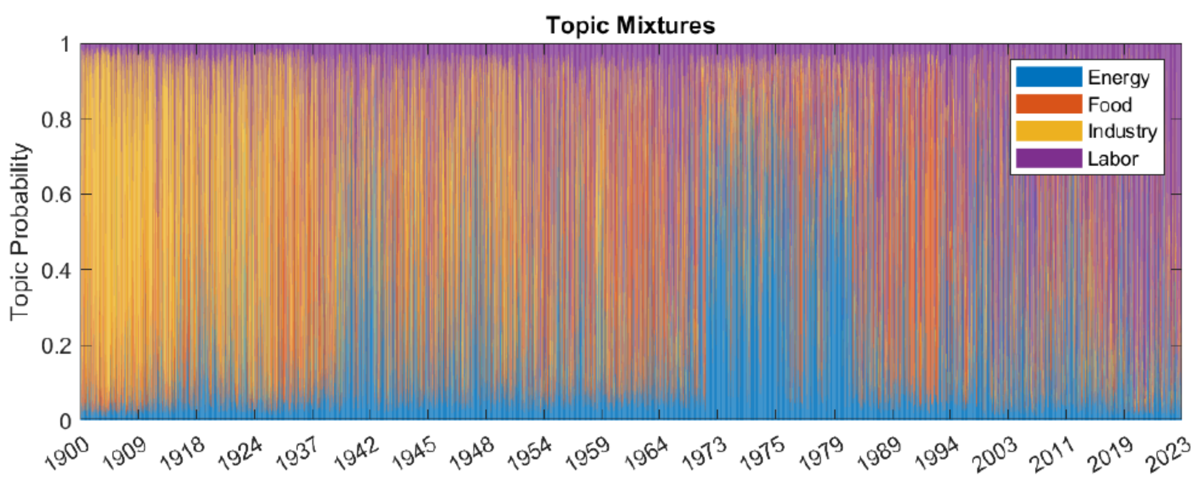


Note: The figure plots the shortage index from January 1900 through December 2024. Updated charts and data can be found at https://www.matteoiacoviello.com/shortages.html.

Figure 3: Decomposition of the Shortage Index by Category



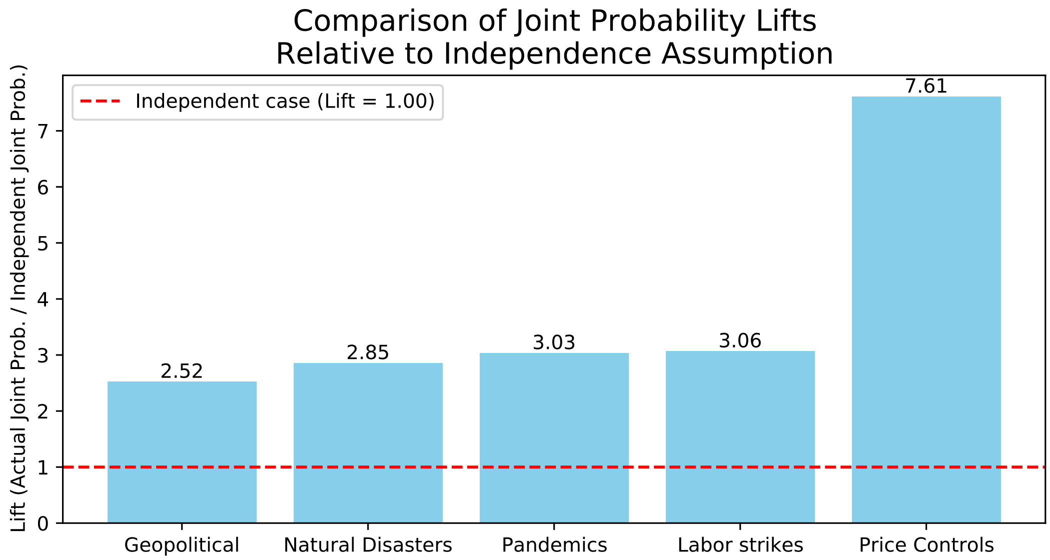
(a) Decomposition of the Shortage Index by Category



(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.

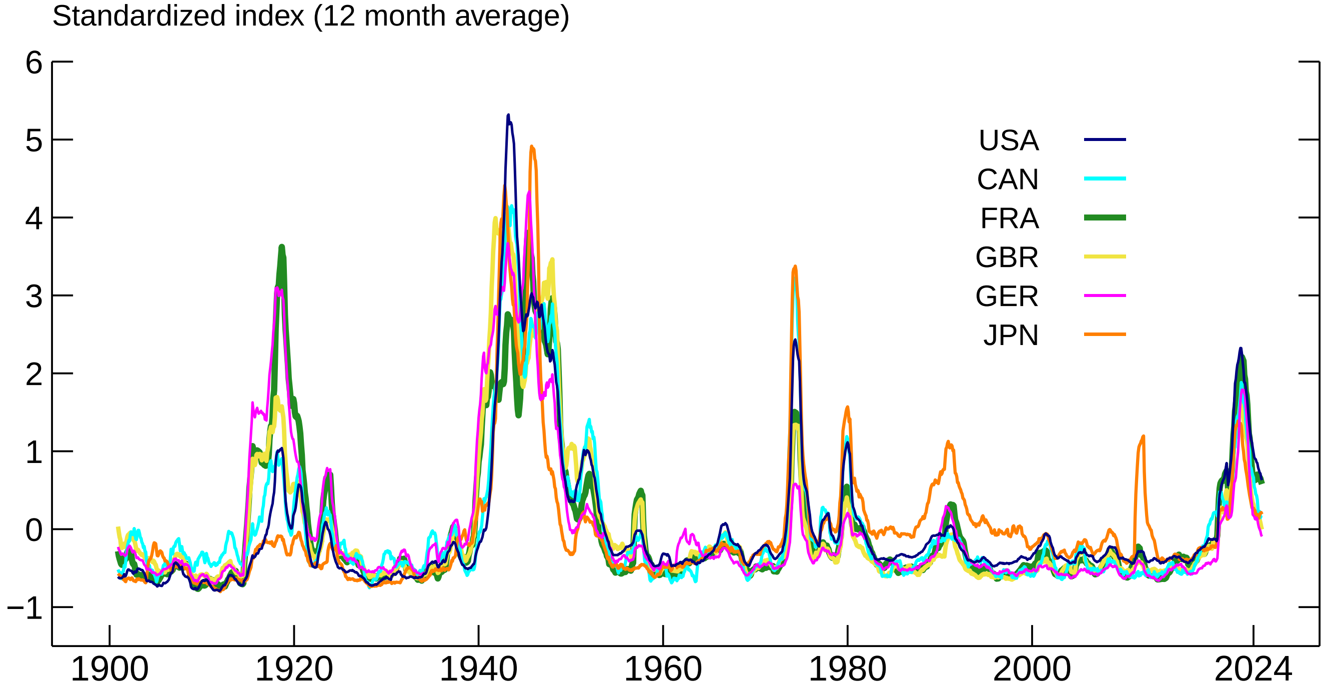
Figure 4: Phenomena Associated With Shortages



