# What Can Stockouts Tell Us About Inflation? Evidence from Online Micro Data*

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**Abstract**

We use a detailed micro dataset on product availability and stockouts to construct a direct high-frequency measure of consumer product shortages during the 2020–2022 pandemic. We document a widespread multi-fold rise in stockouts in nearly all sectors early in the pandemic. Over time, the composition evolved from temporary to more permanently discontinued products, concentrated in fewer sectors. We show that unexpected shocks to stockout levels have significant inflationary effects within three months. These effects are larger and more persistent for imported goods and import-intensive sectors. We develop a model of inventories in a sector facing both demand and cost disturbances, and use the observed joint dynamics of stockouts and prices to show that these effects can be associated with elevated costs of replenishing inventories and higher exposure to trade.

**JEL-Codes**: D22, E31, E37.
**Keywords**: Prices, Stockouts, Inventories, Supply disruptions, COVID-19 pandemic.

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*"As the reopening continues, shifts in demand can be large and rapid, and bottlenecks, hiring difficulties, and other constraints could continue to limit how quickly supply can adjust, raising the possibility that inflation could turn out to be higher and more persistent than we expect."*

– *Jerome Powell (June 2021)*[1]

# 1 Introduction

One of the most striking economic problems of the global COVID-19 pandemic was the severe disruption of the supply of goods to final consumers amid volatile swings in demand. Globally, these forces caused bottlenecks in shipping networks and disrupted the flow of goods along international supply chains.[2] Domestically, the pandemic increased the cost of business operations, undercutting retailers' efforts to manage inventories.[3] As a result, retailers and consumers faced shortages in a wide range of goods, from toilet paper to electronics. By early 2021, the persistence of shortages raised concerns about their inflationary impact, particularly in the United States, where prices were rising at rates not seen in decades, reaching 9.1% per year by June 2022.[4] Although there is some evidence of these disruptions in manufacturing and ports, there is still no systematic evidence of shortages for retail consumer products.[5] Furthermore, the degree of inflationary pressures associated with such shortages has been widely debated but remains unknown.

In this paper, we provide a direct high-frequency measure of consumer product shortages during the pandemic to study their impact on inflation. Our measure captures product unavailability and stockouts in the micro data collected every day from the websites of 70 large retailers in 7 countries—the United States, Canada, China, France, Germany, Japan, and Spain—from November 1, 2019 to July 26, 2022. The dataset spans a wide range of consumer goods, includ-

[1] Transcript of Fed Chair Powell's Statement on June 16, 2021, available at https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20210616.pdf

[2] Alessandria, Khan, Khederlarian, Mix, and Ruhl (2022) review evidence of supply-chain disruptions and study their effect on COVID recovery in a heterogeneous firm model of international trade.

[3] See Hassan, Hollander, Van Lent, Schwedeler, and Tahoun (2020) and Meier and Pinto (2020) for some early results of the COVID-19 impact on the U.S. firms and sectors.

[4] See Foster, Meyer, and Prescott (2021) for survey results that connect firm-level concerns about supply disruptions to rising expectations of inflation.

[5] See Krolikowski and Naggert (2021) for an analysis of shortages in car manufacturing and Leibovici and Dunn (2021) for a discussion of semiconductor shortages. Mahajan and Tomar (2021) provide evidence of food supply chain disruptions in India.

ing Food and Beverages, Household, Health, Electronics, and Personal Care products, covering between 52% and 80% of the goods consumption weights in the Consumer Price Index (CPI) baskets of these countries. The dataset contains prices for almost two million products, allowing us to exploit the rich time and cross-section details to assess the inflationary effects of shortages.

The paper consists of four parts. We first document the dynamics of temporarily unavailable products ("temporary stockouts") and missing products ("permanent stockouts") over the course of the pandemic. We then establish the degree to which stockouts co-move with prices and assess whether this comovement is stronger for goods and sectors exposed to international trade disruptions. Finally, we provide a formal analysis of the link between stockouts, prices, and costs using a model of monopolistic firms with inventories.

There are three distinct patterns of stockout behavior that are common across most sectors and countries during this period. First, there was a widespread increase in stockouts early in the pandemic affecting nearly all categories of consumer goods. In the United States, in particular, our aggregate measure of stockouts using CPI category weights rose from a pre-pandemic level of around 10% in 2019 to over 40% in May 2020. Initially, the stockouts impacted health and personal care goods, but quickly spread to other categories, with increases ranging from 23 percentage points (ppt) for "Furnishings and Household" goods and over 60 ppt for "Food and Beverages." The level of aggregate U.S. stockouts recovered gradually over time, but by November 2021 it was rising again. In July 2022, U.S. stockouts remained at 25%, more than twice the pre-pandemic level. Other countries exhibit similar stockout dynamics, but the U.S. had the most persistent stockouts.

Second, the composition of stockouts changed significantly over time. Temporary stockouts, which are more visible to consumers because they are flagged by retailers with an out-of-stock indicator, rose sharply in most sectors and countries early on and then recovered rather quickly. By the end of 2020, they had fallen below their pre-pandemic levels for most countries. By contrast, permanent stockouts remained elevated in some countries, particularly in the U.S., where they were still at 20% in July 2022.

Third, stockouts became increasingly concentrated in fewer product categories over time. In particular, in the United States stockouts remained persistently high for "Food and Beverages" by July 2022, but had returned to pre-pandemic levels in other major categories.

Next, we show that these product stockouts were associated with rising prices in most sectors and countries. The magnitude of the dynamic inflationary effect is statistically and economically significant. We estimate that an unexpected doubling of the weekly temporary stockout rate from 10% to 20% brought about a 1.5 ppt increase in the annualized inflation rate in a 3-digit sector. The inflation response takes about a month to reach its peak and lasts approximately three months.

To investigate whether the inflationary effects are associated with global supply bottlenecks, we study the behavior of imported products and import-intensive sectors. First, using micro data from one large U.S. retailer with country of origin information for all individual goods, we show that imported products experience both longer stockouts and higher inflation rates than domestically produced goods. After a temporary stockout, prices of domestically produced products quickly return to average levels, whereas prices of imported goods continue to rise for several weeks. Second, when we compare sector responses to temporary stockout disturbances, import-intensive sectors experience larger and more persistent inflation, with roughly twice the impact of domestic goods after six weeks. Overall, this evidence suggests that costs associated with supply-chain disruptions during the pandemic led to significant increases in both product shortages and price increases.

In the final part of the paper, we estimate the cost of replenishing inventories by explicitly accounting for the endogeneity of stockouts.[6] Building on Kryvtsov and Midrigan (2013), we develop a model of joint dynamics of stockouts and prices in a sector facing exogenous demand and cost disturbances, and use it to derive an empirical specification for estimating the underlying costs. We then construct empirical responses of sector stockouts and inflation to the estimated cost shocks.

Our estimation results imply a statistically and economically significant link between costs, temporary stockouts, and inflation. The estimated replacement cost dynamics resemble those from observed stockout behaviors, validating the idea of using them for gauging the emergent shortage pressures. Furthermore, accounting for the endogeneity of stockouts makes the estimated inflationary effects stronger immediately after the cost shock, but also less persistent. At

[6] Studies of inventory management and pricing include (Deaton and Laroque, 1992; Aguirregabiria, 1999; Hall and Rust, 2000). The influence of inventories on prices is especially strong in recessions (Bils and Kahn, 2000; Kryvtsov and Midrigan, 2010, 2013; Bils, 2016) and during emerging market crises and devaluations (Alessandria, Kaboski, and Midrigan, 2010b).

least half of the estimated variation in inflation and nominal costs are common across sectors and represent "pure inflation." The remaining share of variance can be attributed to sector-specific factors driving relative price disturbances. Global common factors reflect, in part, higher cost pressures on retailers exposed to international trade during the pandemic. Indeed, we find that both inflation and stockouts are more responsive to replacement cost shocks in trade-intensive sectors

# 2 Shortages and Stockout Measurement

Shortages are the difference between the quantity demanded and quantity supplied at current prices, and are therefore not directly observable. Previous papers have estimated shortages either by using latent variable models with structural demand/supply equations under strong assumptions, or relying on indirect indicators such as vendor delivery speeds and news-based text analysis (Lamont, 1997).

In this paper, we can directly detect the existence of shortages using binary indicators of stockouts and product availability over time. When supply is unable to satisfy demand at prevailing prices, inventories are depleted and products go out of stock. By tracking stockouts we can measure of the extensive margin of shortages at the product level. We can also estimate the intensity of shortages within narrow categories of goods by computing the share of products with stockouts over time.

To do this, we rely on data obtained from the websites of large retailers that sell products both online and in brick-and-mortar stores. The data were collected by PriceStats, a private firm related to the Billion Prices Project (Cavallo, 2013, and Cavallo and Rigobon, 2016).[7] Table 1 summarizes some key dimensions of our dataset.

[7] See Cavallo (2017) for a comparison of online and brick-and-mortar prices.

| | Products | Retailers | Coverage of All CPI Weights, (%) | Coverage of Goods CPI Weights, (%) |
|---|---|---|---|---|
| Canada | 194,151 | 11 | 27 | 80 |
| China | 49,685 | 3 | 38 | 76 |
| France | 372,962 | 11 | 32 | 63 |
| Germany | 297,320 | 13 | 27 | 52 |
| Japan | 95,313 | 7 | 30 | 68 |
| Spain | 171,400 | 8 | 31 | 56 |
| USA | 777,554 | 17 | 21 | 62 |
| All | 1,958,385 | 70 | 29 | 65 |

Table 1: Data Coverage

Notes: All retailers are large "multi-channel" firms selling both online and in brick-and-mortar stores. To be included in our sample, they must also display an out-of-stock indicator for each product on their websites. Coverage for CPI weights is calculated by adding the official CPI weights of all 3-digit COICOP categories included in the data for each country. Coverage percentages for "All" are unweighted arithmetic means across all countries.

We use information from 70 retailers in 7 countries: Canada, China, France, Germany, Japan, Spain, and the United States. The sample ends on July 26, 2022, and starts on January 1, 2019, for the United States and on November 1, 2019, for all other countries. For each product, we have an id, price, and out-of-stock indicator which can change on a daily basis. In addition, each product is classified using the 3-digit COICOP classification, covering five major types of goods: "Food and Non-Alcoholic Beverages", "Furnishings and Household", "Health", "Recreation and Culture" (mostly electronics), and "Other Goods" (including personal care products).[8] The data cover between 62% and 80% of the Consumer Price Index (CPI) weight of all goods, depending on the country.

Relying on these micro data, we measure two distinct types of stockouts. First, retailers often indicate stockouts on their websites via text or images displayed on or around the product's listing, as illustrated in Figure 1. Such occurrences are recorded in the database as an out-of-stock indicator. The fact that retailers display out-of-stock information implies that they expect these products to eventually be back in stock, which is why we label them as "temporary stockouts." They are similar to a product missing on its shelf in a brick-and-mortar store.[9]

[8] See UN (2018) for details on the COICOP classification structure.

[9] Occasional interruptions in scraping and data collection result in data gaps. We fill these gaps by carrying forward the last available observations.

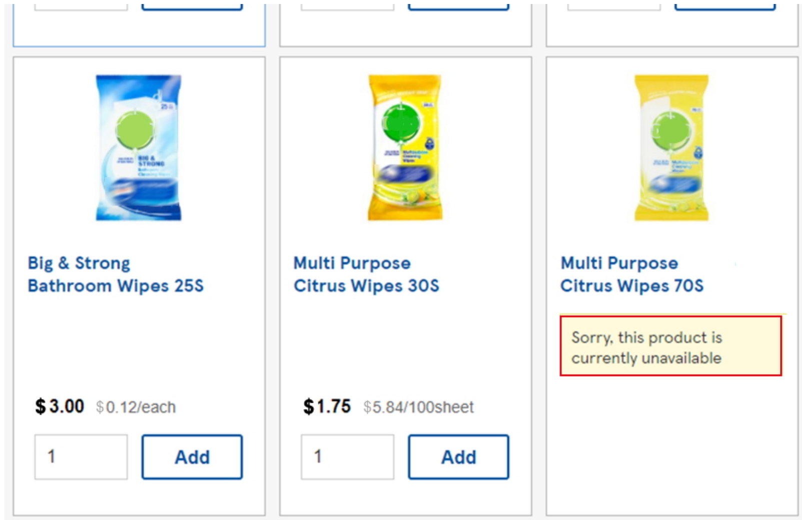



Figure 1: Identifying Stockouts on a Retailer's Website

Notes: This figure provides an illustration of how we identify products that are out of stock. All retailers in our sample display messages like the one in this example, which allows us to create an indicator variable in the dataset for goods that are out-of-stock on a given day ("Temporary Stockouts"). We also identify products that disappear (or appear) from the website and calculate the net number of discontinued goods relative to pre-pandemic levels ("Permanent Stockouts").

To obtain a daily time series, we calculate the share of "Temporary Stockouts" (TOOS) in a 3-digit COICOP sector $j$ in country $c$ on day $t$ as a percentage of all products available for purchase on that day:

$$TOOS_{cj,t} = \frac{\text{out-of-stock}_{cj,t}}{\text{total products}_{cj,t}}. \tag{1}$$

We also need to account for the fact that retailers discontinued many products, removing them from their websites. Some of these goods eventually reappear or are replaced with new varieties, but the total number of products available to consumers declined significantly in most countries.[10] We therefore add a second stockout measure called "Permanent Stockouts" (POOS), computed as the percentage decline in the number of available products in a sector relative to their average level in January 2020, before the pandemic started:

$$POOS_{cj,t} = 1 - \frac{\text{total products}_{cj,t}}{\text{total products}_{cj,Jan2020}}. \tag{2}$$

We also construct a broader measure of stockouts, ($AOOS_{cj,t}$) that combines both temporary and permanent stockouts. It is defined as the share of products that have become unavailable

[10] We validate our strategy to treat events that retailers advertise via out-of-stock signs as more "temporary" by looking at the stockout probabilities and duration in a subset of micro data described in Section 5.5. We found that the probability that a temporary stockout will reappear with a price is 96% and that the median duration is 2 days. The same probability for a permanent stockout is 76% and the median duration is 97 days.

since the pandemic started—either because they are out of stock or discontinued. We note that $POOS_{cj,t}$ and $AOOS_{cj,t}$ can be negative if the total number of products is larger than before the pandemic.

Temporary stockouts can be directly linked to supply disruptions, but the level of permanent stockouts might also be affected by changes in tastes and preferences for varieties induced by the Pandemic. For that reason, in sections 3 and 4 we provide differentiated results for both types of stockouts, while in section 5.2, where we look at trade disruptions, and section 6, where we model inventory decisions, we focus exclusively on temporary stockouts.

Finally, to obtain aggregate stockout indices consistent with the official CPI in each country, we aggregate values of the corresponding 3-digit series using an arithmetic average with official CPI category weights $w_{jc}$ obtained from the national statistical office in each country:

$$OOS_{c,t} = \sum_{j} w_{cj} OOS_{cj,t}, \tag{3}$$

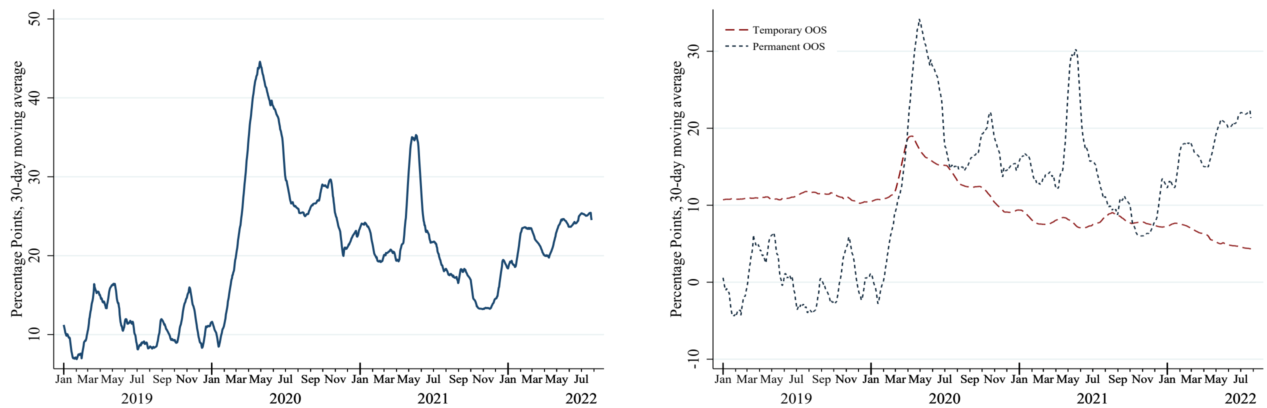
where $OOS = \{TOOS, POOS, AOOS\}$.

