

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

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March 2022

Abstract

We use a detailed micro dataset on product availability to construct a direct high-frequency measure of consumer product shortages during the 2020–2022 pandemic. We document a widespread multi-fold rise in shortages in nearly all sectors early in the pandemic. Over time, the composition of shortages evolved from many temporary stockouts to mostly discontinued products, concentrated in fewer sectors. We show that unexpected product shortages 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.

*We are grateful to Jenny Duan and Joaquin Campabadal for excellent research assistance, and to Caroline Coughlin and Manuel Bertolotto for providing access and help with the micro data. We thank George Alessandria, Greg Kaplan, Jim MacGee, Emi Nakamura, and seminar participants at the Bank of Canada, Bank of Finland, Brandeis, CAER Workshop, CEBRA, Council of Economic Advisers, Danmarks Nationalbank–Deutsche Bundesbank–Norges Bank Conference “Stabilization policies: Lessons from the COVID-19 crisis and prospects for future policy strategies”, Federal Reserve Bank of San Francisco “Macroeconomics and Monetary Policy” Annual Conference, Federal Reserve Board, HBS-PROM, International Centre for Economic Analysis (ICEA) Conference “Inflation”, Indiana, Penn State, the 15th International Conference on Computational and Financial Econometrics, Rochester Virtual International Trade and Macro Seminar, and the Canadian Economic Association meetings for helpful comments and suggestions. Alberto Cavallo is a shareholder of PriceStats LLC, the private company that provided proprietary data used in this paper without any requirements to review the findings. The views expressed here are ours, and they do not necessarily reflect the views of the Bank of Canada.

“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 7.9% by February 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. The measure captures product unavailability 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 January 21, 2022. The dataset spans a wide range of consumer goods, including Food and Beverages, Household, Health, Elec-

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

²Alessandria, 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.

³See 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.

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

⁵See Krolkowski 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.

tronics, and Personal Care products, covering between 62% 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 unavailable products (“temporary stockouts”) and discontinued 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 shortages 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 and by January 2022 they were about 15 ppts above their pre-pandemic levels. Other countries exhibit similar stockout dynamics, but the U.S. had the most persistent stockouts.

Second, the composition of shortages 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 in our sample. By contrast, permanent stockouts remained elevated in some countries throughout the pandemic. In the U.S., they were still at half their peak levels by January 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,” but returned to pre-pandemic levels in other major categories.

Next, we show that these product shortages were associated with rising prices in most sectors

and countries. The magnitude of the dynamic inflationary effect of shortages is statistically and economically significant. We estimate that an unexpected doubling of the weekly temporary stockout rate from 10% to 20% brought about a 1.6 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 lead 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 cost dynamics resemble those from observed stockout behaviors, validating the idea of using shortages for gauging the emergent cost pressures. Furthermore, accounting for the endogeneity of stockouts makes the estimated inflationary effects stronger immediately after the cost shock, but also less persistent. We also find that both inflation and stockouts are more responsive in trade-intensive sectors, suggesting that retailers

⁶Studies 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).

more exposed to international trade experienced higher cost pressures during the pandemic.

2 Data and Stockout Measurement

We use 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.

	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 January 21, 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

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

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

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

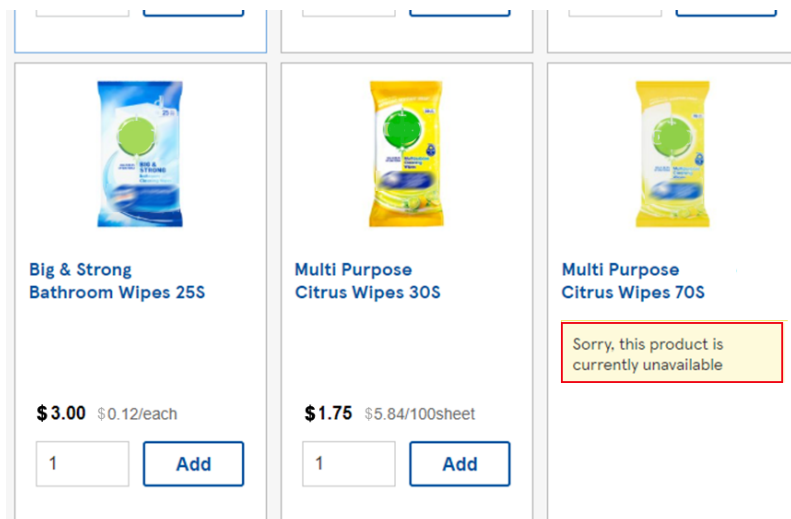


Figure 1: Identifying Stockouts on a Retailer’s Website

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:

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

We also need to account for the fact that retailers discontinued many products, removing them from their websites. Some of these goods were replaced with new varieties, but the total number of products available to consumers declined significantly in most countries. 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

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

2020, before the pandemic started:

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

We also construct a broader measure of shortages, ($AOOS_{cj,t}$), as the sum of both temporary and permanent stockouts. This is the share of products that are no longer available since the pandemic started—either because they are out of stock or discontinued. It can be negative if the total number of products is higher than before the pandemic.