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%

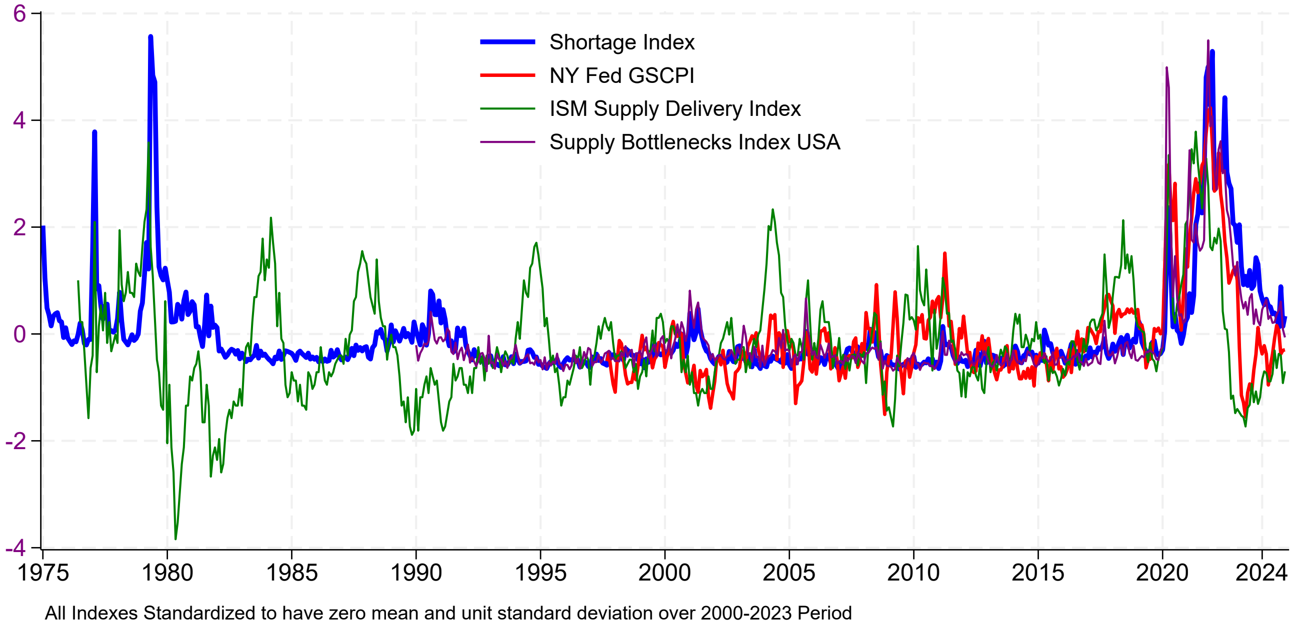
Note: The figure plots lift ratios, calculated as the ratio between the realized joint probability of events in five categories being mentioned in newspaper articles alongside shortages, and the probability that would be expected if these events and shortages were independent. The higher the lift ratio, 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



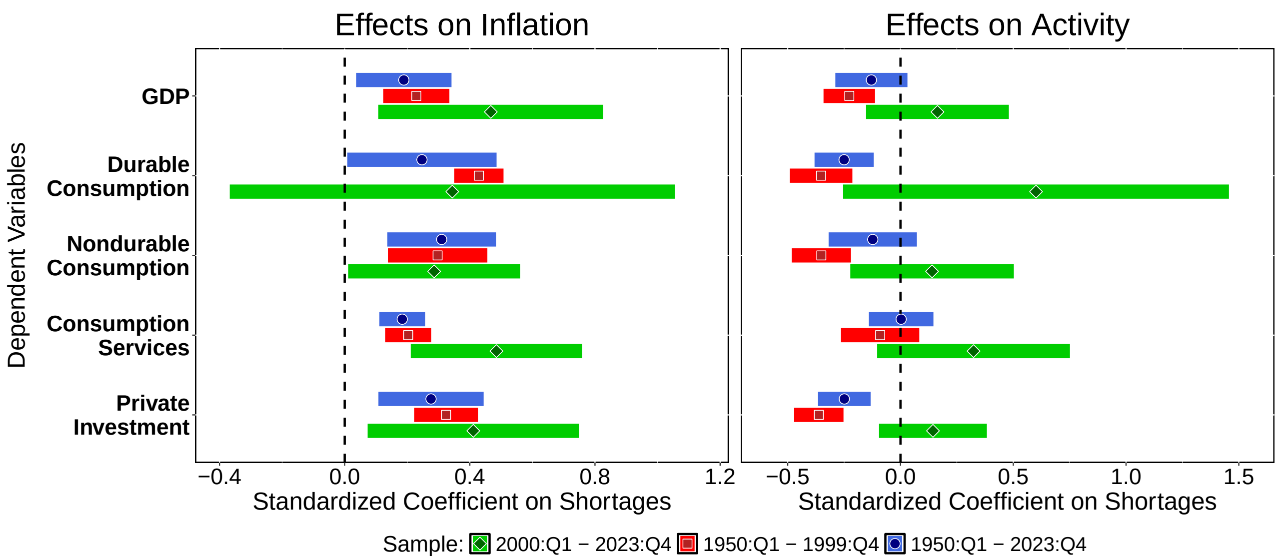
Note: The figure shows the shortage index for six major economies: the United States, Canada, France, Germany, Great Britain, and Japan. The country indexes are proportional to the share of newspaper articles mentioning shortages and the name of a foreign country and/or one of its major cities. Indexes 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. U.S. The Supply Bottlenecks Index is from Burriel et al. (2023).

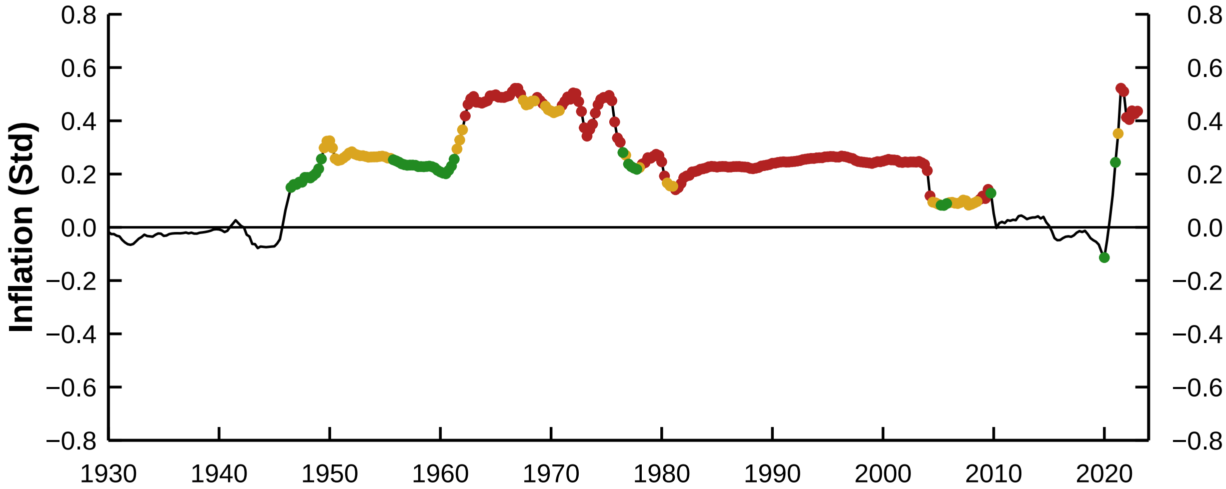
Figure 7: Relationship between Shortages and Inflation and Activity 4-Quarters Ahead



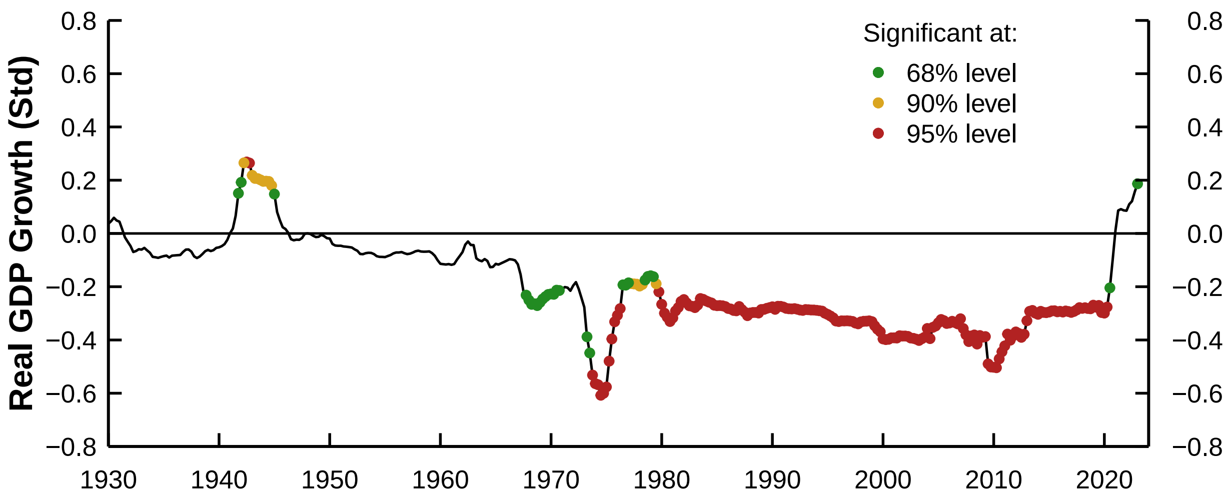
Note: The figure reports standardized coefficients of predictive regressions of inflation and economic activity on the shortage index estimated on quarterly data. The dependent variable for each regression is the log difference between $t+4$ and t of the variable listed in each row (the price deflator 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 1950:Q1 to 2023:Q4. We also partition the sample into two periods: 1950:Q1 to 1999:Q4, and 2000:Q1 to 2023:Q4. Heteroskedasticity and autocorrelation consistent 90% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987).