# 3 Stockout Dynamics

Stockouts experienced substantial variation over the course of the pandemic, but three main patterns stand out. First, there was a large increase in temporary and permanent stockouts in the wake of the crisis, affecting most countries and sectors. Second, temporary stockouts returned to normal levels after a year and a half. By contrast, permanent stockouts remain elevated in some countries and sectors at the end of our sample. Third, stockouts are increasingly concentrated in fewer categories that appear to be more affected by the pandemic's disruptions, such as food and electronics.

## 3.1 U.S. Stockouts

We first highlight these patterns using U.S. data (Figures 2 and 3). The plot in Figure 2(a) shows stockouts ($AOOS_{US,t}$) rising quickly in the first quarter of the crisis, from a pre-pandemic level of around 10% in 2019 to over 45% in early May 2020. They recovered gradually over time, and despite another spike in May 2021, had reached close to pre-pandemic levels in November 2021, when they started rising once again. By July 2022, U.S. stockouts were still at 25%, more than double their pre-pandemic levels. [11]




(a) All Stockouts

(b) Temporary and Permanent Stockouts

Figure 2: Stockouts in the United States, 2019–2021

Notes: In panel (a) we plot all stockouts $AOOS_{c,t}$. In panel (b) we plot separately temporary $TOOS_{c,t}$, measured using the retailer out-of-stock indicators, and permanent stockouts $POOS_{c,t}$, measured as the fall in the total number of available products relative to pre-pandemic levels.

The composition of stockouts changed significantly over time, as shown in Figure 2(b). Temporary stockouts, which are more visible to consumers, rose quickly from 10% to 20% in March 2020, and then recovered gradually over time. By November, they were back to pre-pandemic levels, and continued to fall further in subsequent months. Permanent stockouts also increased sharply at the beginning of the pandemic, but unlike temporary stockouts, they were more persistent, as shown in Figure 2(b). Initially, about 30% of products had been discontinued by the end of April 2020. After recovering for a few months, permanent stockouts remained volatile, and by May 2021, were once again peaking. After November 2021, the share of discontinued products rose again and reached 20% by July 2022.

Elevated stockouts affected all sectors but were more persistent in "Food and Beverages" and, to a lesser degree, in "Electronics" and personal care goods. This can be seen in Figure 3, where we plot stockout levels for five major good categories in the United States. To facilitate the comparisons, we normalize the series by subtracting the average level during January 2020 for each sector.

[11] There is some volatility in the time series that could reflect seasonal patterns. However, the magnitude of the stockouts increase in 2020 is too large to be driven by seasonal factors alone, as the comparison with the 2019 data in Figure 2 shows. Some of this volatility could also be driven by lumpy trade, as modeled in Alessandria, Kaboski, and Midrigan (2010b).

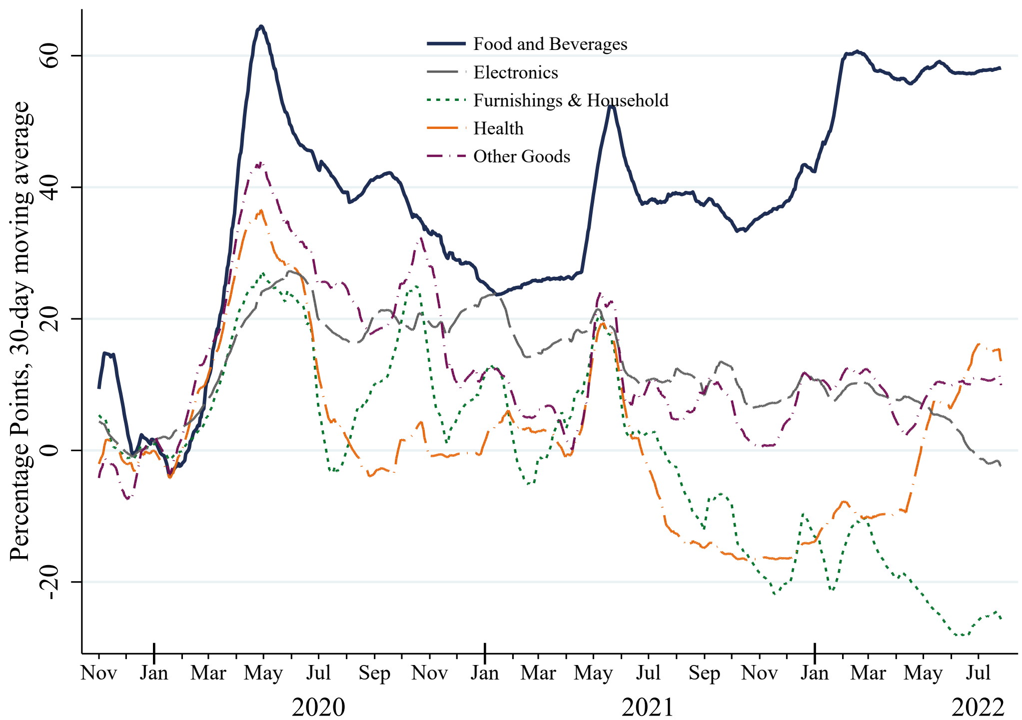



Figure 3: All Stockouts in U.S. Sectors

Notes: The initial level of $AOOS$ varies greatly by sector, so in order to facilitate the comparison, here we plot the change relative to pre-pandemic levels, given by $AOOS_{cj,t} - AOOS_{cj,Jan2020}$.

Stockouts rose first for "Health" and personal care goods, but then quickly spread to other categories. In May 2020, the stockout increase ranged from 23 ppt for "Furnishings and Household" goods to over 60 ppt for "Food and Beverages." Some categories fully recovered. In particular, by mid-2021 'Furnishings and Household" had negative stockouts, which means that there were *more* products available for sale than before the pandemic. By contrast, the disruptions were more persistent for "Food and Beverages," where stockouts remained over 60 ppt above pre-pandemic levels in mid-2022. These findings are consistent with U.S. media reports on this sectors, with labor and transportation disruptions affecting food production and distribution during most of this period.[12]

## 3.2 Other Countries

Figure 4 shows stockouts for all seven countries in our database.[13] To facilitate the comparisons across countries, we plot the incremental change relative to the pre-pandemic levels, given by

[12] See Fitch (2021) and Kang (2021).

[13] See the Appendix for separate graphs for temporary and permanent stockouts.

$AOOS_{c,t} - AOOS_{c,Jan2020}$.

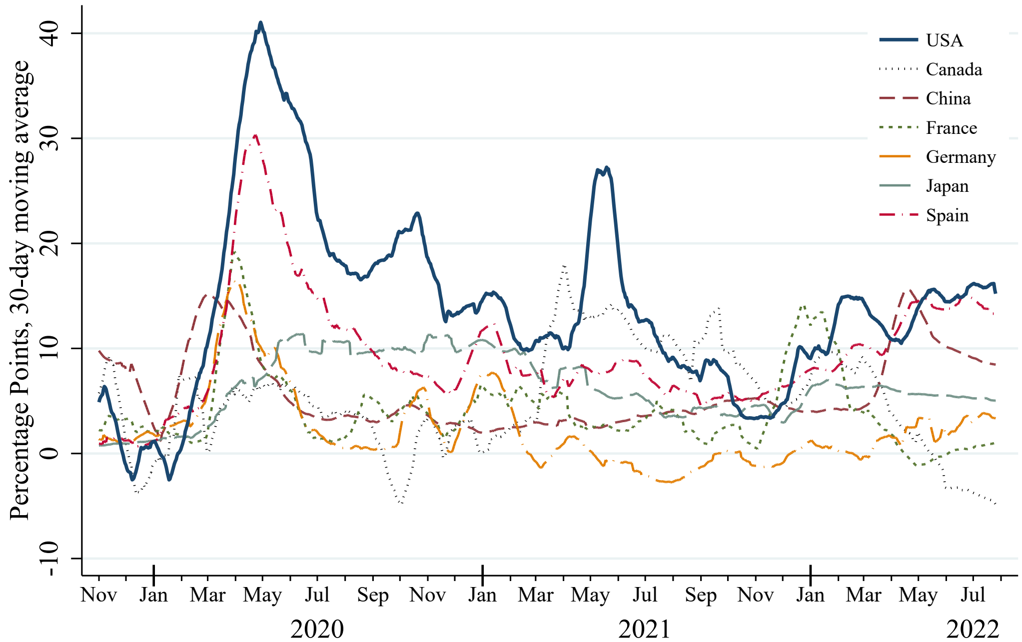



Figure 4: All Stockouts in 7 Countries

Notes: The initial level of $AOOS$ varies greatly by country, so in order to facilitate the comparison, here we plot the change relative to pre-pandemic levels, given by $AOOS_{t,c} - AOOS_{Jan2020,c}$.

Stockout patterns are broadly similar across countries, although the magnitude and persistence is significantly higher in the U.S.. In most countries, stockouts rose sharply during the first two months of the pandemic and then gradually returned to pre-COVID levels over time. Stockouts peaked first in China, where the pandemic started, followed a few weeks later by some European countries. Germany and France had increases of about 20 ppt with a relatively quick recovery back to normal levels by mid-2020, while Spain experienced a larger increase and more gradual recovery. Canada and Japan appear to be outliers, with smaller and gradual increases over time.

After falling for most of 2021, stockouts rose again in November in several countries, including the U.S., France, Spain, and China. In the case of China, the timing coincides with the strict lockdowns imposed in April 2022 in many cities. The Omicron surge and the start of the war in Ukraine likely contributed to higher stockouts in many of these countries.

Why did the U.S. experience higher and more persistent stockouts through most of the pandemic? The answer likely involves a variety of demand and supply shocks affecting the U.S. economy.

On the demand side, the magnitude of the initial spike can be linked to a more extreme surge in "panic buying" behavior (Keane and Neal, 2021 and Messner and Payson, 2022). Also, the extraordinary fiscal and monetary stimulus programs in the U.S. contributed to a quicker recovery of aggregate demand than in other countries (de Soyres, Santacreu, and Young, 2022).

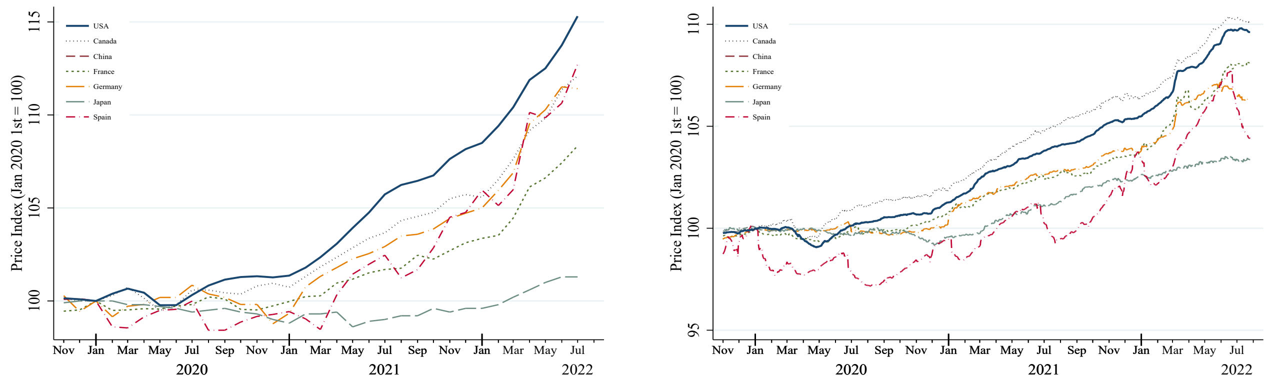
On the supply side, the U.S. experienced tight labor markets during most of the pandemic (Domash and Summers, 2022 and Faberman, Mueller, and Şahin, 2022), with less immigrants working in the food and transportation sectors (Perri and Zaiour, 2022). Fuel prices have also risen more in the U.S. than in other countries, as shown in Appendix Figure A4, contributing to higher distribution costs for many goods. Another persistent supply-side mechanism driving shortages in the U.S. may have been the existence of leaner inventories (Ortiz, 2022) and more complex international supply chains for retail goods. In Section 5 we explore the link between stockouts and trade in the U.S. and find evidence that imported goods were indeed more affected by stockouts and their inflationary pressures.

An alternative demand-driven explanation is that many of the permanent stockouts in the U.S. are reflecting changes in tastes and preferences for less product variety. Indeed, as shown in Cavallo, Feenstra, and Inklaar, 2022, the number of products varieties available for sale in the U.S. was one of the highest in the world before the pandemic started. Whether all those varieties that disappeared will eventually return is still an open question.

Disentangling supply and demand forces causing the stockouts in different countries is outside the scope of this paper, but the rich heterogeneity in the stockouts data suggests this would be a fruitful task for future research efforts.

# 4 Stockouts and Inflation

Having documented the dynamic behavior of stockouts during the pandemic, we now turn to their impact on prices. For most of 2020, inflation was relatively low, but by the end of the year, consumer prices started rising sharply in most countries, as seen in Figure 5. Price indices constructed with the same online data in our sample have similar inflation dynamics, as shown on the graph on the right.[14]




(a) Official CPIs

(b) Online Price Indices

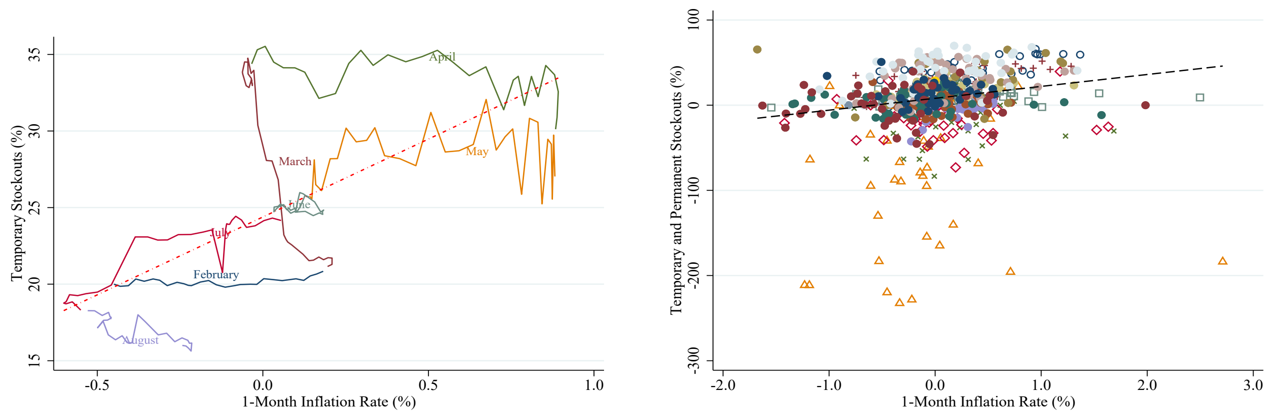
Figure 5: CPI and Online Price Indices

Notes: Figure (a) shows the official all-items CPI in each country. Figure (b) shows equivalent price indices constructed by PriceStats using the same online data source used in this paper.

The sudden rise of inflation led to much debate about its causes (Reis, 2022), particularly in the United States, where supply disruptions were initially cited by policy-makers as a potential source of temporary price pressures (Bernstein and Tedeschi, 2021; Helper and Soltas, 2021). As the crisis deepened, Federal Reserve leaders spoke more explicitly about persistent "demand and supply imbalances" (Powell, 2022), which are directly connected to the shortages we seek to measure with our stockouts indices. Economic theory suggests that shortages put upward pressure on prices to reach a market-clearing equilibrium, but the magnitude and speed of this price adjustment is an open empirical question.

For some categories, the connection between stockouts and prices is apparent in simple graphs, such as the one in Figure 6(a), where we plot a sequential scatter plot with the level of monthly inflation and temporary stockouts for "Food and Beverages" in the United States. The graph shows that stockouts increased sharply in March 2020, prices rose in April 2020, and then both fell in subsequent months. For most categories, however, the correlation between stockouts and prices is not obvious. For example, in Figure 6(b) we find only a weak positive relationship between stockouts and monthly inflation rates at the 2-digit category level in the United States.

[14]The level of U.S. inflation is lower with the online data because it does not include categories that had a significant impact on headline CPI inflation during 2021, such as "Used Cars and Trucks." Additionally, online indices track prices of continuing products and do not take into account price changes associated with product turnover.