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:

$$OOS_{c,t} = \sum_j w_{cj} OOS_{cj,t}, \quad (3)$$

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 in 2020, but rose again in May 2021.¹⁰ By January 2022, these stockouts were still at 20%, almost double

¹⁰Up to May 2021, the pattern is consistent with the percentage of firms reporting some kind of supply disruption in the “Small Business Pulse Survey” conducted by U.S. Census Bureau (2021). But after that month, our measure of stockouts declines while a growing share of firms continues to report supply disruptions. See Figure A1 in the Appendix. One interpretation is that the retailers are still facing supply disruptions but that rising prices have reduced the excess demand.

their pre-pandemic levels.

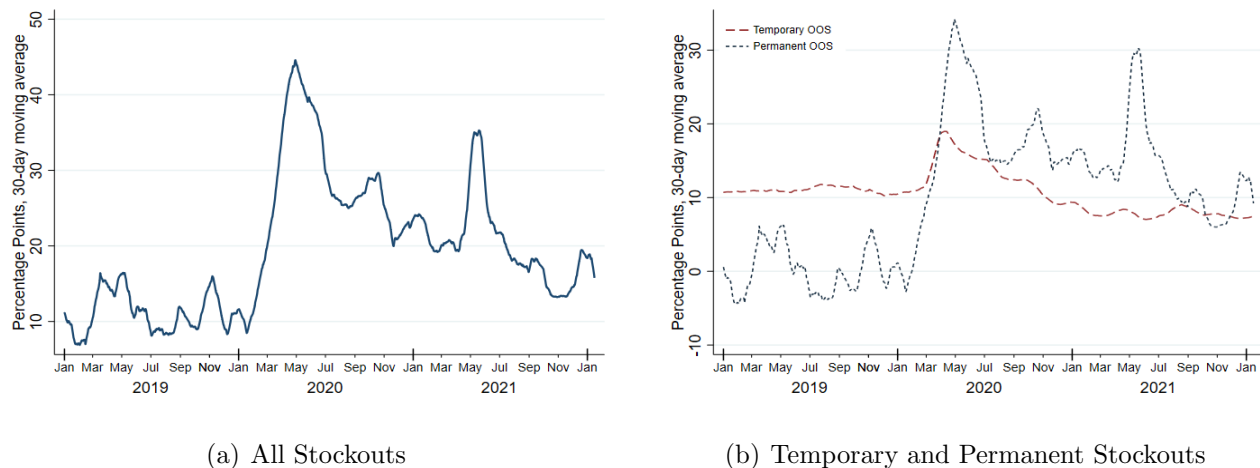


Figure 2: Stockouts in the United States, 2019–2021

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 started to increase again, and by May 2021, were once again peaking. By early 2022, during the Omicron wave of the pandemic, the share of discontinued products remained at roughly a third of its peak level.

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.