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

(a) One-Year Ahead Inflation

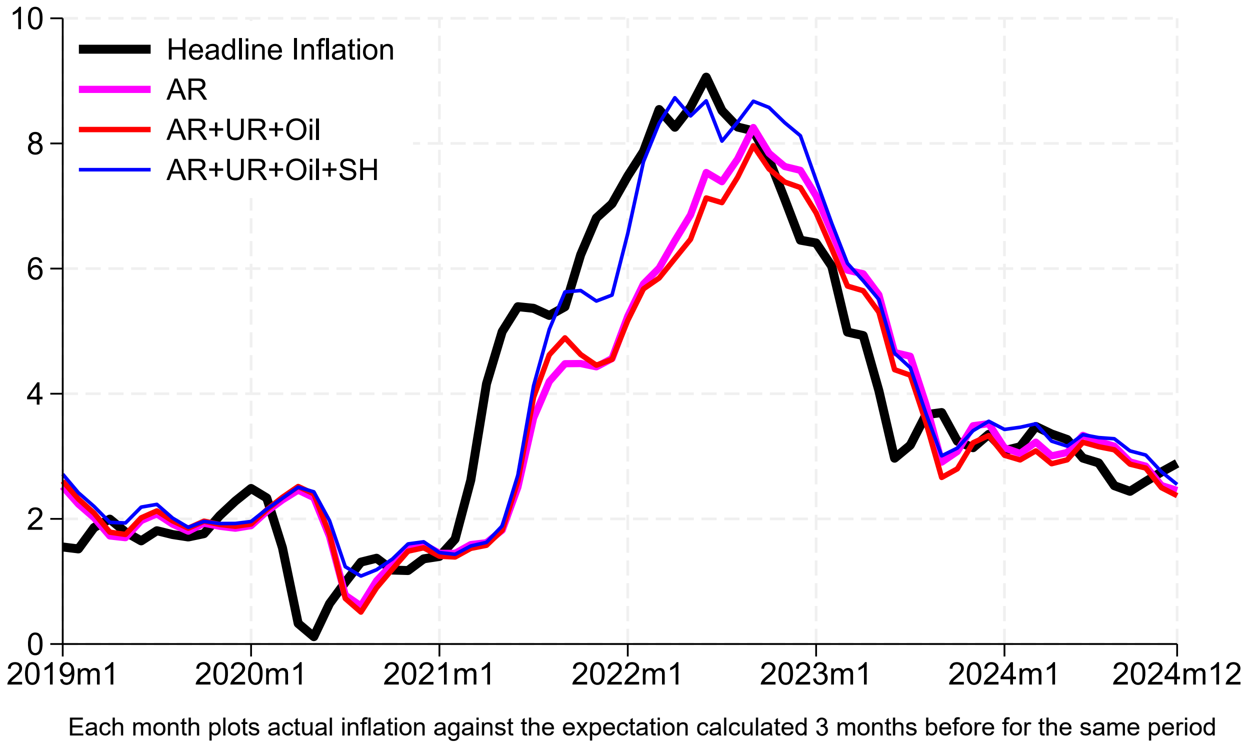


(b) One-Year Ahead Real GDP Growth



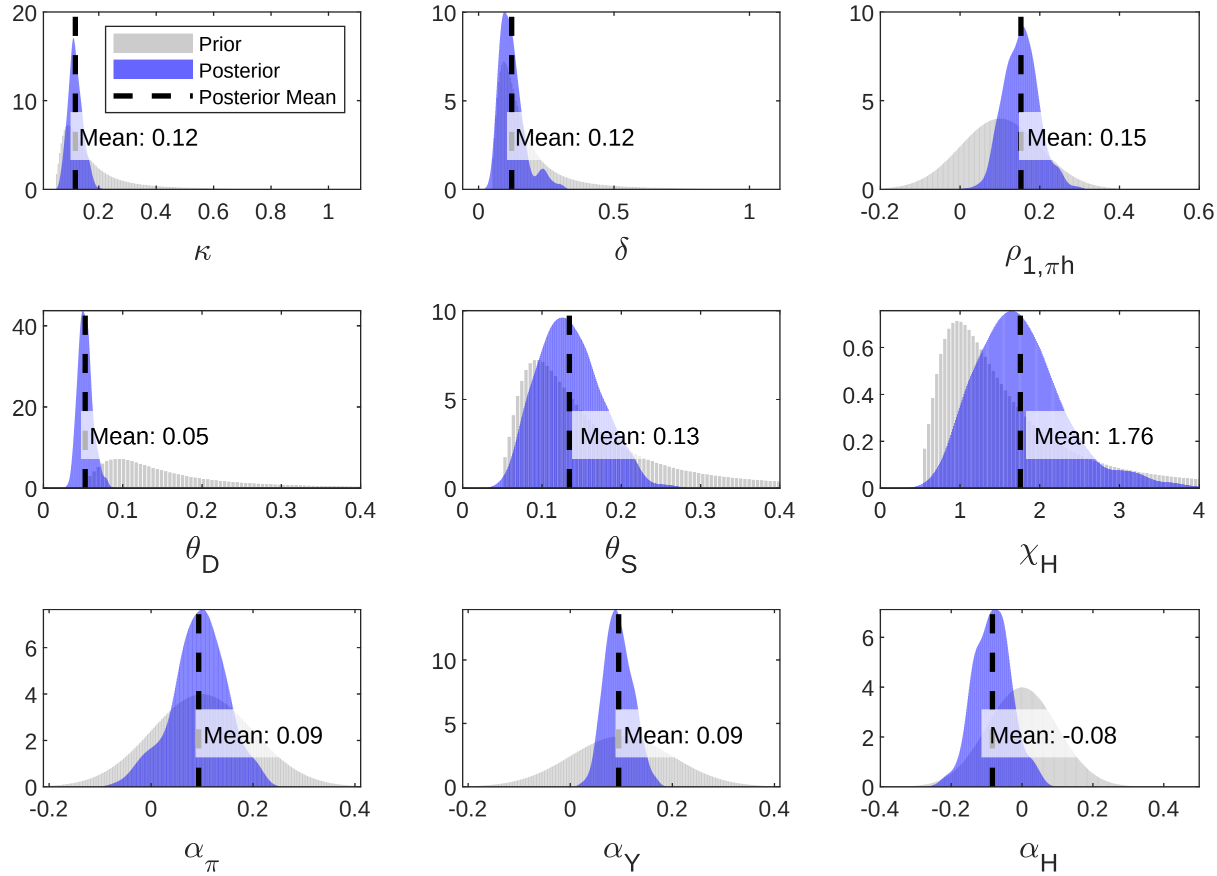
Note: The solid black line shows the time-varying estimated effect of shortages on inflation (top panel) and real GDP growth (bottom panel). The estimates are based on regressions using rolling 30-year windows. In each regression, the dependent variable is the 4-quarter ahead difference in log real GDP 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 9: 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.