(a) Food and Beverages

(b) 2-digit Sectors

Figure 6: U.S. Inflation and Stockouts

Notes: Figure (a) plots the daily level of temporary stockouts (y-axis) and the 1-month inflation rate (x-axis) for the "Food and Beverages" category in the United States from February to August 2020. Each color labels a different month. Figure (b) shows a scatter plot of the levels of total stockouts and 1-month inflation at the 2-digit sector level in the United States, using monthly data and removing some outliers. Each color labels a different 2-digit sector. The dashed line shows the linear prediction between the two variables.

The effects of shortages on inflation are likely to take several weeks, as retailers face constraints on how quickly they can raise prices in an environment that resembles the aftermath of a natural disaster (Cavallo, Cavallo, and Rigobon, 2014). To assess such delayed effects on inflation, we estimate the responses of stockouts and inflation to a stockout disturbance at the 3-digit sector level in seven countries, 199 sectors in total.[15] For now, we treat the stockout shock as exogenous and relax this assumption in Section 6.

First, we estimate innovations to observed variations of sector stockouts over time using an AR(1) process estimated for sector $j$'s weekly stockout rate (in country $c$): $OOS_{cj,t} = c_{cj} + \beta_{cj} OOS_{cj,t-1} + \epsilon_{cj,t}$.[16] The residual term $\epsilon_{cj,t}$ is the measure of the stockout shock. We then estimate the responses of sector inflation and stockouts to those innovations using the linear projections method by Jordà (2005). Let $X_{cj,t}$ denote sector $cj$'s monthly inflation (in %, annualized rate) or stockout rate (in %) in week $t$. We estimate the following empirical specification for the change in $X_{cj,t}$ over $h$ weeks:

$$X_{cj,t+h} - X_{cj,t-1} = c^{(h)} + \sum_{l=0}^{L} \beta_l^{(h)} \epsilon_{cj,t-l} + \sum_{n=1}^{N} \delta_n^{(h)} X_{cj,t-n} + D_{cj} + error_{cj,t}^{(h)} \tag{4}$$

Specification (4) conditions on the history of shocks $\epsilon_{cj,t-l}$, where $l = 0, ..., L$, lags of en-

[15] We exclude 27 sectors with many observations of missing or zero temporary stockout rates.

[16] Adding higher-order lags does not materially improve the results.

dogenous variable $X_{j,t-n}$, $n = 1, ..., N$, and country-sector dummies $D_{cj}$. In both estimations, we use $L = N = 4$.[17] We estimate (4) independently for each dependent variable $X$ by using weighted OLS regression. We conduct the estimation for both temporary stockouts (TOOS) and permanent stockouts (POOS) shocks. Since these shocks can be serially correlated, we use Driscoll and Kraay (1998) standard errors for estimated coefficients. Estimated coefficients $\beta_0^{(h)}$ provide responses of $X_{cj,t}$ to a stockout impulse at horizon $h = 0, 1, ., 12$.

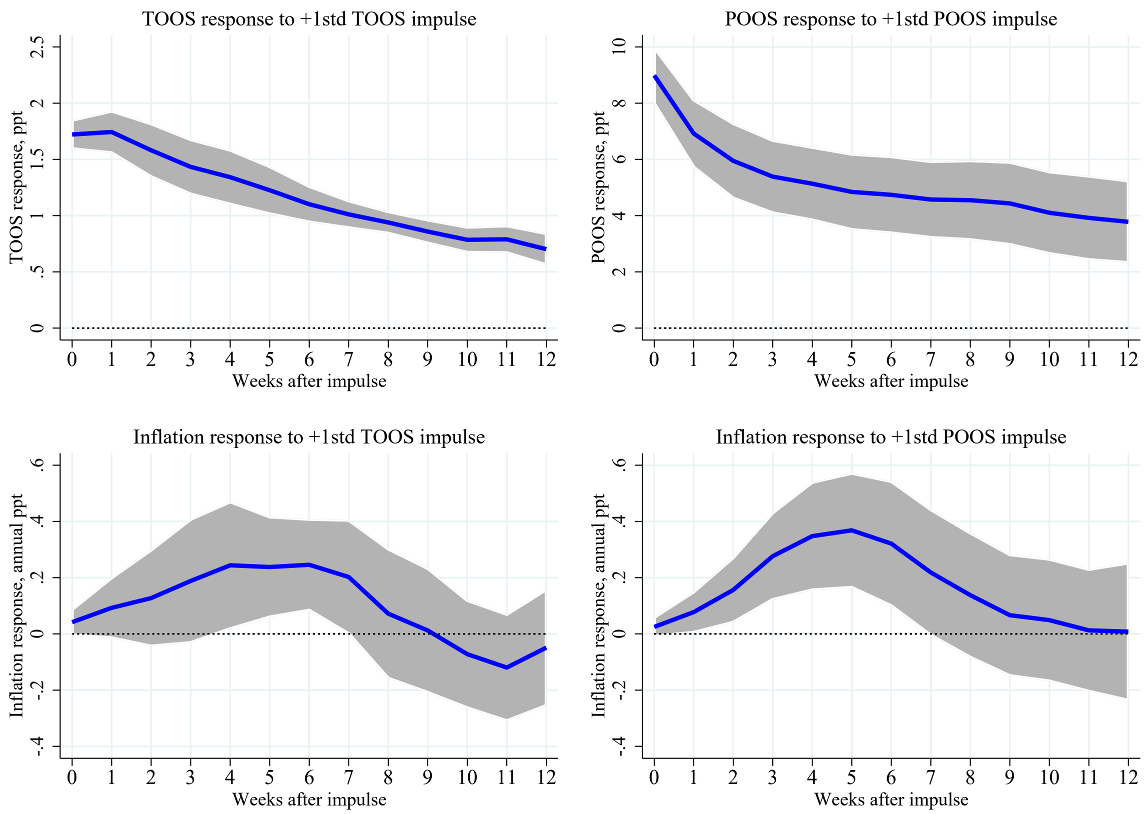



Figure 7: Responses to a Stockout Shock in a 3-digit sector in 7 countries

Notes: The figure provides responses to a +1 standard deviation sector stockout impulse estimated using specification (4) for 3-digit sectors in Canada, China, France, Germany, Japan, Spain, and the United States. Shocks: temporary stockouts TOOS (left) and permanent stockouts POOS (right). Responses: sector stockouts (in ppt, average weekly rate, top), sector monthly inflation (in ppt, annualized rate, bottom). Shaded areas outline 90% bands based on Driscoll-Kraay standard errors.

Figure 7 shows that stockout shocks are associated with significant and persistent responses of both sector stockouts and inflation for the seven countries in our data. Temporary stockouts respond by 1.8 ppt on impact and decrease slowly, with a half-life of roughly 9 weeks. Permanent stockouts are four times more volatile, but their inflationary impact is less persistent. Sector

[17]The number of lags in linear projections is not influencing the results in the paper.

inflation rates respond gradually, reaching 0.27 ppt (annualized rate) by week 4 after a one standard deviation temporary stockout shock, and 0.35 ppt after a permanent stockout shock. The inflationary effect lasts between two to three months, gradually returning to its pre-shock level.

These plots highlight the strong dynamic link between rising stockouts and inflation at a sector level across 7 countries. Although it takes about a month for sector inflation to respond to a stockout disturbance, the response is large and protracted. These estimates suggest that a doubling of the sector's weekly temporary (permanent) stockout rate from 10% to 20%—a common dynamic at the beginning of the pandemic—would bring about a 1.5 ppt (2.0 ppt) increase in the monthly annualized inflation rate of these sectors within a couple of months.

# 5 International Trade and Stockouts

Do shortages and their inflationary effects reflect disruptions in international trade during the pandemic? To investigate this link, we compare price and stockout dynamics across sectors with different exposure to trade, and within sectors for imported and domestically supplied products. It is well-documented that inventories of imported goods are highly sensitive to international trade dynamics.[18]

There is also ample evidence of significant international trade disruptions during the pandemic. For example, according to the U.S. Census Bureau (2021), the share of firms experiencing problems with foreign suppliers more than doubled over 2021, whereas the share of firms reporting disruptions with domestic supply increased by about half (see Figure A1 in the Appendix). Furthermore, the increase in the Global Supply-Chain Pressures Index by Benigno, di Giovanni, Groen, and Noble (2022) from October 2020 to November 2021 was eight times the standard deviation of the index between September 1997 and December 2019 (Figure A2 in the Appendix). Such supply disruptions are therefore expected to bring additional cost pressures on import-intensive sectors and imported goods, leading to higher stockouts, higher prices, or both.

[18] See Alessandria, Kaboski, and Midrigan (2010b,a); Khan and Khederlarian (2021).

## 5.1 Results across sectors by import penetration

First, we extend the results in the previous section by splitting the 199 subsectors in seven countries into two groups: 84 sectors with a low share of imports in total consumption (unprocessed food, plants, printed material) and 115 sectors with a high share of imports (video/audio equipment, furniture, jewelry, and watches).[19] A large portion of low-share sectors are in large countries (China, Japan, and the United States), whereas high-share sectors are more likely to come from small open economies (Canada) or integrated economies (Germany, France). To estimate the differences in responses for these groups of sectors, we replace coefficients $\beta_l^{(h)}$ in specification (4) with $\beta_{0,l}^{(h)} + I_{cj}\beta_{1,l}^{(h)}$, where $I_{cj}$ is equal to 1 if the import of sector $j$ in country $c$ is high, and 0 otherwise.

Figure 8 shows that in response to temporary stockout shocks, trade-intensive sectors experience a higher response of temporary stockouts, by 0.3 ppt on impact, and also a larger and more persistent inflation response, with a 0.5 ppt annualized rate after 12 weeks. This evidence suggests that consumption sectors more exposed to trade at the time of global supply bottlenecks may experience cost pressures, and that they pass heightened costs to both prices and stockouts. As the shock dissipates, prices in trade-intensive sectors end up at permanently higher levels than in other sectors.

There are several channels that can explain why imported goods have higher inflation after stockouts. First, imported goods were exposed to higher transportation costs across borders during this time due to increased international shipping costs, delivery delays by foreign suppliers or difficulty locating alternative foreign suppliers (Alessandria, Khan, Khederlarian, Mix, and Ruhl, 2022). Indeed, between August 15, 2020 and January 16, 2022 the fraction of firms reporting foreign supply disruptions in the "Small Business Pulse Survey" conducted by the U.S. Census Bureau almost doubled from 10% to 18%, whereas the fraction reporting domestic supply disruptions increased by roughly a half, from 29% to 43% (Figure A1 in the Appendix). Second, inventories of imported goods tend to be more sensitive to swings in replacement costs over the business cycle or in response to policy changes (Khan and Khederlarian, 2021), or

[19] We obtain measures of import penetration from World Input-Output Database (WIOD) November 2016 release, https://www.rug.nl/ggdc/valuechain/wiod/wiod-2016-release, see Timmer, Dietzenbacher, Los, Stehrer, and de Vries (2015). For each sector, the import share in total consumption is the ratio of total imports to total output+total imports–total exports. The cutoff for the low import share is 0.22, which is the weighted median share across U.S. sectors.

to variations in economic and policy uncertainty (Alessandria, Khan, and Khederlarian, 2019). Third, for the U.S. in particular, the depreciation of the dollar relative to the Chinese yuan –about 10% between March 2020 and April 2022– likely put additional upward pressure on the prices of Chinese goods, which in 2021 represented 18% of all U.S. imports.

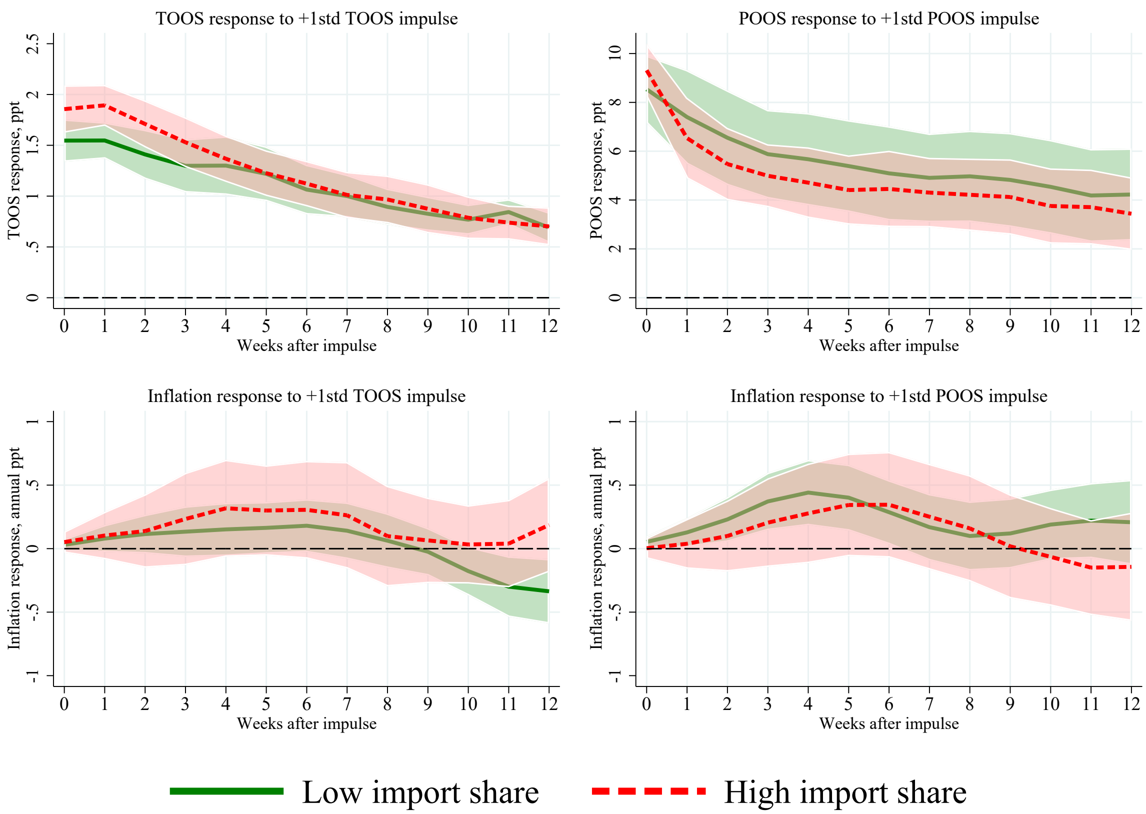



Figure 8: Responses to a Stockout Shock in a 3-digit sector in 7 countries, by import share in consumption

Notes: The figure provides responses to a +1 standard deviation sector stockout impulse estimated for 3-digit sectors in Canada, China, France, Germany, Spain, and the United States. Responses are estimated using specification (4) with additional control for sectors with low import share in total consumption ($\leq$0.22) and high import share (>0.22). Shaded areas outline 90% bands based on Driscoll-Kraay standard errors.

In contrast to the effects of temporary stockouts, we do not find a strong link between trade exposure and inflation responses to fluctuations in discontinued products, suggesting their determinants are also domestic. As noted before, the decision to discontinue products may not only reflect supply disruptions, but also changes in tastes and preferences caused by the Pandemic, which would apply to both domestic and imported products.

## 5.2 Micro Data on Imported and Domestic Goods

We now extend the analysis of temporary stockouts and trade using individual products within sectors. We rely on microdata from one large U.S. retailer for which we know the country of origin for each individual good.[20] This retailer specializes in household products and sold an average of 12,775 distinct products per day during our sample period. About three-quarters of its products are imported, with temporary stockouts levels that averaged 6.0% and lasted approximately 16 days. As can be seen in Table 2, temporary stockouts for imported goods were more frequent and long-lasting (by about a week) than those for domestic goods. Imported goods also exhibited higher average inflation during this time period.

| | **U.S. Retailer** |
|---|---|
| Number of products | 12,775 |
| imported | 10,020 |
| domestic | 2,755 |
| Fraction of stockouts, % | 6.0 |
| imported | 6.5 |
| domestic | 5.9 |
| Stockout duration, days | 16.4 |
| imported | 19.5 |
| domestic | 11.6 |
| Product inflation, ann % | 2.8 |
| imported | 3.3 |
| domestic | 2.3 |

Table 2: Summary statistics for a large U.S. retailer.

Notes: These statistics are provided for goods in the sectors included in the analysis in Sections 3 and 4. Fraction of stockouts is the weighted mean indicator of temporary out-of-stock. Duration is the weighted mean duration of all out-of-stock spells. Product inflation is the weighted mean year-over-year price change. Statistics computed for all products, only imported products ("imported"), or only domestic products ("domestic").