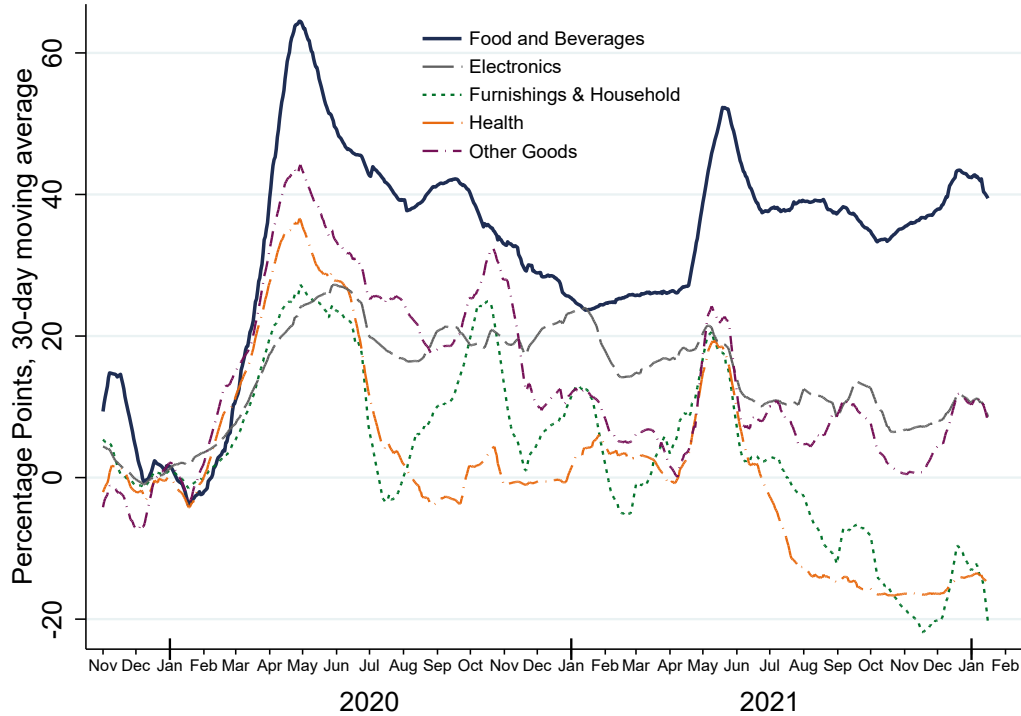


Figure 3: All Stockouts in U.S. Sectors

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 January 2022, “Health” and “Furnishings and Household” actually *more* products available for sale than before the pandemic. By contrast, the disruptions were more persistent for “Food and Beverages,” where stockouts remained over 30 ppt above pre-pandemic levels in early 2022, and to a lesser degree in “Electronics.” These findings are consistent with U.S. media reports on these two sectors, with labor and transportation disruptions affecting food production and computer-chip shortages affecting the supply of electronics.¹¹

3.2 Other Countries

Stockout patterns in the U.S. data are broadly similar to those in other countries. Figure 4 shows both temporary and permanent stockouts for all seven countries. To facilitate the comparisons of

¹¹See Fitch (2021) and Kang (2021).

temporary stockouts, in Figure 4(a) we plot the incremental change relative to the pre-pandemic levels, given by $TOOS_{c,t} - TOOS_{c,Jan2020}$.

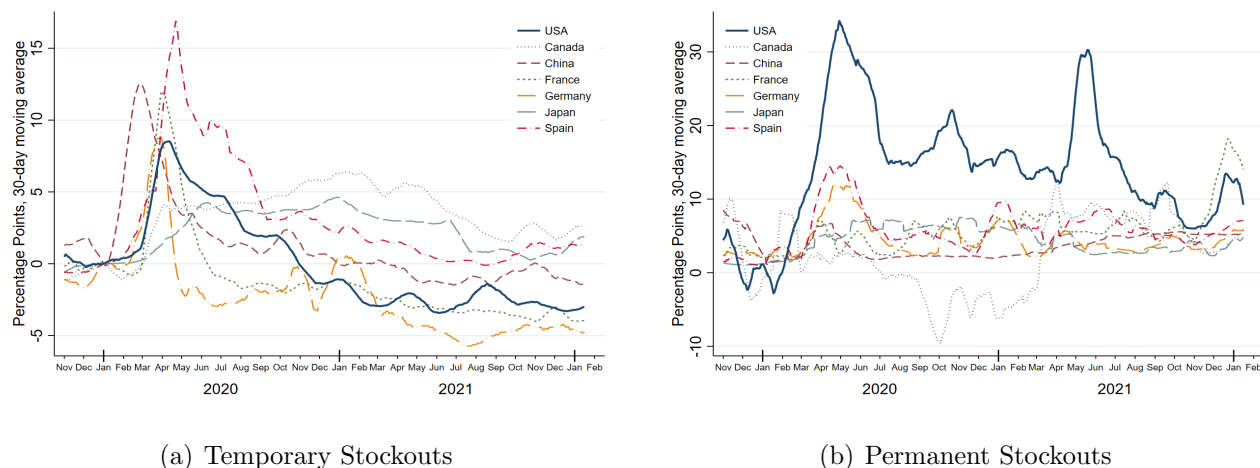


Figure 4: Temporary and Permanent Stockouts in 7 Countries

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.

In most countries, temporary stockouts followed a common pattern, rising sharply during the first two months of the pandemic and then gradually returning to pre-COVID levels over time. Still, there are noteworthy differences in the timing and magnitudes of the changes. Temporary stockouts peaked first in China, where the pandemic started. They rose by 12 ppt from their pre-pandemic levels during the month of February 2020 and then gradually declined back to normal levels by January 2021. European countries were next, peaking in April 2020 with an increase of about 10 ppts. For Germany and France, the recovery back to normal levels was relatively quick, but in Spain temporary stockouts took longer to fall, normalizing only by mid-2021. The outlier is Canada, where temporary stockouts rose slowly and remained elevated throughout the crisis.

The behavior of permanent stockouts differs a lot more across countries, as shown in Figure 4(b). At one end, China and Japan had no significant increase in discontinued goods during the pandemic. In Canada the total number of products grew temporarily in 2020, turning the permanent stockouts measure negative for several months. By contrast, all other countries experienced losses in product varieties.

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. The graph on the left shows that, relative to pre-pandemic levels in January 2020, the rise in the official CPI levels was more pronounced in the United States, where stockouts have also been more persistent in our data. Price indices constructed with the same online data in our sample have similar inflation dynamics, as shown on the graph on the right.¹²

The sudden rise of inflation led to much speculation about its causes, particularly in the United States, where cost pressures and supply disruptions were often cited by policy-makers as a potential source of transitory price pressures (Bernstein and Tedeschi, 2021; Helper and Soltas, 2021).