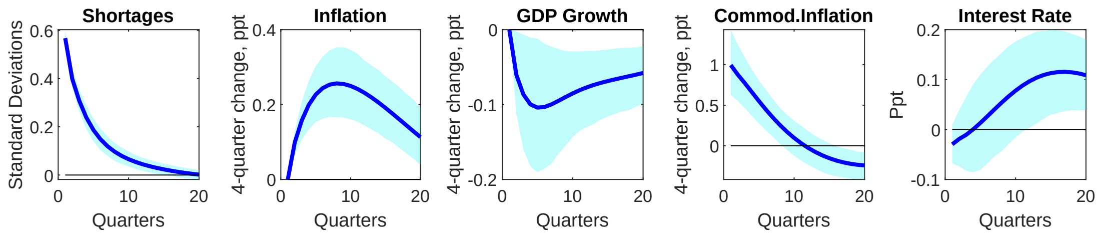
Figure 10: Prior and Posterior Densities of Structural VAR Parameters



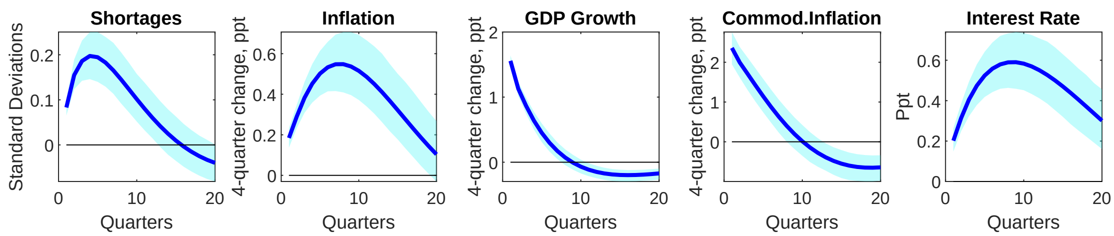
Note: Prior and posterior densities of selected parameters of the structural VAR model. See Section 5 for additional details and the Appendix for the full list of prior and posterior moments of the model parameters.

Figure 11: Effects of Shortages on US Activity and Inflation in the Structural VAR Model