To explore how stockouts influence prices for this retailer, we compare the price behavior for imported and domestic goods before and after a temporary stockout. Let $p_{ij,t}$ denote the log price of product $i$ in a 3-digit sector $j$ on day $t$, and $P_{j,t}$ be the log price index for all products in sector $j$ on day $t$. Let $I^{TOOS}_{ij,t}$ denote an indicator that product $i$ is temporarily out-of-stock on day $t$, and $I^{imp}_{ij}$ is an indicator that product $i$ in sector $j$ is imported. We define price-relative $\tilde{p}_{ij,t_0,t}$

[20] This retailer is in the top ten of U.S. retailers ranked by revenues. More details are available in Cavallo, Gopinath, Neiman, and Tang (2021). For consistency, we study products in only those sectors studied earlier in this section.

as the cumulative price change for product $i$ between dates $t_0$ and $t$ relative to the cumulative price change for all products in that sector $j$: $\tilde{p}_{ij,t_0,t} = p_{ij,t} - p_{ij,t_0} - P_{j,t} + P_{j,t_0}$.

To show how prices evolved before and after a stockout, we compute the average price-relative, $\tau = 1, 2, ...$ days before and $\tau$ days after a temporary stockout in the micro data:

$$\triangle P_{\tau}^{before} = \sum_{T_0} \sum_{ij} \omega_{ij} \tilde{p}_{ij,T_0-1,T_0-\tau} I_{ij,T_0}^{TOOS}, \quad \tau = 1, 2, ..., \tag{5}$$

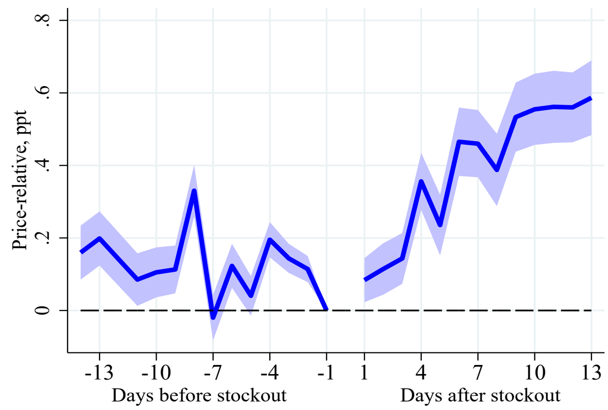
$$\triangle P_{\tau}^{after} = \sum_{T} \sum_{ij} \omega_{ij} \tilde{p}_{ij,T,T+\tau} I_{ij,T}^{TOOS}, \quad \tau = 1, 2, ..., \tag{6}$$

where $T_0$ and $T$ denote the dates of the first and last day of a stockout, $\sum_{T_0}$ and $\sum_T$ are summations over all stockouts, and $\omega_{ij}$ are product weights.[21] We also compute average price-relatives separately for imported and domestically produced goods by multiplying by $I_{ij}^{imp}$ and $1 - I_{ij}^{imp}$ respectively inside the summations in (5) and (6).

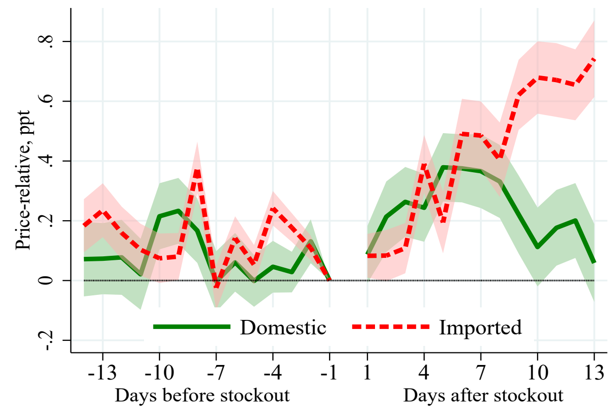
Figure 9(a) shows that products experiencing temporary stockouts have higher prices relative to other products. For goods that are back in stock, prices are 0.6 ppt higher relative to other products after two weeks. Figure 9(b) shows that the higher post-temporary stockout price is mostly driven by imported products, while prices of domestically produced products return to average levels within a couple of weeks.

This evidence is consistent with our findings using cross-country/sector data in that stockouts are associated with subsequently higher prices, and that price increases are larger and more persistent for imported products. Notably, we do not find evidence of price reductions after temporary stockouts predicted by models with large fixed costs of inventory adjustments (Aguirregabiria, 1999). This may indicate that retailers are either able to smooth inventory costs over time and lower the stockout duration, or that they anticipate the cost to persist and continue raising their prices in anticipation of future stockouts. In the next section, we study such mechanisms in a dynamic model of inventory adjustment.

[21] We assume product price at the end of a stockout is equal to the last observed price before the stockout. We drop price changes above 80% in absolute value and 3-digit sectors with fewer than 30 products. We only include those U.S. 3-digit sectors that we used in the sector-level analysis.




(a) All price changes




(b) Domestic versus Imported Goods

Figure 9: Price Levels Before and After a Stockout For a Large U.S. Retailer

Notes: Figure plots the weighted mean price-relatives before and after a stockout, defined in (5) and (6). Panel (a) provides responses for all products, and panel (b) provides responses for imported and domestic goods separately.

# 6 Stockouts, Prices, and Inventory Replacement Costs

When we estimated the dynamic relationship between stockouts and inflation in Sections 4 and 5, we treated stockouts as exogenous. This is a strong assumption because firms decide their inventory levels (and therefore stockout rates) by simultaneously taking into account their prices and demand conditions. In practice, this means that we cannot infer the inventory replacement cost only by looking at the behavior of stockouts. We also need to take into account the behavior of prices.

To illustrate this, consider the data in Figure 10. The fact that the U.S. stockout index was trending downward until late 2021 could suggest that firms were facing lower replacement costs over time, but this is not consistent with the survey conducted by the U.S. Census Bureau, which suggests that supply disruptions were increasing again after April 2021. In practice, firms can adjust to these disruptions (and their associated inventory replacement costs) through an increase in stockouts *or* an increase in prices. Therefore, we need to account for the simultaneous behavior of stockouts and prices to obtain a more realistic estimate of the inventory cost pressure that firms face over time.

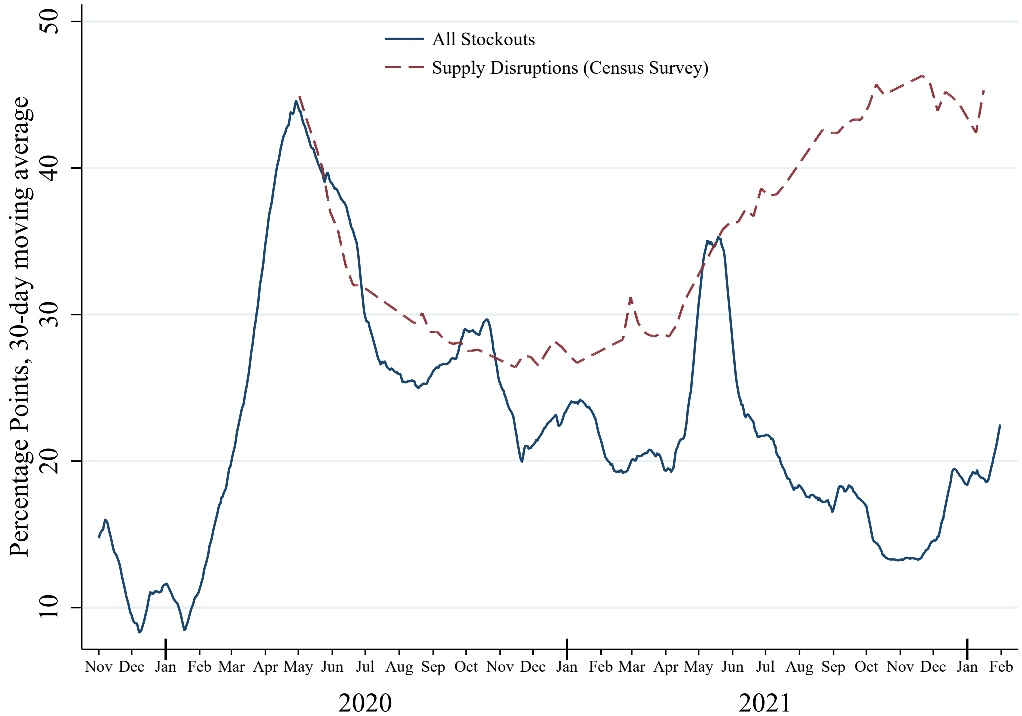



Figure 10: Stockouts (AOOS) vs. U.S. Census Survey of Small Business Disruptions

Notes: This graph compares our measure of all stockouts in the United States with the percentage of firms that reported experiencing domestic or foreign supply disruptions in the "Small Business Pulse Survey" conducted by the U.S. Census Bureau between May 2020 and February 2022. See https://portal.census.gov/pulse/data/#about.

In this section, we incorporate the endogeneity of stockouts into the analysis, proceeding in several steps. First, we use a partial-equilibrium model of inventory adjustment to derive a non-linear dynamic law of motion of the sector's temporary stockouts, given sector prices and costs of replenishing stocks. Second, we estimate this law of motion independently for each sector using sector-level price and temporary stockout data. Third, we use the estimated model to predict the in-sample dynamic of the cost of replenishing inventories. Finally, we estimate the impact of sector cost disturbances on the responses of sector inflation rates.

While helpful for establishing the joint dynamics of stockouts, costs and inflation, this approach is not useful for assessing the fundamental drivers of the replacement costs. The partial-equilibrium model is not explicit on whether cost fluctuations reflect movements along the marginal cost curve vis-à-vis changes in input or delivery costs. Therefore, we cannot identify the contributions of fundamental factors—demand or supply disturbances (aggregate or sector-specific), monetary and fiscal policy—to fluctuations during and after the pandemic period. Furthermore, it is likely that supply and demand factors played reinforcing roles during this period. For example, because of large and asymmetric effects of the pandemic across sectors, supply shocks in some sectors can trigger large changes in aggregate demand, as noted by (Guerrieri, Lorenzoni, Straub, and Werning, 2022). To assess these fundamentals quantitatively, one would need to analyze a model with aggregate demand, aggregate supply and monetary/fiscal policy, and we leave such analysis to future research. Nevertheless, at the end of this section, we exploit the heterogeneity of each sectors' exposure to trade to gauge the salience of global supply factors.

## 6.1 Model with Inventories

The model builds on Kryvtsov and Midrigan (2013), and it is applied at a weekly frequency. Below, we focus on the problem of inventory adjustment by retail firms; full model details are provided in the Appendix.

There is a continuum of monopolistically competitive retailers in sector $j$, each producing a specific variety $i$. Retailers purchase goods from intermediate-good firms at price $P^I_{jt}$, and convert them into the specific varieties that they sell to households or keep in stock. Varieties are subject to i.i.d. demand shocks $v$, drawn from distribution with c.d.f. $F$. The key timing assumption here is that retailer $i$ in sector $j$ places its order $q_{jt}(i)$ and chooses its price $P_{jt}(i)$ prior to the realization of idiosyncratic demand shock $v$, but after the realization of the sector shocks. This assumption introduces a precautionary motive for holding inventories: firms will choose to carry some stock to the next period to help them meet an unexpected increase in demand.

Ordering $q_{jt}(i)$ units entails an additional convex cost expressed as the squared deviation of the order size relative to its average $q_j$, $\frac{\phi_j}{2}(q_{jt+\tau}(i) - q_j)^2$, giving the total dollar cost of the order $P^I_{jt}\left(q_{jt}(i) + \frac{\phi_j}{2}(q_{jt}(i) - q_j)^2\right)$. Convexity of the cost of replacing inventories represents mechanisms that motivate the firm (or its supplier) to smooth orders or production over time. This "production smoothing" motive for holding inventories is standard in inventory-control models.[22] The firm may also face constraints on adjusting its prices.

Let $z_{0jt}(i)$ denote the amount of stock retailer $i$ carries over from period $t-1$. Then the

[22] Abel (1985), Ramey and West (1999). Kryvtsov and Midrigan (2010) discuss alternative assumptions of convex adjustment cost of inventories and their implications in the context of DSGE business cycle models.

quantity of product available for sale in period $t$ is

$$z_{jt}(i) = z_{0jt}(i) + q_{jt}(i). \tag{7}$$

Given its price $P_{jt}(i)$, the stock available for sale $z_{jt}(i)$, and the realization of idiosyncratic shock $v$, the firm's sales in period $t$ are

$$y_{jt}(i) = \min\left(v\left(\frac{P_{jt}(i)}{P_{jt}}\right)^{-\theta} Y_{jt}, z_{jt}(i)\right), \tag{8}$$

where $Y_{jt}$ is the total consumption for sector $j$ in period $t$.

Let $Q_{t,t+1}$ denote the period-$t$ price of the claim that returns 1\$ in period $t+1$. The firm chooses its target stock $z_{jt}(i)$ to maximize

$$E_t \sum_{\tau=0}^{1} Q_{t,t+\tau}\left[P_{jt}(i)y_{jt+\tau}(i) - P^I_{jt+\tau}\left(q_{jt+\tau}(i) + \frac{\phi_j}{2}(q_{jt+\tau}(i) - q_j)^2\right)\right] \tag{9}$$

subject to demand function (8), measurability restrictions on $z_{jt}(i)$, the initial stock of inventories $z_{0j0}(i)$, and the law of motion of inventories

$$z_{0jt+1}(i) = (1-\delta_j)\left(z_{jt}(i) - y_{jt}(i)\right), \tag{10}$$

where $\delta_j$ is the rate of depreciation of inventories.

The convex cost of adjusting inventories implies that the firm's cost of replacing a unit of inventory stock is increasing in size of the order:

$$\Omega_{jt}(i) = P^I_{jt}\left(1 + \phi_j(q_{jt}(i) - q_j)\right). \tag{11}$$

Since the order size depends on the amount of stock carried over from the previous period, the firm that experienced a stockout in period $t-1$ faces higher order costs in period $t$ relative to a similar firm that did not stock out. This feature of the model captures additional costly activities by retailers who face limited product availability, including buying extra inventory, searching for substitutes of out-of-stock products, spending time tracking or replacing suppliers, and re-routing trucks. We rely on this feature of the model in the empirical analysis below.

## 6.2 The Dynamic Law of Motion for Sector Stockouts

The empirical specification is derived from the retailer's first-order condition for inventory holdings. Let $v_{jt}(i) = \left(\frac{P_{jt}(i)}{P_{jt}}\right)^{\theta} \frac{z_{jt}(i)}{Y_{jt}}$ denote the value of the demand shock realization for which the retailer sells all available stock without stocking out. Then the likelihood of stockout by retailer $i$ is given by the derivative $\Psi'(v_{jt}(i))$, where $\Psi(v_{jt}(i)) = \int \min(v, v_{jt}(i))\, dF(v)$.[23]

The first-order condition for stock $z_{jt}(i)$ is

$$\Psi'(v_{jt}(i)) = \frac{\Omega_{jt}(i) - (1-\delta_j)E_t\left[Q_{t,t+1}\Omega_{jt+1}(i)\right]}{P_{jt}(i) - (1-\delta_j)E_t\left[Q_{t,t+1}\Omega_{jt+1}(i)\right]}. \tag{12}$$

The left-hand side of (12) is the likelihood of a stockout by retailer $i$. The right-hand side is the function of the firm's price $P_{jt}(i)$, the cost of replacing inventories $\Omega_{jt}(i)$, and the expected discounted cost $(1-\delta_j)E_t\left[Q_{t,t+1}\Omega_{jt+1}(i)\right]$. A higher price incentivizes the firm to hold more products in stock, reducing the likelihood of a stockout. In turn, higher expected growth in replacement cost makes the firm shift its stock from period $t+1$ to $t$ to avoid replacing stock in period $t+1$. This also increases stock in period $t$, leading to a lower probability of a stockout.

Condition (12) possesses a property that makes it amenable to empirical analysis. For the firm that sets its price at $P_{jt}(i)$ and faces cost $\Omega_{jt}(i)$, the demand conditions (summarized by $v_{jt}(i)$) enter (12) only via their effect on the probability of a stockout $\Psi'(v_{jt}(i))$. Because we directly observe stockouts in the data, this means we can analyze condition (12) without knowing demand conditions $v_{jt}(i)$ or shock distribution $F$. We exploit this model feature in the empirical application.