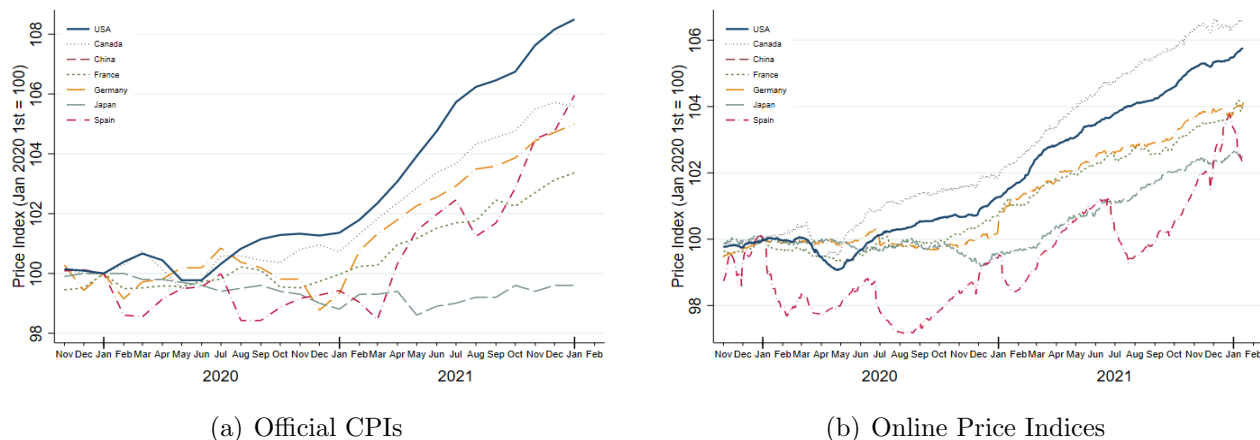


Figure 5: CPI and Online Price Indices

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.

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

¹²The 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.

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.

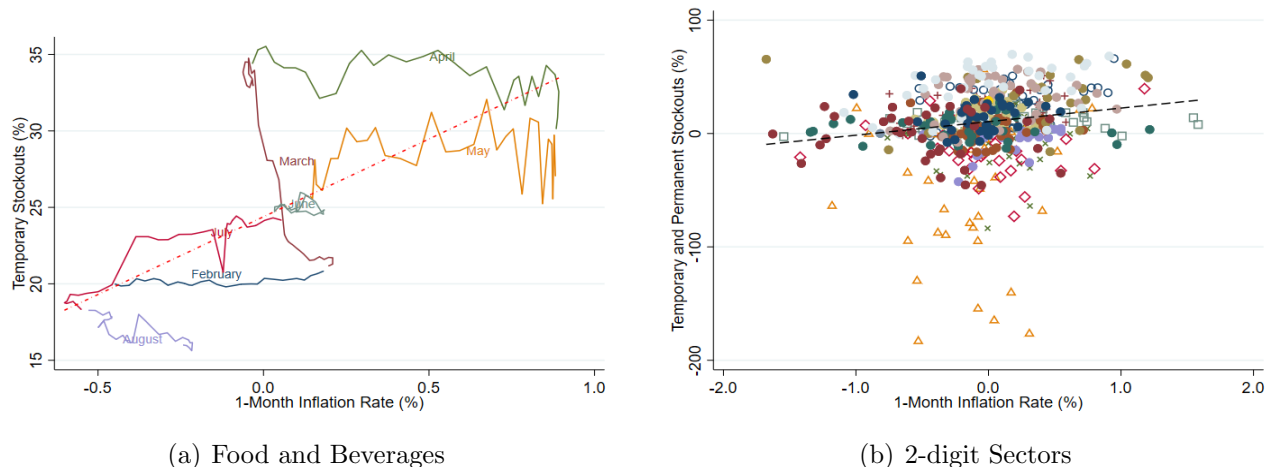


Figure 6: U.S. Inflation and Stockouts

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 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. 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): $OOS_{cj,t} = c_{cj} + \beta_{cj}OOS_{cj,t-1} + \epsilon_{cj,t}$.¹³ 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

¹³Adding higher-order lags does not materially improve the results.

for the change in $X_{cj,t}$ over h weeks:

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

Specification (4) conditions on the history of shocks $\epsilon_{cj,t-l}$, where $l = 0, \dots, L$, lags of endogenous variable $X_{j,t-n}$, $n = 1, \dots, N$, and country-sector dummies D_{cj} . In both estimations, we use $L = N = 4$. 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 $h = 0, 1, \dots, 12$.

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 around 2 ppt on impact and decrease slowly, with a half-life of roughly 9 weeks. Permanent stockouts are four times more volatile but less persistent than temporary stockouts. Sector inflation rates respond gradually, reaching 0.32 ppt (annual rate) by week 4 after a one standard deviation temporary stockout shock, and 0.21 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 stockout rate from 10% to 20%—a common dynamic at the beginning of the pandemic—would bring about a 1.6 ppt increase in the monthly annualized inflation rate of these sectors in 12 weeks.