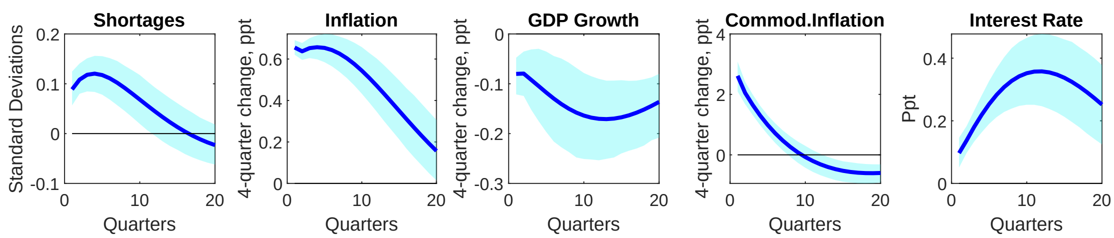
(a) Shock to Shortages



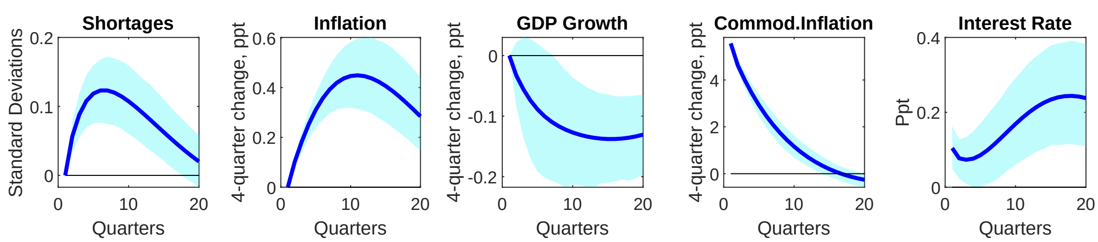
(b) Shock to Demand



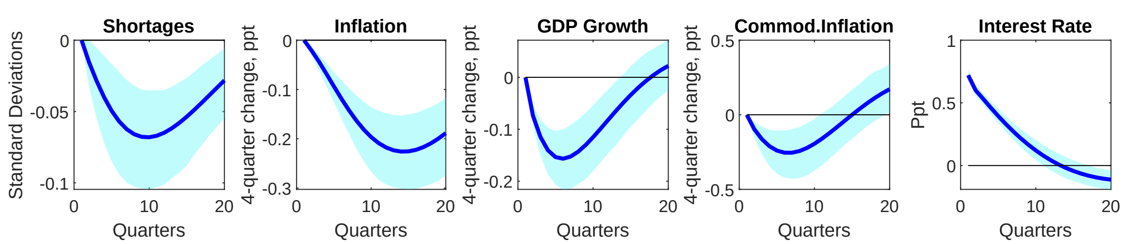
(c) Shock to Supply



(d) Shock to Commodity Prices

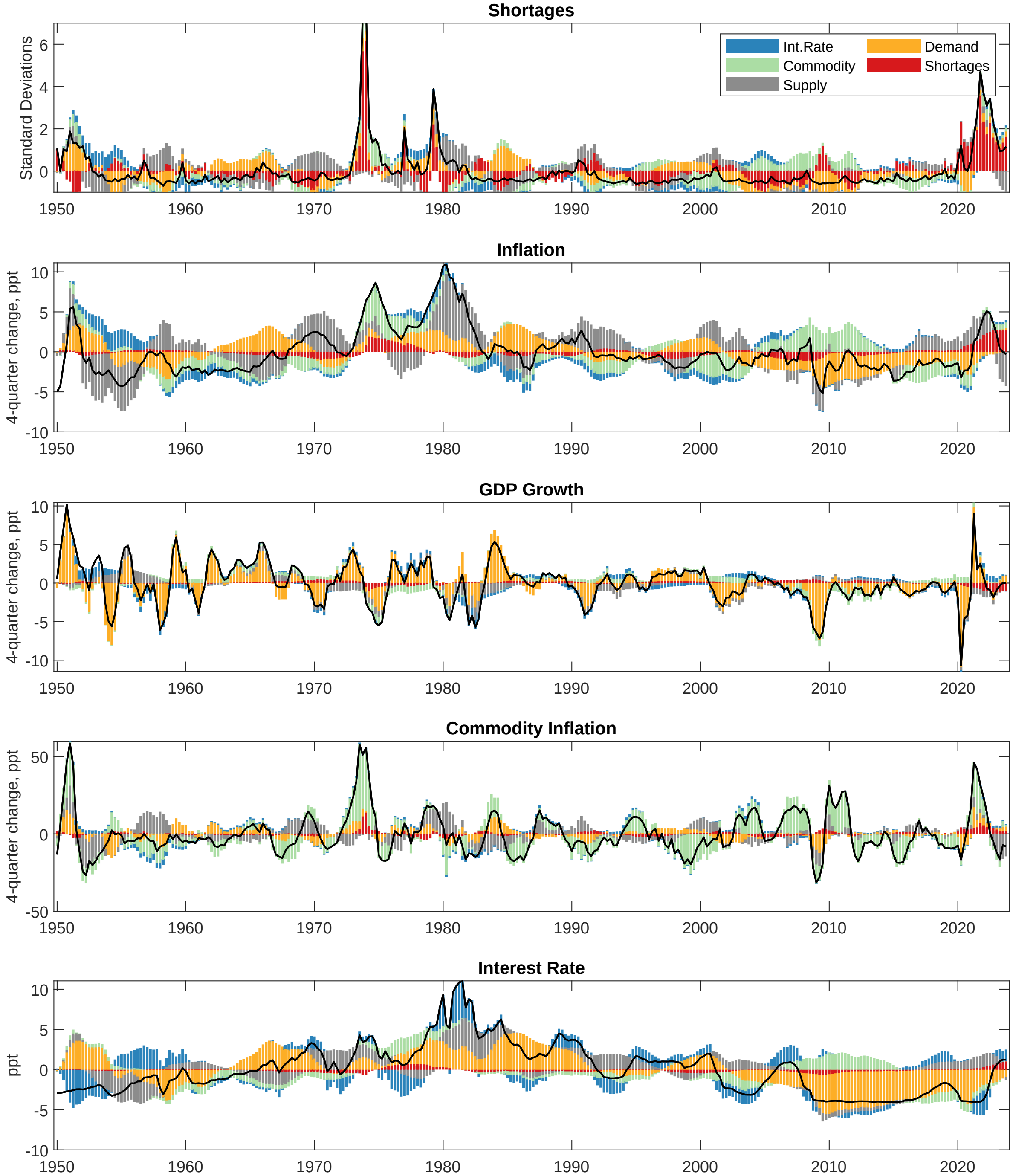


(e) Shock to Interest Rate



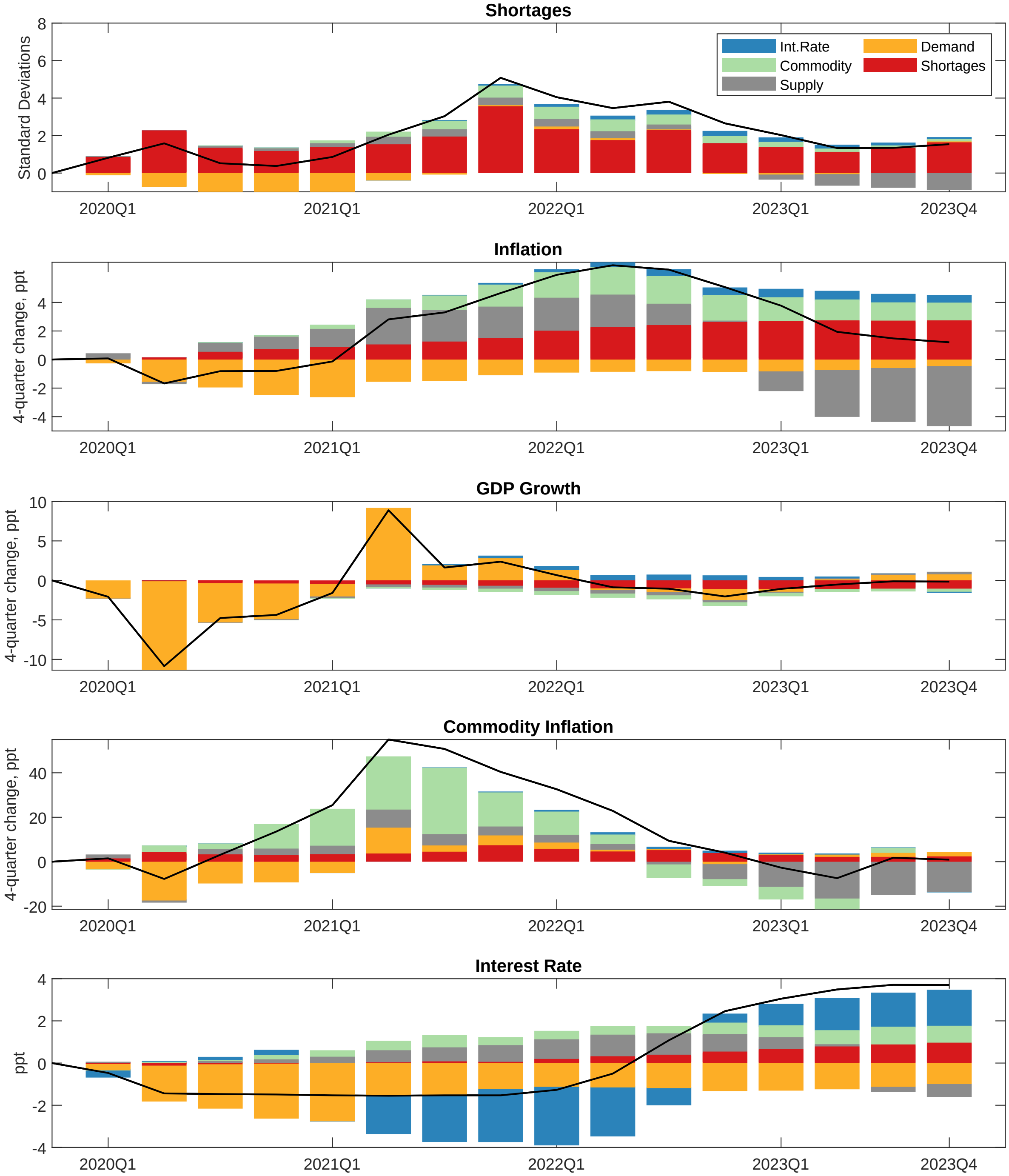
Note: Impulse responses to structural shocks of size one standard deviation estimated using the structural VAR model described in Section 5. Solid lines denote the responses at the posterior mean. Shaded areas denote 80 percent confidence intervals.

Figure 12: 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.

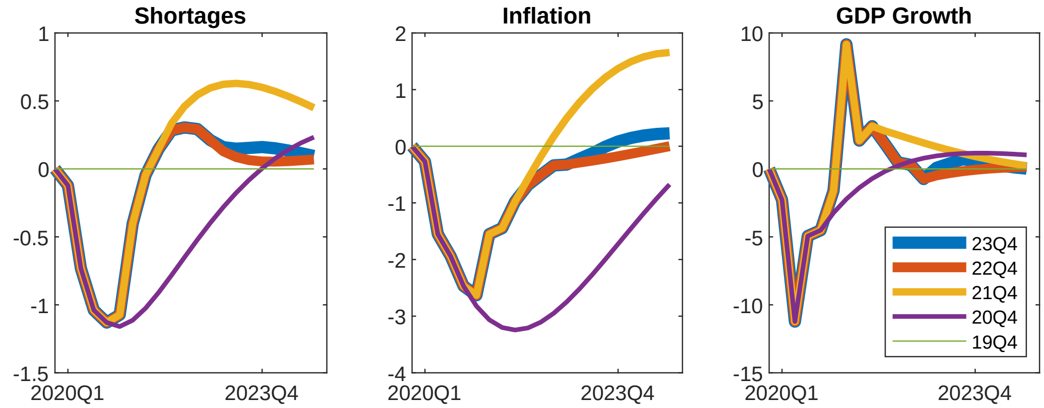
Figure 13: Historical Decomposition from the Structural VAR Model: 2020-2023



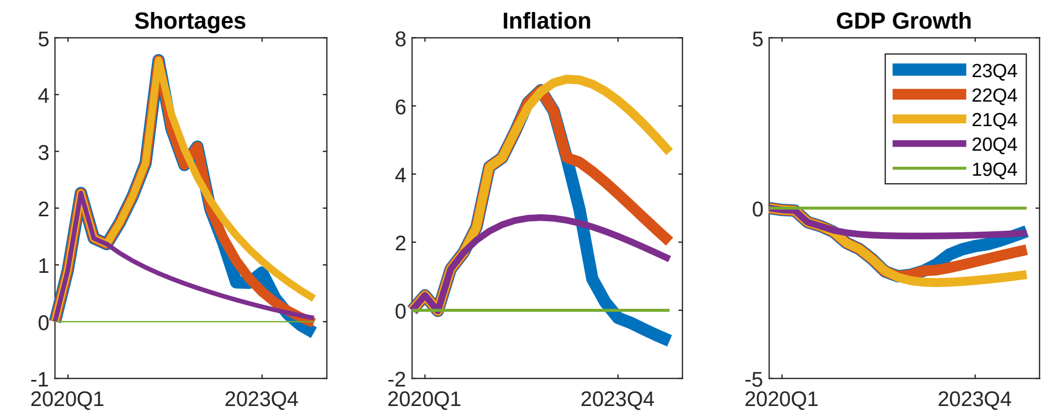
Note: This figure displays the contributions of structural shocks to the evolution of the model's endogenous variables since 2020. All variables are expressed in deviation from their 2019:Q4 value, and any shocks occurred before 2019:Q4 are set equal to zero.

Figure 14: 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 2020:Q1 through the end of the specified date. For instance, the green lines labeled 2019:Q4 correspond to a scenario with no shocks in history; the purple lines labeled 20Q4 assume that shocks are active from 2020:Q1 through 2020:Q4; the yellow lines labeled 21Q4 assume that shocks are active from 2020:Q1 through 2021:Q4.

Appendix for: Measuring Shortages since 1900

A 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.

B Additional Empirical Results

Validation of the Categorical Shortage Indexes

Table A.1 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.[1]

When the four categorical indexes are included one at a time, we find that the industry shortage sub-index predicts PPI materials inflation, the labor shortage index predicts earnings growth, and the energy and food shortage indexes predict energy CPI inflation and food CPI inflation, respectively. In other words, each index forecasts the relevant prices in the sectors 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 predict PPI materials inflation and (weakly) wage growth.

Additional Results from Predictive Regressions

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

$$\Delta Y_{t+h} = \alpha + \beta\, SHORTAGE_t + \sum_{i=0}^{p} \boldsymbol{\gamma}_i' \mathbf{X}_{t-i} + \varepsilon_{t+h} \tag{10}$$

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 $\mathbf{X}$ 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 (10) 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

[1] 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.

real GDP growth includes contemporaneous and lagged values of both real GDP growth and inflation (measured by the log change in the GDP deflator).