To obtain stationary empirical specification, we normalize all period-$t$ variables by period-$(t-1)$ aggregate price $P_{t-1}$, re-arrange the terms in (12), and integrate them across all firms in sector $j$. This yields the following condition:

$$p_{jt}\left(TOOS_{jt} + COV_{jt}\right) = \omega_{jt} - \left(1 - TOOS_{jt}\right)(1-\delta_j)R_t^{-1}\pi_t E_t\left[\omega_{jt+1}\right], \tag{13}$$

where $TOOS_{jt} = \int_i \Psi'(v_{jt}(i))di$ is the fraction of temporary stockouts in sector $j$, $p_{jt} = \frac{\int_i P_{jt}(i)di}{P_{t-1}}$ is sector $j$'s real price, $COV_{jt} = cov\left(\Psi'(v_{jt}(i)), \frac{P_{jt}(i)}{P_{jt}}\right)$ is the term that captures the covariance of stockouts and prices across products in sector $j$ in period $t$, and $\omega_{jt} = \frac{\int_i \Omega_{jt}(i)di}{P_{t-1}}$ is the real replacement cost in sector $j$. Finally, we approximate $E_t\left[Q_{t,t+1}\omega_{jt+1}\right] \approx R_t^{-1}E_t\left[\omega_{jt+1}\right]$, where $R_t = E_t\left[Q_{t,t+1}\right]^{-1}$ is the risk-free rate.

Equation (13) specifies that, given sector prices $p_{jt}$, sector $j$ stockout rate depends on the sector's cost in week $t$, $\omega_{jt}$, relative to the expected cost in the following week discounted by the

[23] Solving the integral yields $\Psi(v_{jt}(i)) = \int_0^{v_{jt}(i)} vdF(v) + v_{jt}(i)\left(1 - F(v_{jt}(i))\right)$. This implies the derivative $\Psi'(v_{jt}(i)) = 1 - F(v_{jt}(i))$.

real interest rate and stock depreciation rate, $(1-\delta_j)R_t^{-1}\pi_t E_t\omega_{jt+1}$.[24] According to (13), lower sector price is associated with higher stockout rate, all else equal. At lower prices firms expect higher sales and, therefore, they experience more frequent stockouts.

## 6.3 Assumptions on pricing decisions and replacement costs

To prepare the estimation of (13), we make two additional assumptions. First, following Bils and Kahn (2000), we treat sector prices $p_{jt}$ as given. At weekly frequency, around 98% of period-$t$ sector prices are set in previous periods, and therefore, they are pre-determined with respect to period-$t$ inventory decisions. For the remaining 2% of prices that change in period $t$, we assume that they can respond to cost in period $t$, but their response is independent of inventory stocks chosen by firms in that period. By not explicitly modeling price decisions, we can use equation (13) to estimate the unobserved cost of replenishing inventories.[25]

Since the unobserved real replacement cost enters (13) as the period-$t$ value, $\omega_{jt}$, and the period-$(t+1)$ expected value, $E_t\omega_{jt+1}$, we make an additional assumption about its dynamic properties. We derive an approximate law of motion for real replacement costs implied by the model. In the model, a firm experiencing a stockout in period $t-1$ tends to place a higher order in period $t$, and therefore, it faces a higher unit replacement cost, per equation (11). Taking a linear approximation of equation (11) and integrating across firms in sector $j$ yields the following specification for real replacement cost in period $t$ (see Appendix):

$$\omega_{jt} = a_j + b_j TOOS_{jt-1} + \varepsilon_{jt}, \tag{14}$$

Equation (14) captures the dynamic link between sector stockouts in period $t-1$ and sector real replacement cost in period $t$. The term $b_j TOOS_{jt-1}$ approximates the persistent component of sector $j$'s real replacement cost. Coefficient $b_j$ reflects two channels through which sector stockouts $TOOS_{jt-1}$ influence the sector's real replacement cost $\omega_{jt}$. The first effect captures costs associated with higher orders needed to replenish stocks that disappear after the stockouts. This effect is stronger for sectors with higher average stocks. The second effect is due to the persistence of replenishment costs, keeping sector stockouts constant (e.g., persistence in supplier's

[24]Equation (13) can be equivalently formulated in nominal terms. Given sector's *nominal* prices $P_{jt}$, sector $j$ stockout rate depends on the sector's *nominal* cost in week $t$, $\Omega_{jt}$, relative to the expected cost in the following week discounted by the *nominal* interest rate and stock depreciation rate, $(1-\delta_j)R_t^{-1}E_t\Omega_{jt+1}$.

[25]Kryvtsov and Midrigan (2010, 2013) analyze dynamic general equilibrium models with sticky prices, inventories and stockouts. The firm's optimal price reflects the present value of the inventory cost expected over price duration.

real price $P^I_{jt}/P_t$). Sectors where higher average costs are more likely to be passed through to stockouts, or where these costs are more persistent, are likely to have higher costs following a hike in stockout rates. The residual term $\varepsilon_{jt}$ are zero-mean innovations to period $t$ replacement cost that are uncorrelated with period-$(t-1)$ stockouts.[26]

## 6.4 GMM Estimation

Using (14) to substitute $\omega_{jt}$ in empirical specification (13) yields

$$G(p_{jt}, TOOS_{jt}, TOOS_{jt-1}, COV_{jt}, R_t, \pi_t; a_j, b_j, \delta_j) = \varepsilon_{jt}\,, \tag{15}$$

where $G(\cdot)$ is a non-linear function of observed variables, depreciation rate $\delta_j$, and coefficients $a_j$, $b_j$; and $\varepsilon_{jt}$ are innovations in sector $j$ cost from equation (14).

For each sector $j$, we estimate the coefficient $b_j$ by a two-step GMM using weekly data for sector price index and the fraction of products out-of-stock. GMM estimation uses the set $\boldsymbol{Z_t}$ of $N \geq 1$ instruments. We define the following $N$ orthogonality conditions for GMM estimation:

$$E\left[Z^i_t \varepsilon_{jt}\right] = E\left[Z^i_t G(p_{jt}, TOOS_{jt}, TOOS_{jt-1}, COV_{jt}, R_t, \pi_t; \overline{a_j}, b_j, \overline{\delta_j})\right] = 0,$$

where $Z^i_t$ is the $i$th element of the set of instruments $\boldsymbol{Z_t}$, $i = 1, ..., N$, and $\overline{a_j}, \overline{\delta_j}$ are calibrated values of $a_j, \delta_j$. In equations (14)–(15), the errors $\varepsilon_{jt}$ can be conditionally heteroskedastic and serially correlated.

The sample used for estimation starts the week of November 1, 2019, and ends the week of May 22, 2022, spanning 134 weeks. We estimate the empirical model for both temporary out-of-stock measure (TOOS) for 199 sectors in 7 countries. The GMM estimation uses the following instruments: $\boldsymbol{Z_t} = [TOOS_{jt-1}, ..., TOOS_{jt-4}, p_{jt-1}, ..., p_{jt-4}, \boldsymbol{X_{t-1}}, ..., \boldsymbol{X_{t-4}}]'$, where $\boldsymbol{X_t}$ is a vector of aggregate (monthly) controls.[27] These controls include the change in the lockdown stringency index from "Oxford-Our World in Data,"[28] which scores the number and strictness of government containment and mitigation policies during the COVID-19 pandemic and the weekly change in the number of confirmed infections from the same source. We use a country's equivalent of the 3-month Treasury bill rates as a measure of the risk-free rate $R_t$. We

[26] Augmenting the law of motion (14) with additional lags of sector stockouts or sector prices does not significantly alter estimation results.

[27] Estimation results are robust to the number of lags in the vector of instruments.

[28] https://ourworldindata.org/coronavirus-testing.

compute the time series for the cross-section covariance $COV_{jt}$ between stockouts and relative prices using the micro data—it turns out to be very close to zero and not influential for the U.S. results, so we assume it is zero for other countries. Finally, in the baseline estimation, we assume a weekly depreciation rate of 0.46% (2% monthly rate). We then pick for each sector the value of parameter $a_j$ to equal the average real replacement cost implied by (13) over the pre-pandemic period, between November 1, 2019, and January 4, 2020.

### 6.5 Estimated Replacement Costs

We first demonstrate the validity of the estimation method for the United States. Table 3 reports estimation results based on temporary stockout measure in five 1-digit U.S. sectors: "Food and Beverages," "Furnishings and Household," "Health," "Electronics," and "Other Goods" (composed mostly of personal care products).

Estimates indicate a statistically and economically significant effect of stockouts on real replacement cost. The estimated coefficient $b_j$ for the effect of out-of-stock on real replacement cost varies from 0.09 for "Food and Beverages" to 0.56 for "Electronics," and all estimates are highly statistically significant, except for "Other Goods" where the coefficient is estimated to be around zero. Intuitively, a coefficient value of 0.50 (seen for "Furnishings and Household") means that an increase in the weekly temporary stockout rate from 10% to 20% increases the replacement cost by roughly 2.5% in annualized terms.

| **1-digit sectors** | Estimated $bj$ (st.dev.) | First-stage $F$-statistic | Hansen's $J$-stat $p$-value |
|---:|:---:|:---:|:---:|
| Food & Beverages | 0.09*** (0.00) | 384.62 | 0.36 |
| Furnishings & Household | 0.50*** (0.03) | 196.45 | 0.65 |
| Health | 0.11*** (0.01) | 352.81 | 0.38 |
| Electronics | 0.56*** (0.02) | 125.43 | 0.89 |
| Other Goods | 0.01 (0.01) | 105.63 | 0.36 |

Table 3: Estimation Results for the United States, 1-Digit Sectors

Notes: The table reports coefficients $b_j$ in specification for sector $j$ replacement cost (14) based on temporary stockout measure, estimated by two-step GMM estimator and a weight matrix that allows for heteroskedasticity and autocorrelation up to four lags with the Bartlett kernel. The table also provides the first-stage $F$-statistic for testing weak instruments for the endogenous regressor (TOOS), and $p$-values for Hansen's $J$-statistic to test over-identifying restrictions in the GMM. * p<0.10, ** p<0.05, *** p<0.01.

The table also provides the results of the tests for weak instruments and over-identifying restrictions. The first-stage $F$-statistic for the endogenous regressor in the model, temporary stockouts, is above the threshold value of 10 in all cases (Stock, Yogo, and Wright, 2002). Hence, the test rejects the null of weak instruments. The table also reports that $p$-values for Hansen's $J$-statistic are above 10%, implying that the model is correctly specified.[29]

These differences in the estimated sensitivity of cost to stockouts across sectors can be related to different dynamics of prices and stockouts. According to the first-order condition for inventories (12), if the firm faces a higher cost but does not adjust its price, its stockout probability is higher. But if the firm can increase its price, the demand for its product decreases, and the likelihood of a stockout is dampened. Hence, conditional on the cost, stockouts, and prices are negatively correlated. Therefore, when the increase in stockouts is accompanied by a rise in prices, the estimated increase in replacement cost is higher than if prices are flat or falling.

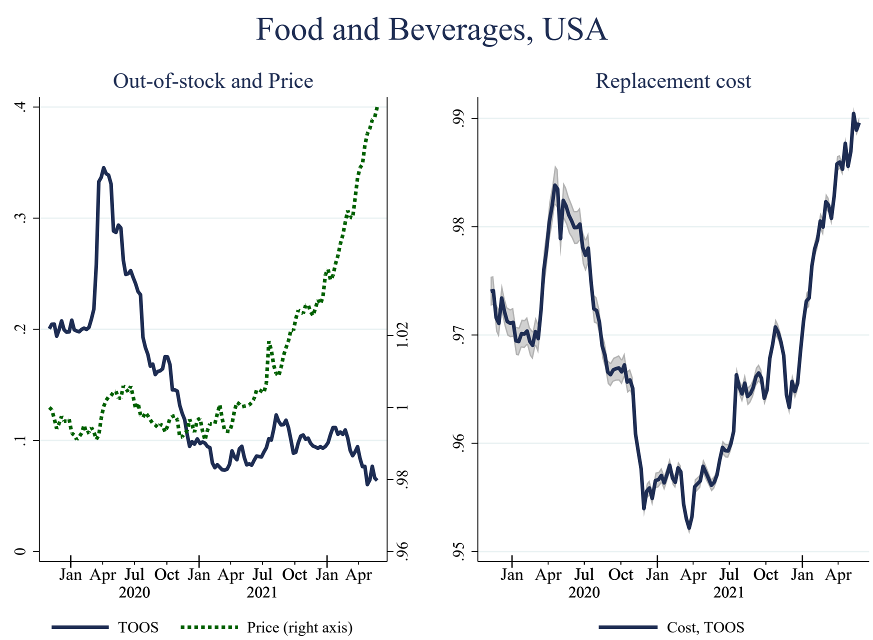



Figure 11: Stockouts, Prices, and Estimated Costs in Food & Beverages, United States

Notes: The figure provides the time series for price indices, temporary stockouts for U.S. Food & Beverages (left panel), and estimated nominal replacement cost index (right panel for each sector) for the period between the week of January 4, 2020, and the week of May 22, 2022. Shaded areas provide 95% confidence bands for estimated replacement cost.

Using these sensitivity estimates we can create time series of the replacement costs by sector.

[29]When we conduct estimation using 34 3-digit U.S. sectors, 29 out of 34 estimated coefficients are positive and statistically significant. For all 34 sectors, the first-stage $F$-statistic rejects weak instruments for the endogenous temporary out-of-stock regressor, and the $p$-values for Hansen's over-identifying restrictions test is above 0.10.

The impact that this methodology has on the cost estimates can be clearly seen in Figure 11 for the "Food and Beverages" category. Using stockouts alone would imply that replacement costs were low during 2021 and 2022. However, once we account for the increase in prices, the estimated replacement cost increase again in mid-2021 and surpass their previous pandemic peak levels by early 2022.

Table 4 summarizes estimation results for all 1-digit U.S. sectors. It provides cumulative changes in temporary stockouts, prices, and estimated nominal costs between January 2020 and May 2022. To illustrate the complex dynamics of these variables over time, we split this period in two halves—before and after the end of March 2021.[30] In the first sub-period, during the brunt of the pandemic, stockouts rose in the first quarter of 2020 but then fell for over a year, reaching pre-pandemic levels or lower by the first quarter of 2021. The exception here is "Electronics" where stockouts remained 2.6 ppt above pre-pandemic levels. During this sub-period prices rose only for household durables, remained flat for food and fell in other sectors. The combination of normalized stockouts and relatively stable prices results in the estimated nominal cost falling by more than 1% in all sectors during this period, except for "Electronics" where the cost increased by 0.72%. After the worst of the pandemic has passed, in 2021–2022, prices increased for all goods. Although stockouts stabilized or continued to fall, the estimated nominal cost increased in all sectors, reflecting the dominance of price ascendance.

The acceleration of inflation in 2021 is reflected in the change in passthrough of sector cost into prices. In 2020–Q1:2021, prices were slow to respond to falling costs (in "Food and Beverages" and "Furnishings and Household") or to rising costs in "Electronics." Hence, retailers in these sectors were not passing through cost changes into prices. By contrast, when costs increased in Q2:2021–Q2:2022, prices increased on par with costs in "Electronics" and "Health", and even faster than costs in "Food and Beverages" and "Furnishings and Household." At the micro level, the proportion of price increases in all price changes went up in all sectors (Table A1 in the Appendix). Hence, unlike slow price adjustments in the first sub-period, price changes caught up with or even over-compensated for rising costs in the second sub-period. Such acceleration of price changes suggests retailers –after experiencing many quarters of persistent shocks – expected the rise in costs to continue.

[30] See Appendix Figure A6 for details on the changes over time in each sector.

| **1-digit sectors** | **Jan 4, 2020 – Apr 2, 2021** Price index *% chg* | Temp OOS *ppt chg* | Nominal Cost (Est.) *% chg* | **Apr 3, 2021 – May 22, 2022** Price index *% chg* | Temp OOS *ppt chg* | Nominal Cost (Est.) *% chg* |
|---|---|---|---|---|---|---|
| Food & Beverages | 0.05 | -12.57 | -1.85 | 8.84 | -2.28 | 3.52 |
| Furnishings & Household | 0.81 | -1.36 | -1.14 | 3.45 | -3.73 | 1.69 |
| Health | -1.23 | -1.55 | -1.08 | 2.49 | -4.45 | 2.59 |
| Electronics | -1.09 | 2.58 | 0.72 | 1.18 | -3.99 | 1.20 |
| Other Goods | -2.58 | -0.60 | -1.01 | 0.84 | -2.49 | 3.17 |

Table 4: Cumulative Changes in Stockouts, Prices, and Estimated Replacement Costs between January 2020 and May 2022, United States, 1-Digit Sectors

Notes: The table reports changes between the week of January 4, 2020, and the week of May 22, 2022: % change of the sector price index, ppt difference between average fraction of products temporarily out-of-stock, and % difference between average estimated nominal replacement cost (based on temporary out-of-stock).