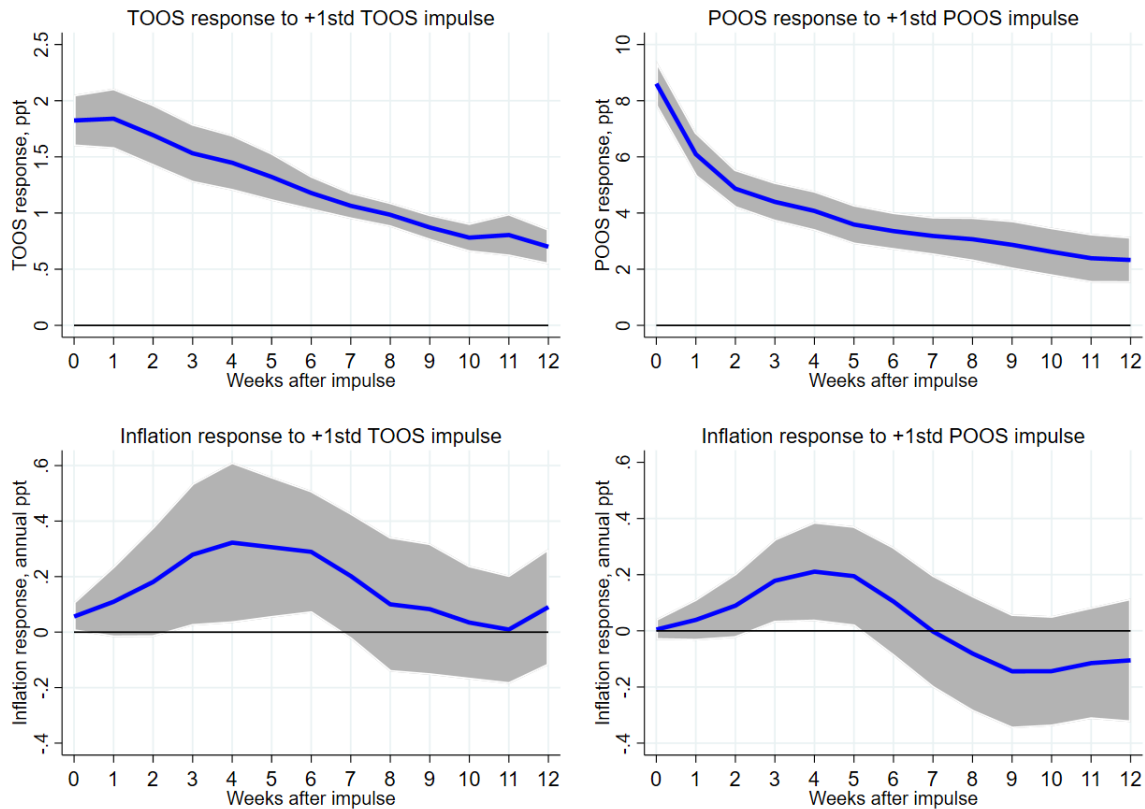


Figure 7: Responses to a Stockout Shock in a 3-digit sector in 7 countries

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.

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.¹⁴ 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 a half (see Figure

¹⁴See Alessandria, Kaboski, and Midrigan (2010b,a); Khan and Khederlarian (2021).

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 8 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 shortages, higher prices, or both.

5.1 Results across sectors by import penetration

First, we extend the results in the previous section by splitting the 235 subsectors in seven countries into two groups: 109 sectors with a low share of imports in total consumption (below the weighted median of 0.24 across sectors in all countries) and 126 sectors with a high share of imports (above 0.24).¹⁵ In specification (4) we replace coefficients $\beta_l^{(h)}$ 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 0.6 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 cost to both prices and stockouts. As the shock dissipates, prices in trade-intensive sectors end up at permanently higher levels than in other sectors. These results coalesce with findings in Alessandria, Khan, Khederlarian, Mix, and Ruhl (2022) who develop an international trade model with inventories and supply-chain frictions. They show that transitory changes in shipping delays can raise prices, particularly for imported goods. 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 mainly domestic.

¹⁵We 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.