Figures A.1 and A.2 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.

Does the Shortage Index Contain Information Beyond Traditional Indicators?

One concern discussed in the paper is whether the shortage index contains information beyond that captured by other macroeconomic variables. We address this issue by augmenting our baseline regression with additional controls, including oil prices, commodity prices, wage growth, and inflation expectations. The inclusion of these controls only slightly attenuates the effect of shortages on inflation and activity, but the coefficients remain in large part statistically significant. See Figure A.3 for details. These findings suggest that our shortage index contains additional information beyond that captured by traditional macroeconomic indicators.

VAR Results: Additional Detail

Table A.2 provides details of the prior distributions for all model parameters, along with their posterior mean, standard deviation, and 80 percent credible intervals. Figure A.4 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.

Alternative VAR Specifications

Figure A.5 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 $\delta = 3$. 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 is worse than for the baseline model, as measured by the marginal likelihood of the models (the log marginal data density is -2574.1 for the flatter demand curve model compared to -2249.9 for the benchmark model). Assuming a steeper supply curve (panel (c)) only marginally reduces the role of supply shocks in explaining the post-pandemic inflation surge, but also lowers the marginal likelihood of the model relative the baseline (the log marginal data density is is $-2,393.93$). Finally, the results are unchanged relative to the benchmark model when activity is measured using the CBO measure of the output gap instead of 4-quarter GDP growth (panel (d)).

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

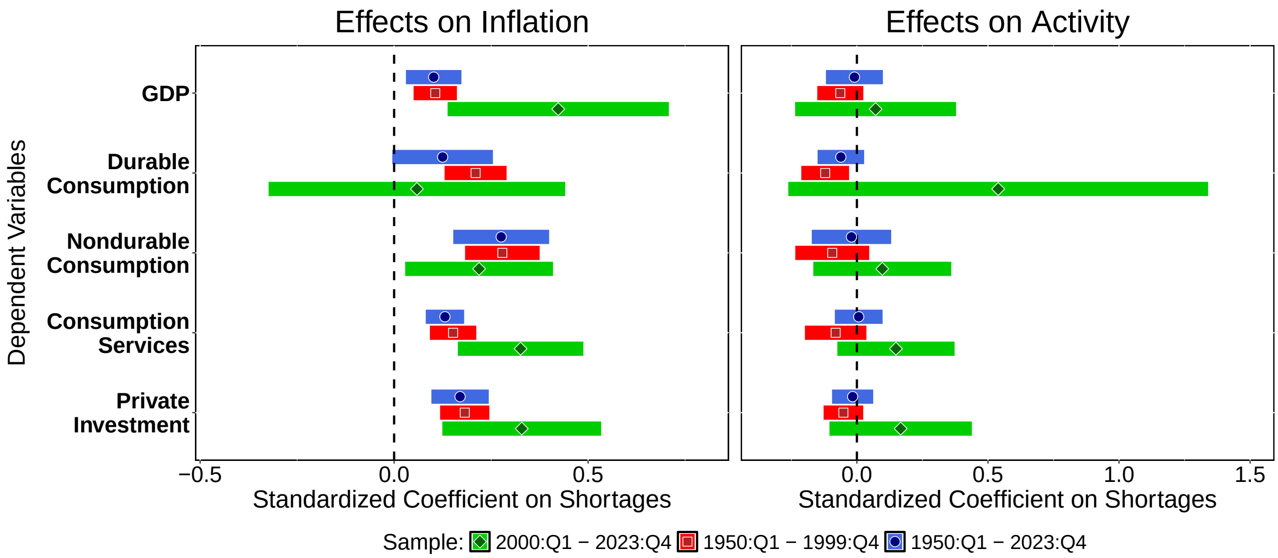
Note: The table reports standardized coefficients of predictive monthly regressions of selected prices and wages indicators on the categorical shortage indexes. The dependent variable for each regression is the 3-month log difference of the producer price index (PPI) for processed goods for intermediate 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: VAR Model: Estimated Parameters

		Prior		Posterior			
Parameter	Type	**Mean**	St. Dev	**Mean**	St. Dev	10%	90%
σ_{ε_d}	Inv. Gamma	**2.10**	0.50	**1.58**	0.07	1.49	1.67
σ_{ε_s}	Inv. Gamma	**1.20**	0.50	**0.67**	0.03	0.63	0.70
σ_{ε_c}	Inv. Gamma	**6.10**	0.50	**5.56**	0.20	5.30	5.80
σ_{ε_h}	Inv. Gamma	**0.50**	0.50	**0.57**	0.03	0.54	0.60
σ_{ε_r}	Inv. Gamma	**2.00**	0.50	**0.72**	0.03	0.68	0.76
$\rho_{1,HH}$	Beta	**0.65**	0.10	**0.68**	0.04	0.63	0.73
$\rho_{1,YY}$	Beta	**0.65**	0.10	**0.75**	0.04	0.70	0.80
$\rho_{1,\pi\pi}$	Beta	**0.65**	0.10	**0.89**	0.03	0.85	0.92
$\rho_{1,CC}$	Beta	**0.65**	0.10	**0.83**	0.03	0.80	0.87
$\rho_{1,RR}$	Beta	**0.65**	0.10	**0.85**	0.03	0.81	0.88
$\rho_{1,\pi R}$	Beta	**0.10**	0.05	**0.02**	0.01	0.01	0.03
$\rho_{1,YR}$	Beta	**0.50**	0.10	**0.11**	0.02	0.08	0.13
δ	Inv. Gamma	**0.20**	1.00	**0.12**	0.05	0.07	0.18
κ	Inv. Gamma	**0.20**	1.00	**0.12**	0.02	0.09	0.15
θ_D	Inv. Gamma	**0.20**	1.00	**0.05**	0.01	0.04	0.06
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	**0.09**	0.03	0.06	0.13
α_H	Normal	**0.00**	0.10	**-0.08**	0.05	-0.15	-0.02
α_π	Normal	**0.10**	0.10	**0.09**	0.05	0.02	0.16
χ_D	Inv. Gamma	**2.00**	5.00	**1.49**	0.21	1.23	1.75
χ_S	Inv. Gamma	**2.00**	5.00	**3.93**	0.53	3.19	4.60
χ_H	Inv. Gamma	**2.00**	5.00	**1.76**	0.56	1.10	2.46
$\rho_{1,HY}$	Normal	**0.00**	0.10	**0.04**	0.02	0.02	0.06
$\rho_{1,H\pi}$	Normal	**0.00**	0.10	**0.04**	0.02	0.01	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	**-0.09**	0.08	-0.19	0.02
$\rho_{1,Y\pi}$	Normal	**0.00**	0.10	**0.12**	0.05	0.06	0.20
$\rho_{1,YC}$	Normal	**0.00**	0.10	**-0.00**	0.01	-0.01	0.01
$\rho_{1,\pi H}$	Normal	**0.10**	0.10	**0.15**	0.04	0.10	0.21
$\rho_{1,\pi Y}$	Normal	**0.00**	0.10	**-0.04**	0.03	-0.07	-0.01
$\rho_{1,\pi C}$	Normal	**0.10**	0.10	**0.02**	0.00	0.02	0.02
$\rho_{1,CH}$	Normal	**0.10**	0.10	**0.07**	0.10	-0.06	0.20
$\rho_{1,CY}$	Normal	**0.00**	0.10	**0.05**	0.08	-0.06	0.15
$\rho_{1,C\pi}$	Normal	**0.00**	0.10	**-0.18**	0.09	-0.30	-0.07
$\rho_{1,R\pi}$	Normal	**0.00**	0.10	**0.03**	0.05	-0.04	0.10
$\rho_{1,RY}$	Normal	**0.00**	0.10	**0.01**	0.03	-0.03	0.05
$\rho_{1,RC}$	Normal	**0.00**	0.10	**-0.02**	0.01	-0.03	-0.01
$\rho_{1,RH}$	Normal	**0.00**	0.10	**0.07**	0.06	-0.00	0.14
$\rho_{1,CR}$	Beta	**0.10**	0.05	**0.13**	0.06	0.06	0.21
$\rho_{1,HR}$	Normal	**0.00**	0.10	**0.02**	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	0.07
$\rho_{2,\pi\pi}$	Beta	**0.10**	0.05	**0.06**	0.02	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	**0.06**	0.02	0.03	0.09