## 6.6 Inflation Responses to Replacement Cost Shocks

Having estimated the replacement cost process using observed variations in sector prices and stockouts, we can now project the dynamic responses of stockouts and inflation at a sector level to the disturbance $\varepsilon_{jt}$ from the cost equation (14). For this estimation, we use the same method as in Section 4, applying it to the full sample of 199 3-digit sectors in 7 countries. Figure 12 provides the estimated impulse responses.

As we reported in Sections 4 and 5, the timing of a stockout increase is followed by the quick acceleration of inflation, which peaks after about a month. Such timing can be explained by sluggish price adjustments— only 2% or so of products change their prices in a given week. When prices are sticky, rising costs make it harder for retailers to replenish their stocks, which raises the likelihood of stockouts. Over time, inventories fill up and rising prices curb the demand, helping to bring down the occurrence of stockouts.

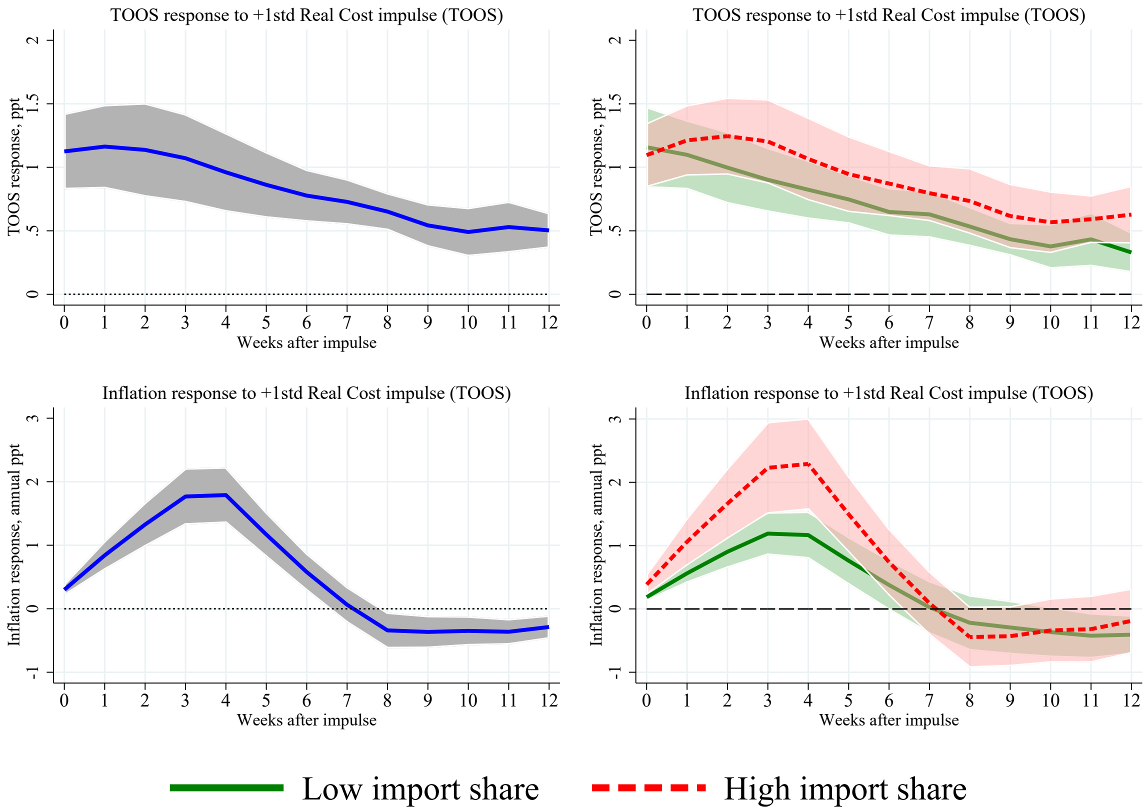



Figure 12: Responses to Real Replacement Cost Shocks in 3-Digit Sectors, in 7 Countries

Notes: The figure provides responses to a +1 standard deviation real replacement cost impulse (in %) estimated using specification (4) for 3-digit sectors in Canada, China, France, Germany, Japan, Spain, and the United States. Shocks: real replacement cost based on temporary stockouts TOOS. Responding variables: temporary stockout rates (top plots); sector inflation rates (bottom plots). Responses on the right are estimated using additional control for sectors with low import share in total consumption ($<0.22$) and high import share ($\geq 0.22$). Shaded areas outline 90% bands based on Driscoll-Kraay standard errors.

There are two key differences from the responses in Section 4, where we treated stockouts as exogenous. First, the inflation response is more volatile than the stockout response after a cost shock. While the stockout response is somewhat smaller, the inflation response is six times larger, reaching 1.8 ppt (annualized rate) three weeks after the cost impulse (left panels in Figure 12). This difference reflects the implication of model (13)–(14) that conditional on cost shocks, prices, and stockouts are negatively correlated. In the model, firms can respond to a cost hike by raising their prices or by cutting their stocks and tolerating higher stockouts. When this feature is incorporated, inflation will be conditionally more volatile relative to stockouts.

The second implication of incorporating endogeneity of stockouts is that the estimated inflation responses are less persistent. Positive inflation response is shortened by a few weeks to less than two months. Because in the data stockouts are highly serially correlated, the model implies that retailers curb their price hikes relatively soon after the cost shock, thus letting the stockouts last longer. These additional results underscore the importance of accounting for the endogeneity of stockouts when estimating the inflationary effects of cost disturbances.

When we split the responses for high- and low-import-share sectors, we document that both inflation and stockouts are more responsive in trade-intensive sectors. Conditional on the cost shock, the estimated differences between the two responses are larger and more significant. The stockout response is higher by 0.3 ppt after three weeks, and the inflation response is higher by 1.2 ppt (annualized rate) after four weeks. This evidence suggests that costs associated with supply-chain disruptions during the pandemic lead to significant increases in both product stockouts and price increases.

In our analysis, we estimated the replacement cost separately for each sector, so we did not make a distinction between common and sector-specific components in the estimated inflation responses. Fluctuations in sector-level prices rates may be driven by factors common across many sectors resulting in aggregate inflation, or by sector-specific factors leading to movements in relative prices. To get a sense of how much variation in sector prices, stockouts, and estimated costs are common across sectors, we compute common factors separately for each of these variables using the same panel of 199 sectors across 7 countries (details can be found in the Appendix). We find that at least half of the estimated variation in inflation and nominal costs are common across sectors and represent "pure inflation." The remaining share of variance can be attributed to sector-specific factors driving relative price disturbances.

# 7 Conclusion

Rising inflation in 2021 spurred a lively debate on its causes. The quick recovery of demand in the presence of supply disruptions are often mentioned by policy-makers and economists as playing an important role in creating shortages, but little is known empirically about their actual impact on prices. The rich variation of prices and shortages during the pandemic provides a good opportunity to analyze their mutual relationship.

In this paper, we construct a high-frequency measure of product shortages by using data on stockouts collected directly from the websites of large retailers in multiple sectors and countries.

We focus not just on the "out-of-stock" signals that are visible to consumers but also on the higher incidence of discontinued goods, which are harder to detect. Our stockout measures show that shortages were widespread early on in the pandemic, affecting far more than just toilet paper or disinfecting wipes. Over time, the composition of stockouts evolved from many temporary stockouts to mostly discontinued products, concentrated in fewer sectors. This may have made the stockout problem less visible, but no less important.

We find that an unexpected jump in a retail sector's stockout rate is associated with an inflationary effect that peaks within a couple of months. Whether measured directly from stockouts or through our model-based estimation of the underlying inventory replacement costs, the impact on prices is significant. For the United States, for example, an increase in a stockout rate from 10% to 20% raises monthly inflation by about 1.5 ppt (annualized rate). The inflationary effect of such standalone shock lasts on average two to three months. We also find evidence linking temporary stockouts to stronger and more persistent inflationary effects for products and sectors exposed to trade.

We draw several conclusions from this analysis. Product stockouts likely reflect emergent cost pressures due, in part, to supply bottlenecks and positive demand shocks. Unexpected stockouts are quickly followed by inflation. During a protracted event, such as a global health pandemic, the stockouts are temporary at first but gradually become more permanent in nature and increasingly concentrated in some sectors. Persistently high inflation rates in these sectors can be explained by a series of adverse cost shocks, for example, due to recurring waves of virus infections and energy cost shocks driven by geopolitical events. At least half of the variance of cost disturbances are global or country-specific, influencing aggregate inflation rates.

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# A Additional Tables and Figures

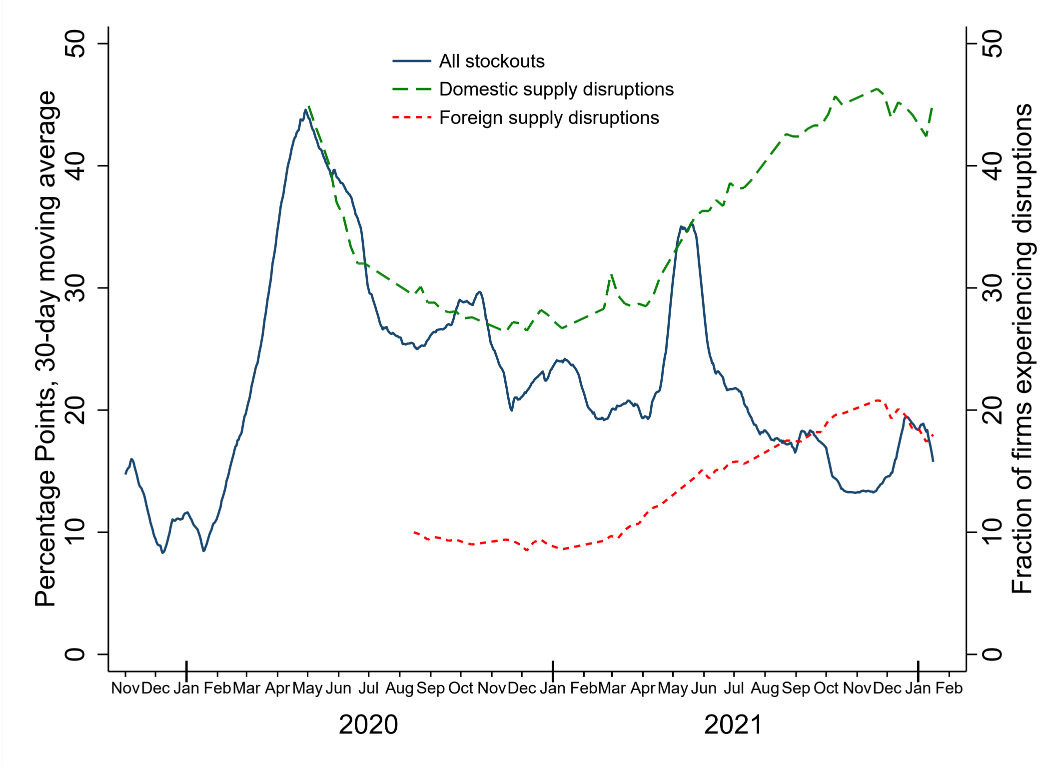



Figure A1: Stockouts (AOOS) vs. U.S. Census Survey of Small Business Disruptions

Notes: This graph compares our measure of all stockouts in the United States with the percentage of firms that reported experiencing domestic or foreign supply disruptions in the "Small Business Pulse Survey" conducted by the U.S. Census Bureau between May 2020 and February 2022. See https://portal.census.gov/pulse/data/#about.

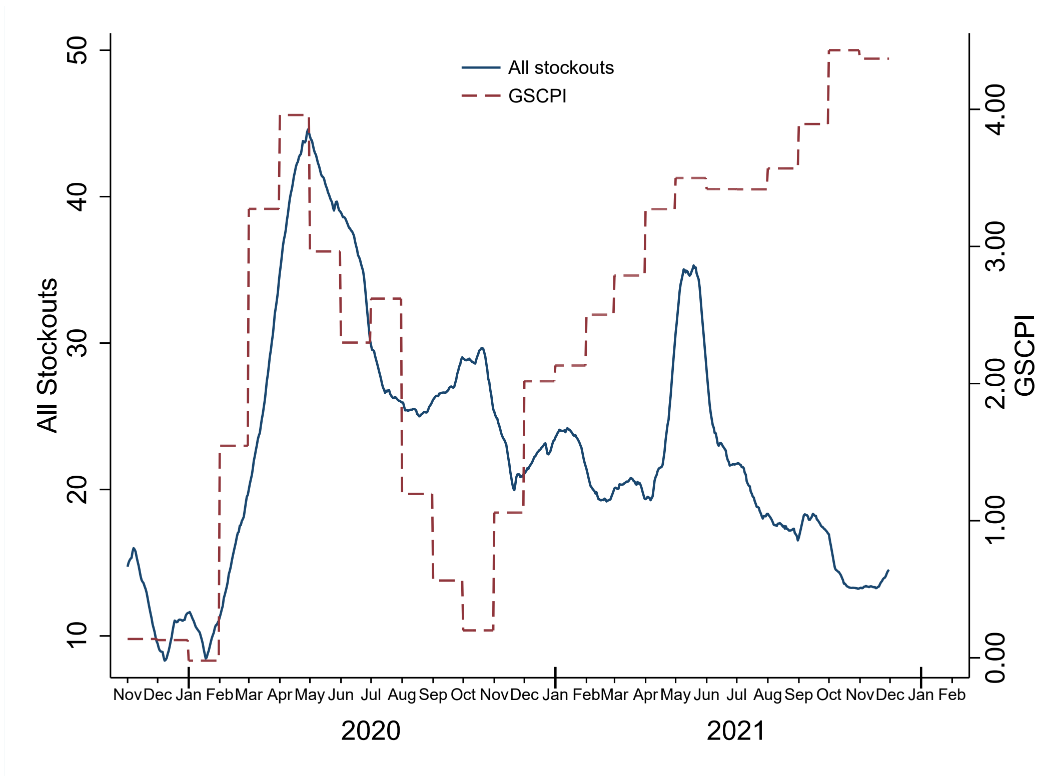
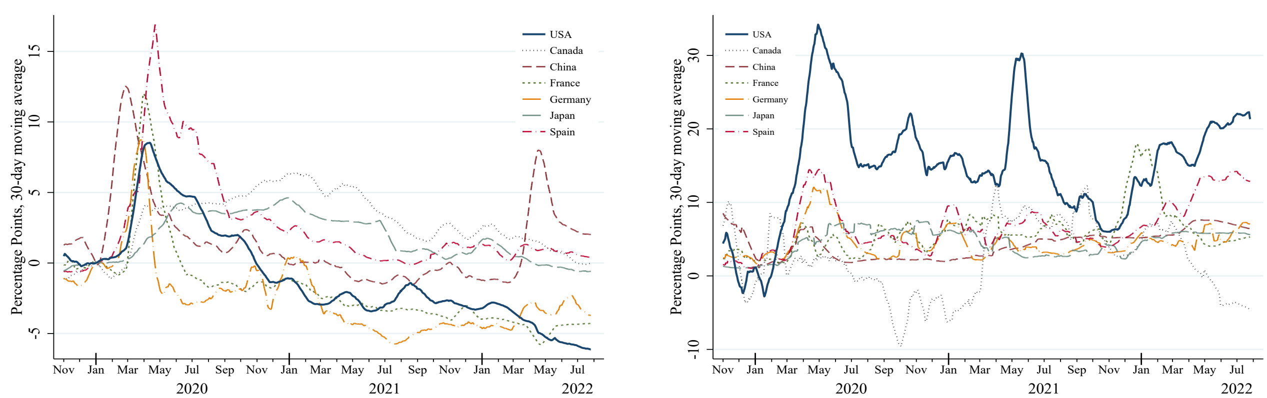



Figure A2: Stockouts (AOOS) vs. Global Supply Chain Pressure Index

Notes: This graph compares our measure of all stockouts in the United States with the Global Supply Chain Pressure Index (Benigno, di Giovanni, Groen, and Noble, 2022).