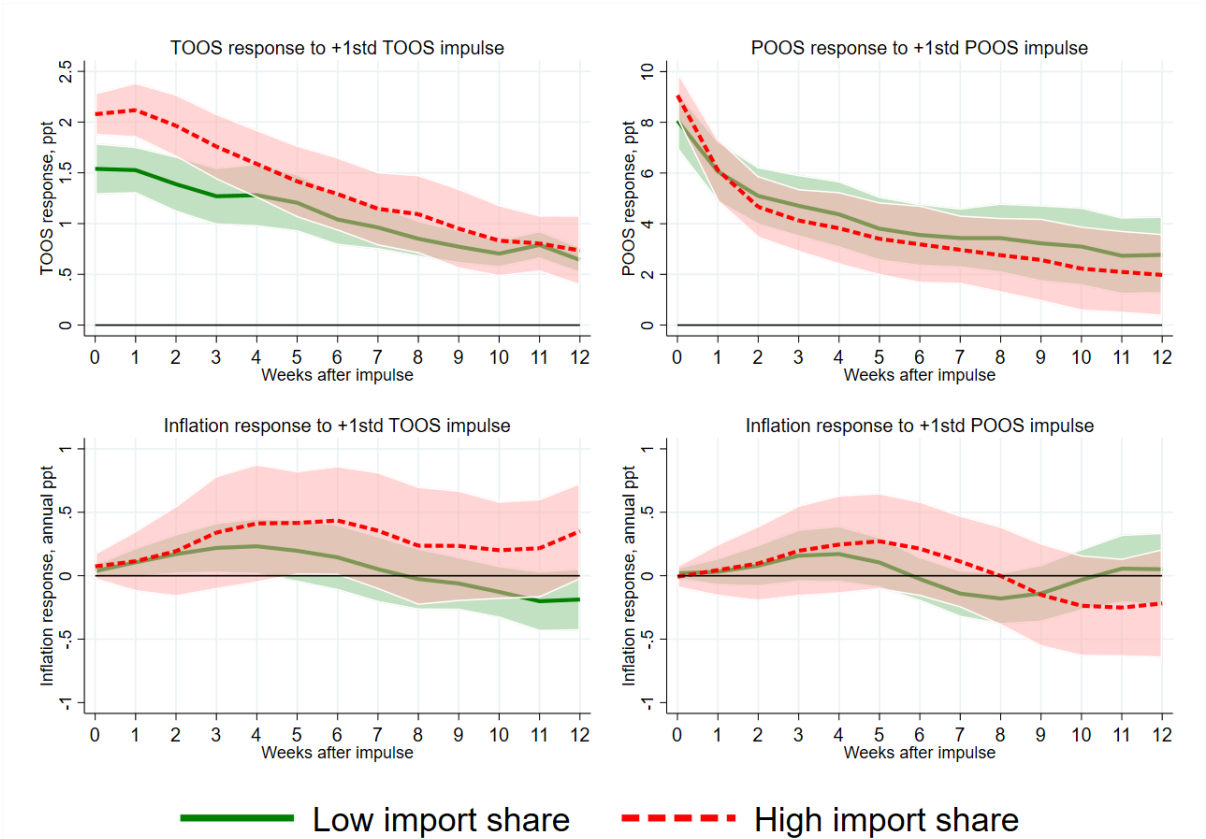


Figure 8: Responses to a Stockout Shock in a 3-digit sector in 7 countries, by import share in consumption

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 using specification (4) with additional control for sectors with low import share in total consumption (≤ 0.24) and high import share (> 0.24). Shaded areas outline 90% bands based on Driscoll-Kraay standard errors.

5.2 Micro Data on Imported and Domestic Goods

We now extend the sector-level evidence on trade with results for 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.¹⁶ This retailer specializes in household products and sold an average of 16,953 distinct products per day during our sample period. About three-quarters of its products are imported, with stockouts levels that averaged 5.3% and lasted approximately 27 days. As can be seen in Table 2, 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.

¹⁶This 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.

		U.S. Retailer
Number of products		16,953
	imported	12,275
	domestic	4,678
Fraction of stockouts, %		5.3
	imported	5.2
	domestic	4.0
Stockout duration, days		27.4
	imported	26.0
	domestic	18.5
Product inflation, ann %		0.55
	imported	1.98
	domestic	-2.22

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

Notes: 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 daily price change multiplied by 365. These statistics are provided for goods in the sectors included in the analysis in Sections 3 and 4.

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 $I_{ij,t}^{TOOS}$ denote an indicator that product i is temporarily out-of-stock on day t , and I_{ij}^{imp} is an indicator that product i in sector j is imported. We define price-relative $\tilde{p}_{ij,t_0,t}$ 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, $\tau = 1, 2, \dots$ days before and τ days after a temporary stockout in the micro data:

$$\Delta P_{\tau}^{before} = \sum_{T_0} \sum_{ij} \omega_{ij} \tilde{p}_{ij,T_0-1,T_0-\tau} I_{ij,T_0}^{TOOS}, \quad \tau = 1, 2, \dots, \quad (5)$$

$$\Delta P_{\tau}^{after} = \sum_T \sum_{ij} \omega_{ij} \tilde{p}_{ij,T,T+\tau} I_{ij,T}^{TOOS}, \quad \tau = 1, 2, \dots, \quad (6)$$

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 ω_{ij} are product weights.¹⁷ We also compute average price-

¹⁷We 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.

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 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-stockout price is mostly driven by imported products, while prices of domestically produced products return to average levels within a couple of weeks.