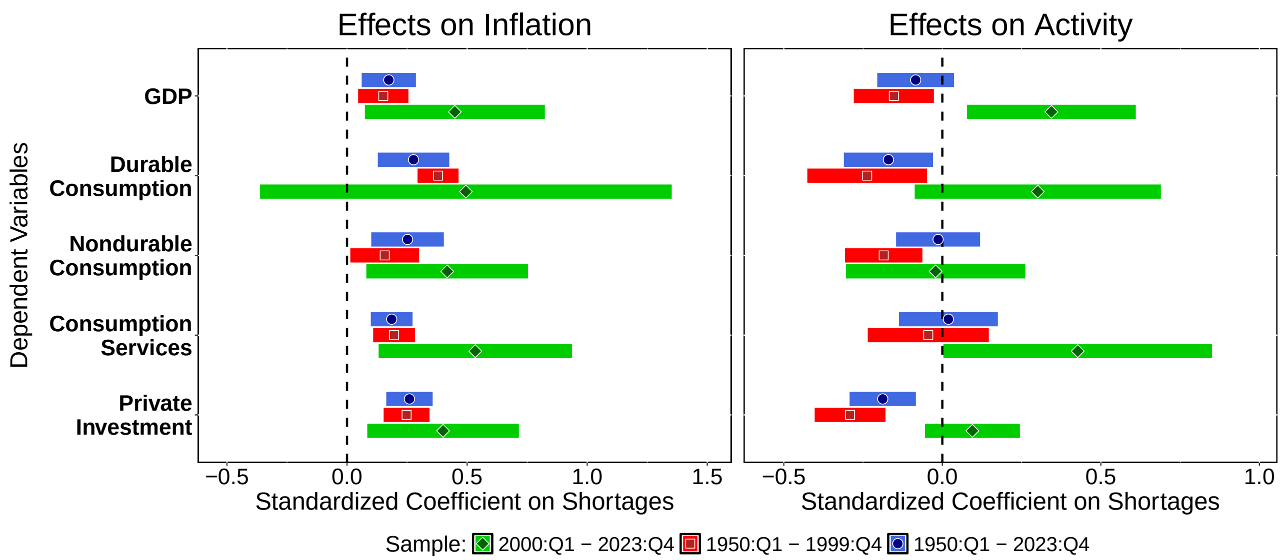
Note: The table shows estimated parameters of the model described in Section 5. The coefficients describing lagged response of π, y, c, and h to interest rates—$\rho_{1,\cdot R}$—are written with a negative sign in the model specification of the VAR model to impose a negative lagged impact of interest rates on each of these variables.

Figure A.1: Relationship between Shortages and Inflation and Activity One Quarter Ahead



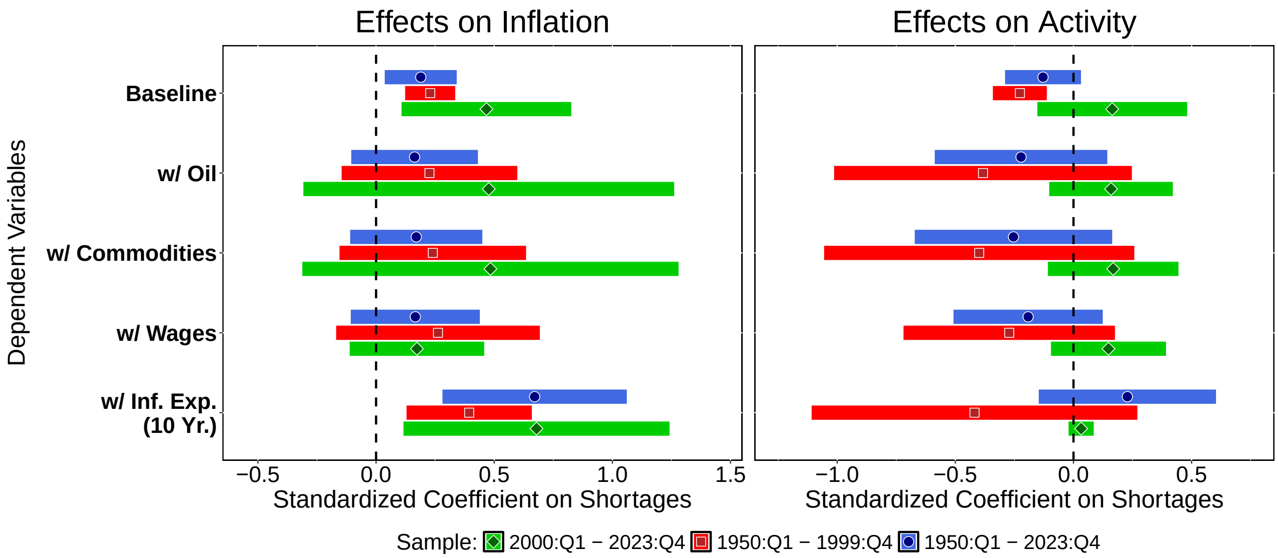
Note: The figure reports standardized coefficients of predictive regressions of inflation and economic activity on the shortage index estimated on quarterly data. The dependent variable for each regression is the log difference between $t+1$ and t of the variable listed in each row (the price deflator 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 1950:Q1 to 2023:Q4. We also partition the sample into two periods: 1950:Q1 to 1999:Q4, and 2000:Q1 to 2023:Q4. Heteroskedasticity and autocorrelation consistent 90% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987).

Figure A.2: Relationship between Shortages and Inflation and Activity 2-Years 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 1950:Q1 to 2023:Q4. We also partition the sample into two periods: 1950:Q1 to 1999:Q4, and 2000:Q1 to 2023:Q4. Heteroskedasticity and autocorrelation consistent 90% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987).

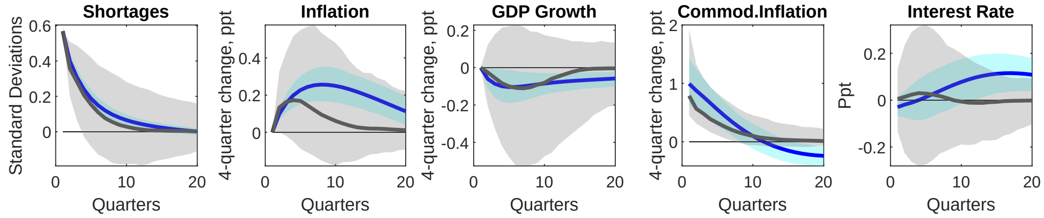
Figure A.3: Effects of Shortages on Inflation and Economic Activity 1-Year Ahead, with and without controls



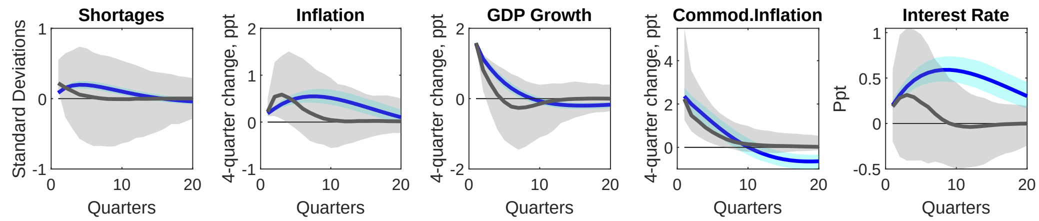
Note: The figure reports standardized coefficients of predictive regressions of inflation and economic activity on the shortage index estimated on quarterly data. The dependent variable for each regression is the log difference between $t + 4$ and t of the variable listed in each row (the price deflator for inflation and real quantities for growth). Each row in the Figure shows how the standardized coefficients change with the inclusion of the controls listed. The full sample runs from 1950:Q1 to 2023:Q4. We also partition the sample into two periods: 1950:Q1 to 1999:Q4, and 2000:Q1 to 2023:Q4. Heteroskedasticity and autocorrelation consistent 90% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987). The regressions controlling for inflation expectations for the earlier sample start in 1982:Q1. Inflation expectations are from the Federal Reserve Bank of Cleveland via FRED. Heteroskedasticity and autocorrelation consistent 90% confidence intervals are reported using shaded horizontal bars and computed according to Newey and West (1987).