(a) Temporary Stockouts

(b) Permanent Stockouts

Figure A3: Temporary and Permanent Stockouts in 7 Countries

Notes: In panel (a) we plot $TOOS_{c,t} - TOOS_{c,Jan2020}$, the change in temporary stockouts relative to pre-pandemic levels. In panel (b) we plot permanent stockouts $POOS_{c,t}$ measured as the fall in the total number of available products relative to pre-pandemic levels.

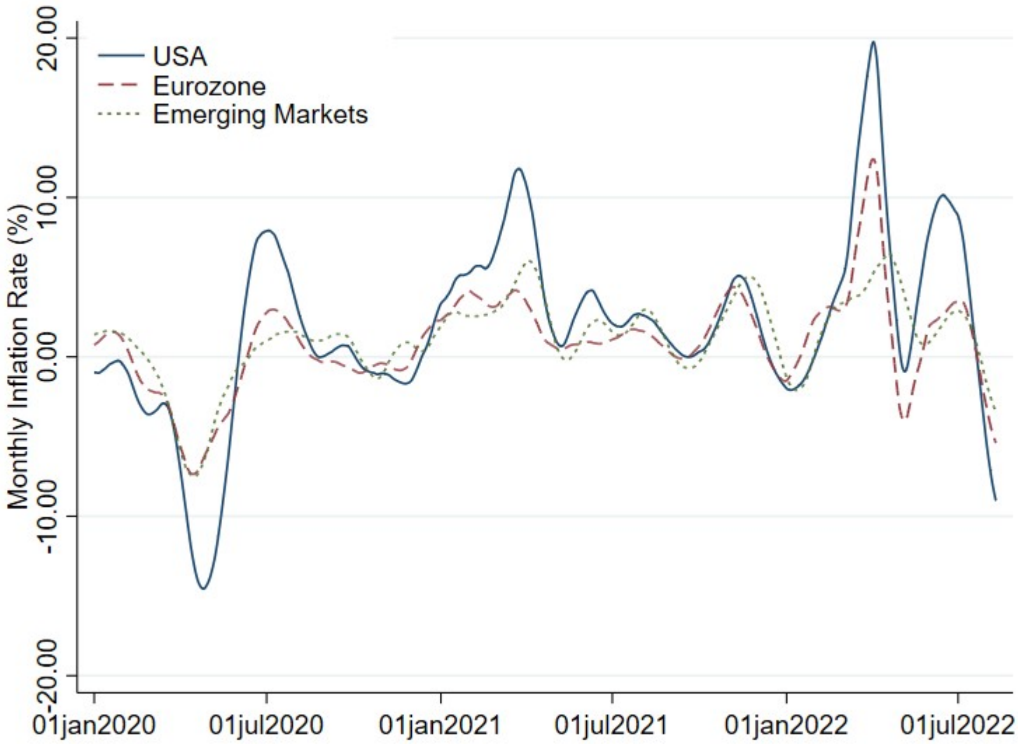
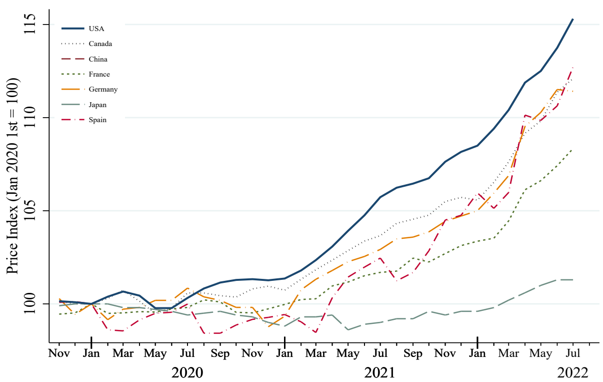
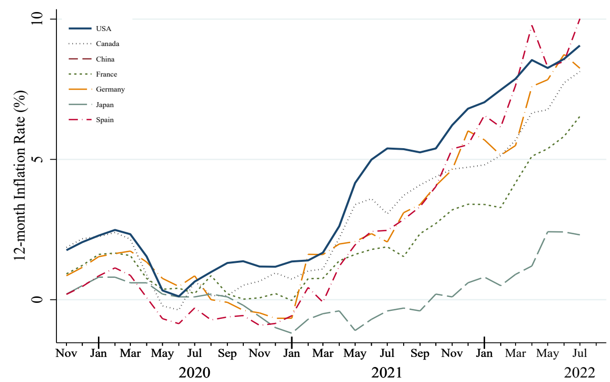



Figure A4: Fuel Monthly Inflation Rates

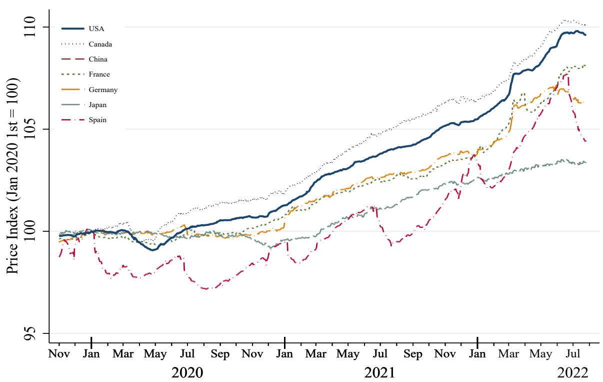
Notes: This graph shows monthly inflation rates computed every day using motor fuel prices collected from online data sources. The Eurozone index is a consumption-weighted average of fuel price indices in Germany, France, Spain, Greece, Italy, Ireland, and the Netherlands. The Emerging Markets index is a consumption-weighted average of fuel price indices in Argentina, Brazil, Chile, China, Colombia, Mexico, South Africa, Russia, Turkey and Uruguay.



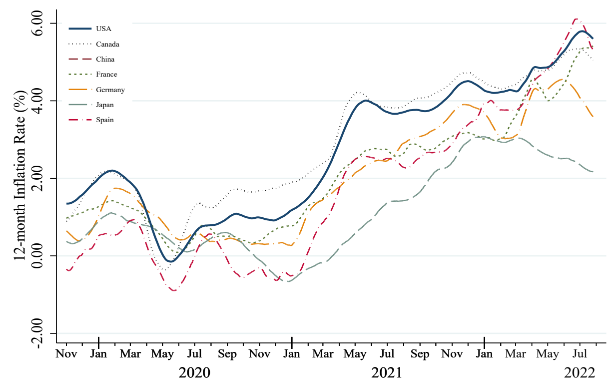

(a) CPI - Price Index




(b) CPI - Annual Inflation




(c) Online - Price Index




(d) Online - Annual Inflation

Figure A5: Inflation Rates

Notes: The top graphs show the price index and the annual inflation rate for the official all-items CPI in each country. The bottom graphs show equivalent indices constructed by PriceStats using the same online-data source used in our paper.

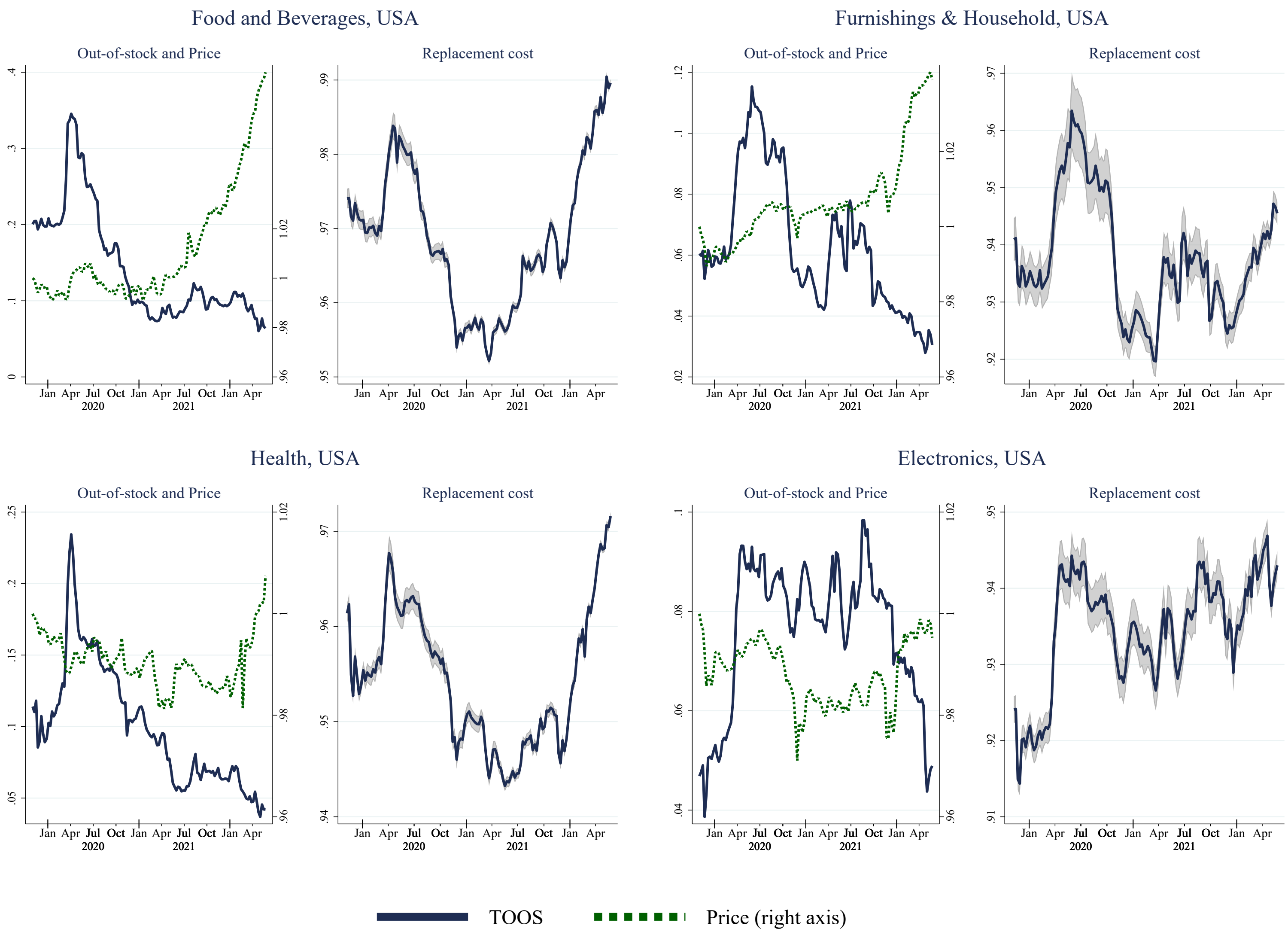



Figure A6: Stockouts, Prices, and Estimated Costs in 1-Digit U.S. Sectors

Notes: The figure provides the time series for price indices, stockouts for four U.S. 1-digit sectors (left panel for each sector), and estimated nominal replacement cost index (right panel for each sector) for the period between the week of January 4, 2020, and the week of January 17, 2022. Estimation uses two out-of-stock measures: temporary stockouts (TOOS) and all stockouts (AOOS). Shaded areas provide 95% confidence bands for estimated replacement cost.

| 1-digit sectors | fr | fr+ | fr- | abs | size+ | size- | share+ |
|---|---|---|---|---|---|---|---|
| | **Jan 4, 2020 – Apr 2, 2021** | | | | | | |
| Food & Beverages | 2.6 | 1.3 | 1.3 | 20.1 | 24.8 | -15.5 | 0.49 |
| Household | 3.3 | 1.6 | 1.7 | 13.2 | 15.8 | -10.6 | 0.48 |
| Health | 1.0 | 0.5 | 0.5 | 24.3 | 30.7 | -18.5 | 0.49 |
| Electronics | 3.2 | 1.4 | 1.7 | 15.3 | 19.0 | -12.2 | 0.45 |
| Other Goods | 2.1 | 1.0 | 1.1 | 23.4 | 29.2 | -18.2 | 0.47 |
| | **Apr 3, 2021 – May 22, 2022** | | | | | | |
| Food & Beverages | 4.0 | 2.1 | 1.9 | 21.1 | 25.7 | -15.6 | 0.54 |
| Household | 4.1 | 2.1 | 2.0 | 14.4 | 16.7 | -12.0 | 0.51 |
| Health | 0.9 | 0.5 | 0.4 | 21.2 | 24.3 | -17.7 | 0.54 |
| Electronics | 2.8 | 1.3 | 1.5 | 15.3 | 18.1 | -12.7 | 0.47 |
| Other Goods | 2.2 | 1.1 | 1.1 | 20.2 | 23.1 | -17.2 | 0.51 |

Table A1: Price adjustment statistics for the U.S. 1-digit sectors

Notes: This table reports price adjustment statistics for two sub-periods: January 4, 2020 – April 2, 2021, and April 3, 2021 – May 22, 2022. Statistics include: mean weekly frequency of price changes/increases/decreases (fr, fr+, fr-), mean absolute size of price changes (abs), mean size of price increases/decreases (size+, size-), and the share of price increases in all price changes (share+).

# B A Model of Stockouts and Prices

What can the joint behavior of sector prices and stockouts tell us about the underlying cost pressures facing retailers? In this section, we present a model of a sector of monopolistically competitive firms that face costs of adjusting their prices and their inventory holdings. The model builds on Kryvtsov and Midrigan's (2013) model where firms hold inventories to buffer against possible stockouts. The optimal stock of inventories—and the associated probability of a stockout—is determined by the trade-off between the firm's cost of replenishing the stock and its price level. At a sector level, this implies a dynamic relationship between sector price, the fraction of stockouts, and the cost of replenishing inventories. We use weekly time series for sector price and stockouts to estimate unobserved sector replacement cost. The estimation uses the identifying assumption derived in the model: a firm that experiences a stockout faces a higher cost of replenishing an additional unit of stock in the next period.

## B.1 Setup

The economy is populated with a unit measure of infinitely-lived ex-ante identical households. Households derive utility from consuming storable products of differentiated varieties $i$ that belong to many sectors, indexed $j$. Households supply hours worked required in the production of consumption goods.

There are two types of firms in each sector: intermediate good producers and retailers. In each sector a continuum of competitive intermediate good firms invest in capital stock, hire labor, and produce a homogeneous good using a Cobb-Douglas technology. The homogeneous good is sold to monopolistically competitive retail firms in that sector for producing consumption varieties. Below we present problems of household's final consumption and intermediate good producers. Retailer's problem and derivation of the first-order condition for inventories are provided in the main text.

## B.2 Final Consumption

The final consumption good for sector $j$ is obtained by combining product varieties sold by retailers in sector $j$:

$$Y_{jt} = \left[ \int_0^1 v_{jt}^{1/\theta}(i) y_{jt}^d(i)^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}} \tag{B.1}$$

where $y^d_{jt}(i)$ is the quantity of variety $i$ in sector $j$, $\theta$ is the elasticity of substitution across varieties, and $v_{jt}(i)$ is the demand shock specific to variety $i$. We assume that $v_{jt}(i)$ is an i.i.d. log-normal variable. Kryvtsov and Midrigan (2013) discuss the implications and robustness of this assumption.

At the beginning of period $t$, retailers hold $z_{jt}(i)$ units of variety in stock and available for sale at price $P_{jt}(i)$. Occasionally, retailers will not be able to satisfy the demand for their product and will sell all of their stock, i.e., stock out. We assume that, in case of a stockout, all households get an equal share of the variety $i$ of sector $j$ final good.

Household chooses $Y_{jt}$ and $\left\{y^d_{jt}(i)\right\}$ to maximize

$$P_{jt}Y_{jt} - \int_0^1 P_{jt}(i)y^d_{jt}(i)di$$

subject to the stockout constraint

$$y^d_{jt}(i) \leqslant z_{jt}(i)\ \forall i \tag{B.2}$$

and the final good production technology (B.1). Cost minimization implies the following demand for variety $i$:

$$y^d_{jt}(i) = v_{jt}(i)\left(\frac{P_{jt}(i)+\mu_{jt}(i)}{P_{jt}}\right)^{-\theta} Y_{jt},$$

where $\mu_{jt}(i)$ is the multiplier on the constraint (B.2), and $P_{jt}$ is the price of final good in sector $j$

$$P_{jt} = \left[\int_0^1 v_{jt}(i)\left[P_{jt}(i)+\mu_{jt}(i)\right]^{1-\theta} di\right]^{\frac{1}{1-\theta}}.$$

Because some retailers stock out, in equilibrium $P_{jt}$ is larger than $\hat{P}_{jt} = \left[\int_0^1 v_{jt}(i)P_{jt}(i)^{1-\theta}di\right]^{\frac{1}{1-\theta}}$, the usual formula for the aggregate price index. Thus financing the same level of the final consumption good requires a higher expenditure in this setup with love-for-variety and stockouts.