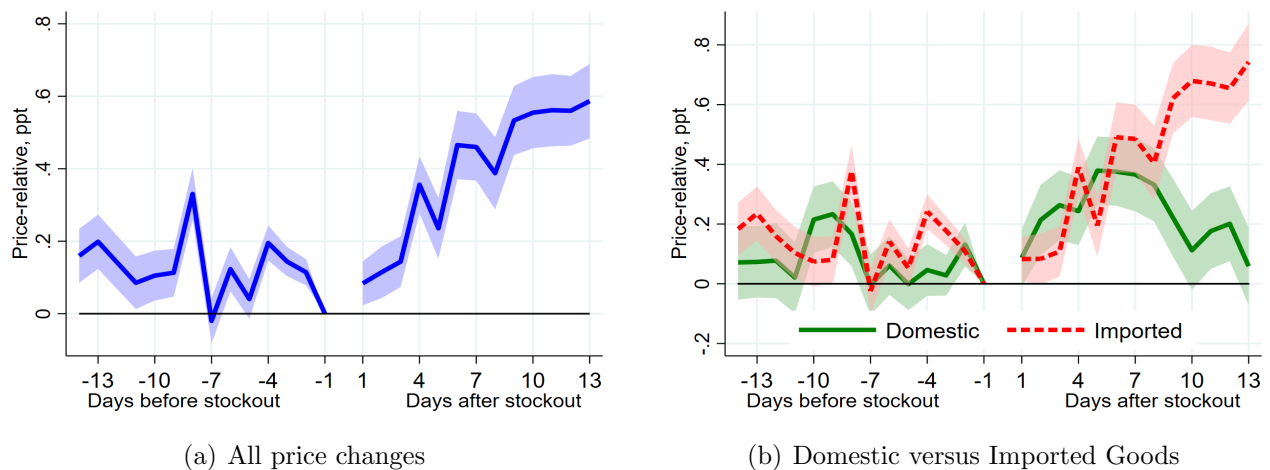


Figure 9: Price Levels Before and After a Stockout For a Large U.S. Retailer

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.

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 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.

6 Inventory Costs, Prices, and Stockouts

When we estimated the dynamic relationship between shortages and inflation in Section 4, we treated stockouts as exogenous. This is a strong assumption because firms decide their inventory levels (and therefore stockout rates) jointly with their prices. In fact, stockouts are endogenous, and, like prices, they depend on the cost of supplying products to consumers and other sector factors. To incorporate this mechanism in the analysis, we develop a model of the joint behavior of stockouts and prices in a sector facing exogenous cost and demand disturbances. In the model, single-product firms hold inventories to buffer against possible temporary stockouts, so our analysis in this section is focused exclusively on this type of shortage.

This approach provides two additional contributions. First, we use sector-level price and temporary stockout data to estimate the unobserved cost of replacing unavailable products. This allows us to report the degree to which the pandemic affected the replacement cost. Second, we estimate the impact of cost disturbances over this period on the responses of temporary stockouts and inflation. This allows us to re-assess the joint co-movement of shortages and inflation, while taking into account the endogeneity of stockouts with respect to prices and the underlying costs.

6.1 Model with Inventories

The model builds on Kryvtsov and Midrigan (2013), and it is applied at a weekly frequency. 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 the work required in the production of consumption goods. There are two types of firms in each sector: intermediate good producers and retailers. A continuum of competitive intermediate good firms hire labor and produce a homogeneous good using a Cobb-Douglas technology.¹⁸ Below, we focus on the problem of retailers; 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_{jt}^I , and convert them into the specific varieties that they then 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

¹⁸It is straightforward to extend this framework to include capital in production technology.

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. For simplicity, we assume that it takes a week for the firm to implement its pricing decision. Under this assumption, the firm's inventory decision is not influenced by its price decision, and the firm takes its price as given.

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 $P_{jt}^I \left(q_{jt}(i) + \frac{\phi_j}{2}(q_{jt}(i) - q_j)^2 \right)$. Convexity of the cost of replacing inventories represents mechanisms that motivates 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.¹⁹

Let $z_{0jt}(i)$ denote the amount of stock retailer i carries over from period $t - 1$. Then the quantity of product available for sale in period t is

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

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

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

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's problem is to choose $z_{jt}(i)$ to maximize

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

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

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

¹⁹Abel (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.

where δ_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:

$$\Omega_{jt}(i) = P_{jt}^I (1 + \phi_j(q_{jt}(i) - q_j)). \quad (11)$$

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 Empirical Specification for Prices, Stockouts, and Costs

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 $\Psi(v_{jt}(i)) = \int \min(v, v_{jt}(i)) dF(v)$.²⁰

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

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

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 $(1 - \delta_j)E_t [Q_{t,t+1}\Omega_{jt+1}(i)]$. 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

²⁰Solving the integral yields $\Psi(v_{jt}(i)) = \int_0^{v_{jt}(i)} v dF(v) + v_{jt}(i)(1 - F(v_{jt}(i)))$. This implies the derivative $\Psi'(v_{jt}(i)) = 1 - F(v_{jt}(i))$.

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 the 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:

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

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 $E_t [Q_{t,t+1} \omega_{jt+1}] \approx R_t^{-1} E_t [\omega_{jt+1}]$, where $R_t = E_t [Q_{t,t+1}]^{-1}$ is the risk-free rate.