Figure A.4: Effects of Shortages in the Estimated VAR Model: Prior vs Posterior

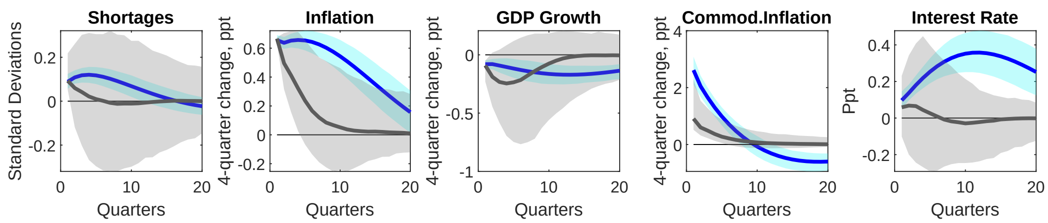
(a) Shock to Shortages



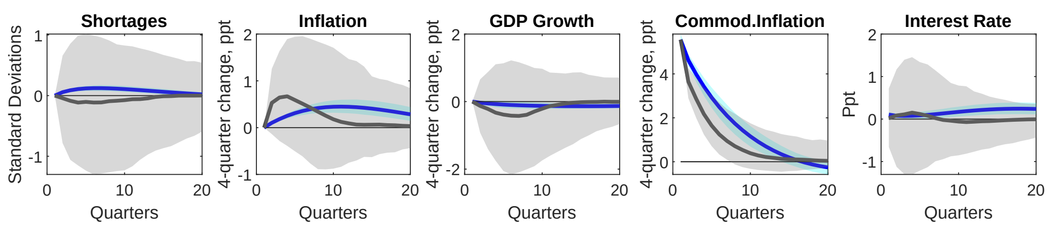
(b) Shock to Demand



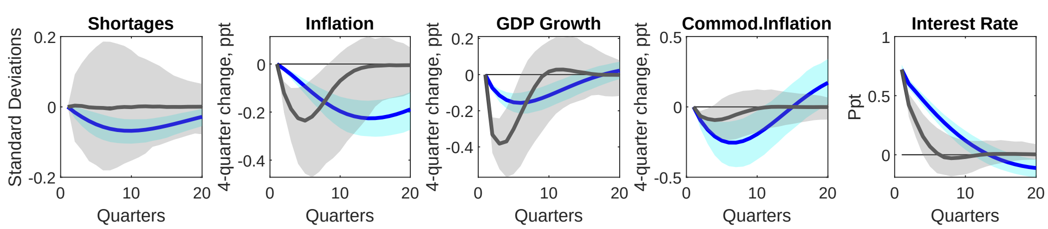
(c) Shock to Supply



(d) Shock to Commodity Prices



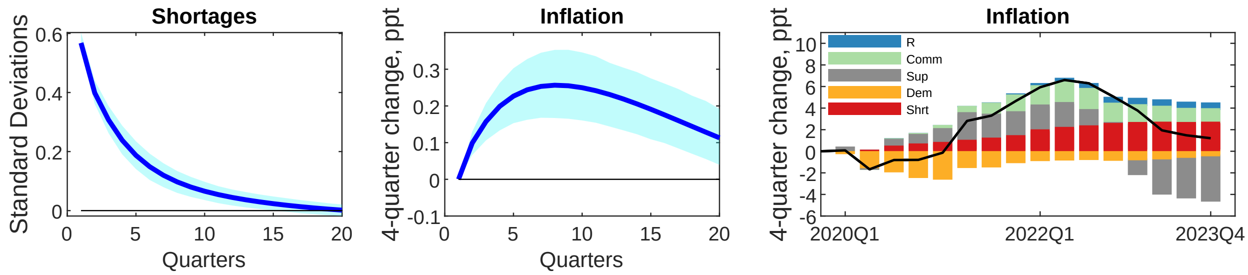
(e) Shock to Interest Rate



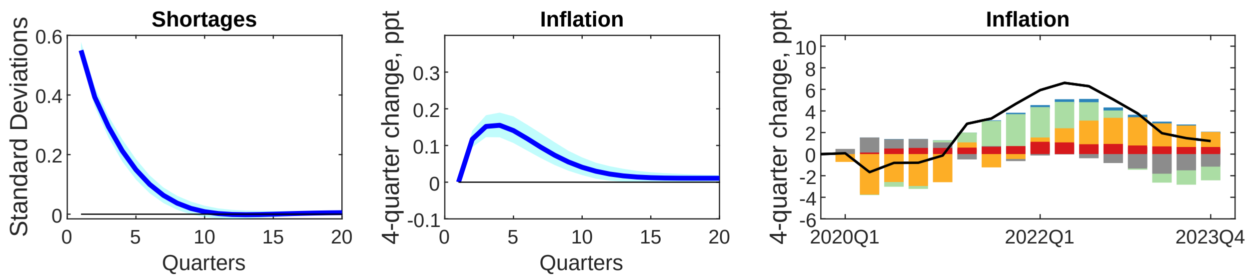
Note: Gray lines and areas, prior; Blue lines and areas, posterior. Impulse Response from the VAR: comparison of prior vs. posterior. Posterior shocks are one-standard deviation in size. Solid lines denote the response at the mean. Shaded areas denote 80 percent confidence intervals. The Impact of the shocks at the prior mean has been normalized to match the impact effect of the estimated shocks at the posterior mean on (a) shortages, (b) GDP, (c) inflation, (d) commodities, (e) interest rates.

Figure A.5: Comparison of baseline VAR model with alternative versions

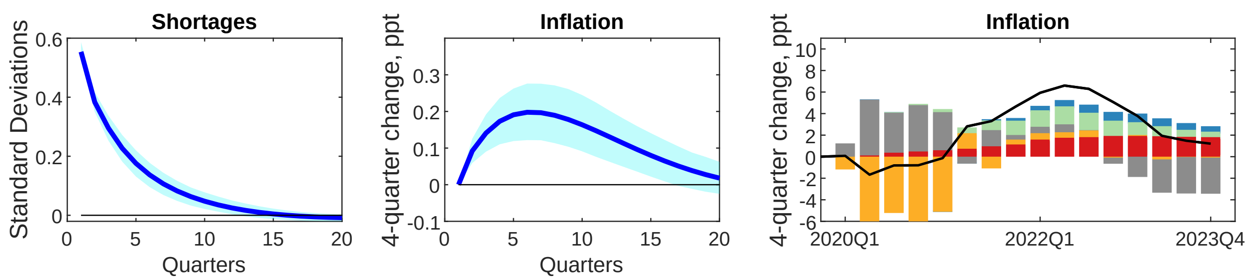
(a) Baseline Model



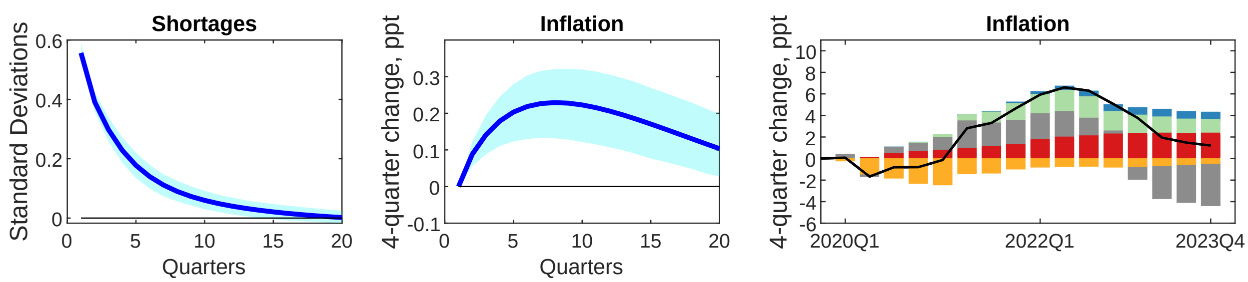
(b) Flatter Demand Curve ($\delta = 3$)



(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 $\delta = 4$ and $\kappa = 1$, respectively. Model (d) replaces 4-quarter GDP growth with the output gap constructed using the CBO measure of the output gap.