Note also that if the stockout constraint binds, then $\mu_{jt}(i)$ satisfies

$$P_{jt}(i)+\mu_{jt}(i) = \left(\frac{z_{jt}(i)}{v_{jt}(i)P^{\theta}_{jt}Y_{jt}}\right)^{1/\theta}$$

The left-hand side is the desired price that a retailer with stock $z_{jt}(i)$ would like to set to avoid a binding stockout constraint. Since such a retailer cannot sell more than the available stock, it would like to raise its price. Hence, price adjustment frictions give rise to stockouts because they prevent retailers from raising their prices.

## B.3 Intermediate Input Producers

A continuum of competitive intermediate good firms in sector $j$ acquire labor service of type $j$ $N_{jt}$ and produce homogeneous good $M_{jt}$ using a Cobb-Douglas technology[31]

$$M_{jt} = N_{jt}\,. \tag{B.3}$$

The homogeneous good is sold at the competitive price $P^I_{jt}$ to retailers as input in the production of product varieties. The intermediate good producer chooses sequences of output $M_{jt}$ and labor services $N_{jt}$ to maximize

$$E_0 \sum_{t=0}^{\infty} Q_{0,t}\left[P^I_{jt} M_{jt} - W_{jt} N_{jt}\right] \,,$$

subject to the technology constraint (B.3), and where $Q_{0,t}$ is the period-0 price of the claim that returns 1\$ in period $t$.[32] The firm takes wages as given.

Cost minimization gives the expression for marginal cost of intermediate good production, which in turn is equal to the price of the intermediate input due to perfect competition:

$$P^I_{jt} = W_{jt}\,.$$

## B.4 The Dynamic Link Between Sector Stockouts and Replacement Cost

The real replacement cost for firm $i$ in sector $j$ in period $t$ is given by equation (11):

$$\frac{\Omega_{jt}(i)}{P_{t-1}} = \frac{P^I_{jt}}{P_{t-1}}\left(1 + \phi_j(q_{jt}(i) \; - q_j)\right). \tag{B.4}$$

From equation (7)

$$q_{jt}(i) = z_{jt}(i) - z^+_{0jt}(i) + OOS_{jt-1}(i) z^+_{0jt}(i), \tag{B.5}$$

where $OOS_{jt-1}(i)$ is the indicator that firm $i$ stocked out in period $t-1$, and $z^+_{0jt}(i)$ is the beginning of period $t$ stock for firm $i$ conditional on not stocking out in period $t-1$. Hence, the firm's order is the top-up of the stock $z_{jt}(i) - z^+_{0jt}(i)$ left from the previous period if there was no stockout ($OOS_{jt}(i) = 0$), or the entire stock if there was a stockout ($OOS_{jt}(i) = 1$). The term $OOS_{jt-1}(i) z^+_{0jt}(i)$ captures the stock at risk in the event of a stockout.

[31] It is straightforward to extend this framework to include capital in production technology.

[32] From the household's problem we have that $Q_{0,t} = \pi(s^t|s^0)\frac{U'(C_t)}{P_t}$, where $U'(C_t)$ is marginal utility of consumption, $P_t$ is the price of $C_t$, and $\pi(s^t|s^0)$ is the probability measure of the state history $s^t$.

Let $\hat{p}^I_{jt} = ln\frac{P^I_{jt}/P^I_j}{P_{t-1}/P}$, and let $dq_{jt}(i) = q_{jt}(i) - q_j$, $z^+_{0jt} = z^+_{0jt} - z^+_{0j}$ denote deviations of the right-hand side variables from their average levels.

Firm $i$'s real replacement cost can be approximated, up to a second order, by

$$\omega_{jt}(i) \approx \omega_j(1 + \hat{p}^I_{jt} + \phi_j dq^+_{jt}(i) + \phi_j OOS_j dz^+_{0jt}(i) + \phi_j(OOS_{jt-1}(i) - OOS_j)z^+_{0j}), \tag{B.6}$$

where $\omega_j$, $OOS_j$, $z^+_{0j}$ denote average levels of $\omega_{jt}$, $OOS_{jt}$, $z^+_{0jt}$ respectively.

Integrating (B.6) over $i$ and denoting $\omega_{jt} = \int_i \omega_{jt}(i)di$, $\hat{p}^I_{jt} = \int_i \hat{p}^I_{jt}di$, $dq^+_{jt} = \int_i dq^+_{jt}(i)di$, $dz^+_{0jt} = \int_i dz^+_{0jt}(i)di$, $OOS_{jt-1} = \int_i OOS_{jt-1}(i)di$ gives the following expression:

$$\omega_{jt} = a_j + \tilde{b}_j OOS_{jt-1} + \tilde{\varepsilon}_{jt},$$

where

$$a_j = \omega_j(1 - \phi_j OOS_j z^+_{0j}),$$

$$\tilde{b}_j = \omega_j \phi_j z^+_{0j},$$

$$\tilde{\varepsilon}_{jt} = \omega_j(\hat{p}^I_{jt} + \phi_j dq^+_{jt} + \phi_j OOS_j dz^+_{0jt}), \tag{B.7}$$

The innovation term $\tilde{\varepsilon}_{jt}$ in (B.7) includes deviations of the suppliers real price $\hat{p}^I_{jt}$ and the adjustment costs associated with average deviations of orders in sector $j$ (keeping stockouts constant), $\phi_j(dq^+_{jt} + OOS_j dz^+_{0jt})$.

Note that the term $\tilde{\varepsilon}_{jt}$ is serially correlated if supplier's price $\hat{p}^I_{jt}$ or average orders $\phi_j(dq^+_{jt} + OOS_j dz^+_{0jt})$ are serially correlated. Because high supplier price or higher average orders in period $t-1$ are associated with higher sector stockouts $OOS_{jt-1}$, the term $\tilde{\varepsilon}_{jt}$ is positively correlated with past stockouts $OOS_{jt-1}$. Denoting by $b^+_j = \frac{cov(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{var(OOS_{jt-1})}$ the conditional correlation of $\tilde{\varepsilon}_{jt-1}$ and $OOS_{jt-1}$, and $\rho_\varepsilon = \frac{cov(\tilde{\varepsilon}_{jt}, \tilde{\varepsilon}_{jt-1})}{var(\tilde{\varepsilon}_{jt-1})}$ serial correlation of average costs $\tilde{\varepsilon}_{jt}$, we can write

$$\tilde{\varepsilon}_{jt} = \triangle\tilde{\varepsilon}_{jt} + \rho_\varepsilon b^+_j OOS_{jt-1} + \rho_\varepsilon \epsilon_{jt-1}, \tag{B.8}$$

where $\triangle\tilde{\varepsilon}_{jt} = \tilde{\varepsilon}_{jt} - \rho_\varepsilon \tilde{\varepsilon}_{jt-1}$ is the innovation in the average cost keeping stockouts constant, and $\epsilon_{jt-1} = \tilde{\varepsilon}_{jt-1} - b^+_j OOS_{jt-1}$ is the period $t-1$ average cost that is uncorrelated with period $t-1$ stockouts.

This leads to a specification for real replacement cost (14) in the paper:

$$\omega_{jt} = a_j + b_j OOS_{jt-1} + \varepsilon_{jt},$$

where

$$b_j = \omega_j \phi_j z_{0j}^{+} + \rho_\varepsilon b_j^{+}, \tag{B.9}$$

$$\varepsilon_{jt} = \triangle\tilde{\varepsilon}_{jt} + \rho_\varepsilon \epsilon_{jt-1}. \tag{B.10}$$

Coefficient $b_j$ in (B.9) reflects two channels through which sector stockouts $OOS_{jt-1}$ influence sector's real replacement cost $\omega_{jt}$. The first effect, $\omega_j \phi_j z_{0j}^{+}$, captures costs associated with higher orders to replenish stocks that disappear after stockouts. This effect is proportional to the adjustment cost parameter $\phi_j$ and to the average size of the stock-at-risk—the average stock that firms in sector $j$ carry over from period $t-1$ to period $t$. Sectors with higher average stocks will face higher average cost of managing the same stockout rates. The second effect, $\rho_\varepsilon \frac{cov(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{var(OOS_{jt-1})}$, is due to persistence $\rho_\varepsilon$ in average costs (average supplier's price and adjustment cost), keeping sector stockouts constant, and its effect on higher likelihood of stockouts $\frac{cov(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{var(OOS_{jt-1})}$. Sectors where higher average costs are more likely to be passed through to stockouts and where these costs are more persistent are likely to have higher costs following a hike in stockout rate.

The residual term $\varepsilon_{jt}$ also consists of two parts. The first term, $\triangle\tilde{\varepsilon}_{jt}$ is the change in the average cost keeping stockouts constant. For example, this term is i.i.d. if the average cost follow an AR(1) process. The second term, $\rho_\varepsilon \epsilon_{jt-1}$, is the end of period $t-1$ average cost that is uncorrelated with period $t-1$ stockouts. This term is zero, if the average cost are not serially correlated.

# C Country-specific impulse responses

In our local projections, specified in (4), we pool data across countries and allow for country-sector dummies. This specification estimates the average impulse response across countries. To demonstrate whether and how country-specific responses differ from the common response, we estimate the following alternative specification, where we allow coefficients in front of shock variables $\epsilon_{cj,t}$ to vary with country dummies:

$$X_{cj,t+h} - X_{cj,t-1} = c^{(h)} + \sum_{l=0}^{L} (\beta_{0,l}^{(h)} + \beta_{1,l}^{(h)} D_c) \epsilon_{cj,t-l} + \sum_{n=1}^{N} \delta_n^{(h)} X_{cj,t-n} + D_j + error_{cj,t}^{(h)} \tag{C.1}$$

Figure C1 provides the estimated responses of stockouts (top left) and inflation rates (bottom left) to a stockout shock from Figure 7, and the responses of sector stockouts (top right) and inflation rates (bottom right) to a cost shock from Figure 12.

There are clearly differences in responses across countries, but the tendencies remain consistent with the baseline responses using pooled data. Two notable exceptions are Canada and Japan, for which the estimated sector-level inflation responses are close to zero (or even negative) after a stockout disturbance. This is not surprising since temporary stockouts in Canada and Japan responded the least during the pandemic relative to the other 5 countries in the sample as we note in the main text (see also Figure 4 in the main text and Figure A3(a) in the Appendix).

The estimated inflation responses to real cost shocks are more in tune (bottom right): for all countries estimated responses are positive after the cost impulse, although for Japan it is close to zero.

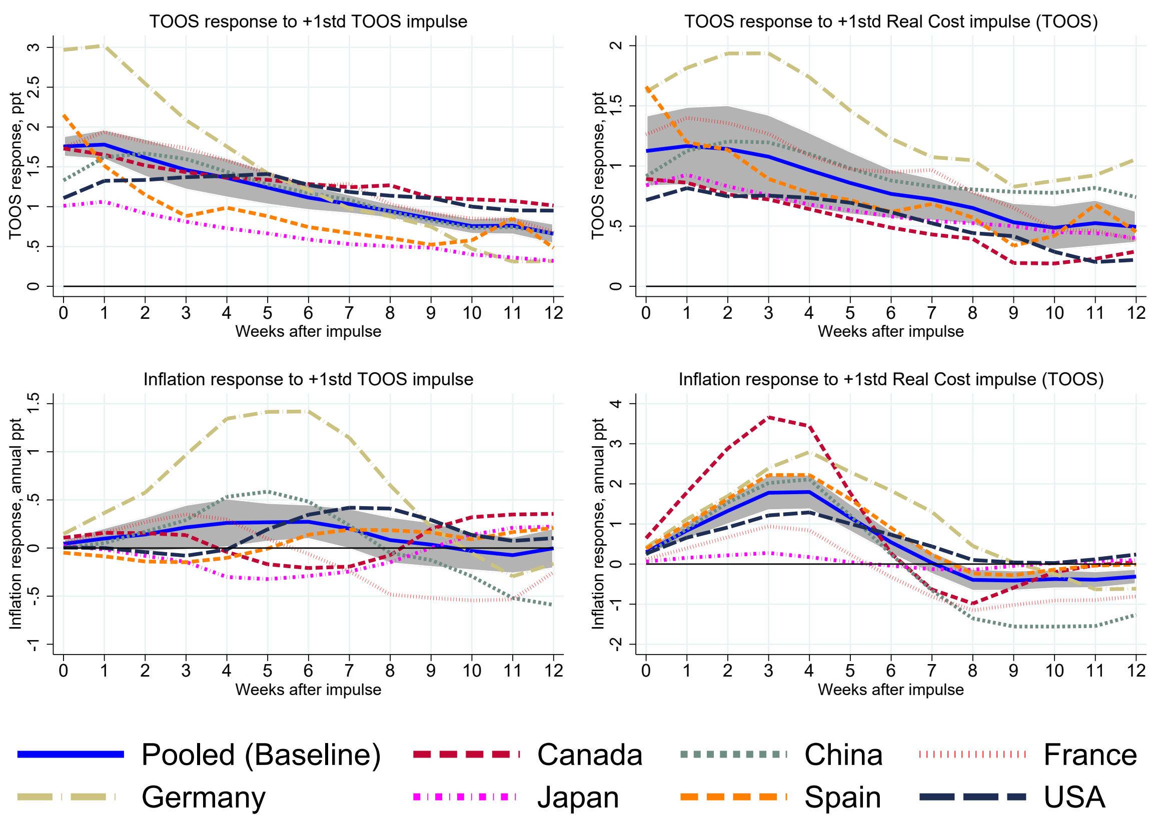



Figure C1: Responses by country

Notes: The figure provides the estimated responses of temporary stockouts (top left) and inflation rates (bottom left) to a temporary stockout shock from Figure 7, and the responses of temporary stockouts (top right) and inflation rates (bottom right) to a cost shock from Figure 12. Responses: sector temporary stockouts (in ppt, average weekly rate, top), sector monthly inflation (in ppt, annualized rate, bottom). Blue solid line and shaded areas provide responses and 90% bands for the baseline estimation using pooled data.

# D Relative Prices and Inflation

Fluctuations in sector-level prices rates may be driven by factors common across many sectors resulting in aggregate inflation, or by sector-specific factors leading to movements in relative prices. Because we estimated the replacement cost separately for each sector, we did not make a distinction between common and sector-specific components in the estimated inflation responses.

To get a sense of how much variation in sector prices, stockouts, and estimated costs are common across sectors, we now compute common factors for each variable using the panel of 199 sectors across 7 countries used in the paper. Table D1 reports the fraction of variance of the sector's monthly inflation rates, stockouts rates, and monthly growth rates of estimated nominal costs attributed to common factors.

The top common factor can be interpreted as representing global fundamental forces, influenced to a large degree by the COVID-19 pandemic over this period. This factor exerts significant influence on sector-level inflation, accounting for 15% of the variance. The global factor is twice as important for our measures of stockouts, accounting for 35% of TOOS variance and 29% of AOOS variance. Lower share for all stockouts implies temporary stockouts are more "global" than discontinued products, consistent with our findings in previous sections.

| Factors | Inflation monthly % | TOOS % | POOS % | Nom cost monthly % |
|---|---|---|---|---|
| Top 1 | 0.15 | 0.35 | 0.29 | 0.19 |
| Top 2 | 0.24 | 0.52 | 0.44 | 0.32 |
| Top 3 | 0.30 | 0.62 | 0.56 | 0.40 |
| Top 4 | 0.36 | 0.68 | 0.64 | 0.48 |
| Top 5 | 0.41 | 0.74 | 0.69 | 0.53 |
| Top 6 | 0.46 | 0.77 | 0.73 | 0.58 |
| Top 7 | 0.50 | 0.80 | 0.75 | 0.62 |

Table D1: Fraction of Variance Explained by Top 7 Common Factors, 3-Digit Sectors in 7 countries

Notes: The table provides the share of variance for variables in columns attributed to their top 7 common factors for the weekly panel of 199 3-digit sectors in 7 countries used in the paper.

We interpret the top 7 factors as representing a combination of global *and* country-specific forces. For example, fluctuations in larger and more integrated economies (e.g., the United States and China) or sectors (e.g., "Electronics") may have global influence. Altogether, the top 7 factors account for 50% of sector-level inflation variance, 80% of the stockout variance, and 62% of the nominal cost growth variance. Therefore, at least half of the estimated inflation responses and nominal costs represent shocks to aggregate inflation. The remaining share of variance can be attributed to sector-specific factors, accounting for more idiosyncratic relative-price disturbances.