6.3 The Dynamic Link Between Sector Stockouts and Replacement Cost

Although in equation (13) the sector's real replacement cost ω_{jt} is unobserved, we can use the model to approximate its law of motion. 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):

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

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 sector's real replacement cost ω_{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 real price P_{jt}^I/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 ε_{jt} are zero-mean innovations to period t replacement cost that are uncorrelated with period- $(t - 1)$ stockouts.

6.4 GMM Estimation

Using (14) to substitute ω_{jt} in empirical specification (13) yields

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

where $G(\cdot)$ is a non-linear function of observed variables, depreciation rate δ_j , and coefficients a_j, b_j ; and ε_{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 \mathbf{Z}_t of $N \geq 1$ instruments. We define the following N orthogonality conditions for GMM estimation:

$$E [Z_t^i \varepsilon_{jt}] = E [Z_t^i G(p_{jt}, TOOS_{jt}, TOOS_{jt-1}, COV_{jt}, R_t, \pi_t; \bar{a}_j, b_j, \bar{\delta}_j)] = 0,$$

where Z_t^i is the i th element of the set of instruments \mathbf{Z}_t , $i = 1, \dots, N$, and $\bar{a}_j, \bar{\delta}_j$ are calibrated values of a_j, δ_j . In equations (14)–(15), the errors ε_{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 January 17, 2022, spanning 116 weeks. We estimate the empirical model for both temporary out-of-stock measure (TOOS) for 235 sectors in 7 countries. The GMM estimation uses the following instruments: $\mathbf{Z}_t = [TOOS_{jt-1}, TOOS_{jt-2}, p_{jt-1}, p_{jt-2}, p_{jt-3}, \mathbf{X}_{t-1}, \mathbf{X}_{t-2}]'$, where \mathbf{X}_t is a vector of aggregate (monthly) controls. These controls include the change in the lockdown stringency index from “Oxford-Our World in Data,”²¹ which scores the number and strictness of government containment and mitigation policies during the COVID-19 pandemic and the 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 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

²¹<https://ourworldindata.org/coronavirus-testing>.

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 for two stockout measures in five 1-digit U.S. sectors: “Food and Beverages,” “Furnishings and Household,” “Health,” “Electronics,” and “Other Goods” (mostly 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 0.08 for “Food and Beverages” to 0.57 for “Electronics,” and all estimates are highly statistically significant. Intuitively, a coefficient value of 0.49 (seen for “Household goods”) 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.

The table also provides the results of the tests for weak instruments and over-identifying restrictions. The first-stage F -statistic for each of the two endogenous regressors in the model, sector price and 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.²²

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.

Table 4 illustrates estimation results for 1-digit U.S. sectors. It provides cumulative changes in temporary stockouts, prices, and estimated nominal costs between January 2020 and January

²²When we conduct estimation using 34 3-digit U.S. sectors, the first-stage F -statistic rejects weak instruments for the endogenous price regressor and endogenous temporary out-of-stock regressor in all 34 cases. In 25 out of 34 cases, the p -values for Hansen’s over-identifying restrictions test are above 0.10.

1-digit sectors	b_j (st.dev.)	First-stage F -statistic		Hansen's J -stat
		price	TOOS	p -value
Food & Beverages	0.08*** (0.00)	495.77	586.71	0.10
Household	0.49*** (0.03)	482.44	231.81	0.39
Health	0.12*** (0.01)	83.85	355.06	0.13
Electronics	0.57*** (0.02)	77.87	163.43	0.57
Other Goods	0.01 (0.01)	428.22	124.67	0.12

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) 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 two endogenous regressors (price and OOS), and p -values for Hansen's J -statistic to test over-identifying restrictions in the GMM. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2022.²³ For “Household,” “Health” and “Other Good” nominal cost index is at or below pre-pandemic levels reflecting the fact that stockouts have been at or around their normal levels for most of 2021. For “Electronics”, the cost index is 1.44% above its pre-pandemic level as stockouts have been at double their usual level for most of the pandemic period.

Finally, the cost in “Food & Beverages” is 0.87% above its pre-pandemic level despite stockouts being half their normal levels for the most part of 2021. The joint dynamics of prices and stockouts in this sector is provided in Figure 10. Since the initial peak in April 2020, stockouts fell to their low levels by January 2021, while prices were stable. Accordingly, the estimated replacement cost fell during this time by about 3%. Thereafter, these dynamics switched, and over 2021 stockouts were stable but prices increased. Accordingly, the replacement cost index rose by about 2% since the beginning of 2021.

²³See Appendix Figure A6 for details on the changes over time in each sector.

1-digit sectors	Data		Estimated Cost
	Price Index %	TOOS ppt	Nominal index %
Food & Beverages	4.31	-10.04	0.87
Household	2.20	-1.72	-0.62
Health	-0.92	-3.94	-0.67
Electronics	0.03	1.86	1.44
Other Goods	-3.31	-1.27	-0.04

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

Notes: The table reports % change of the sector price index between the week of January 4, 2020, and the week of January 17, 2022, ppt difference between average fraction of products out-of-stock in January 2022 and in January 2020, and % difference between average estimated nominal replacement cost in January 2022 and in January 2020.

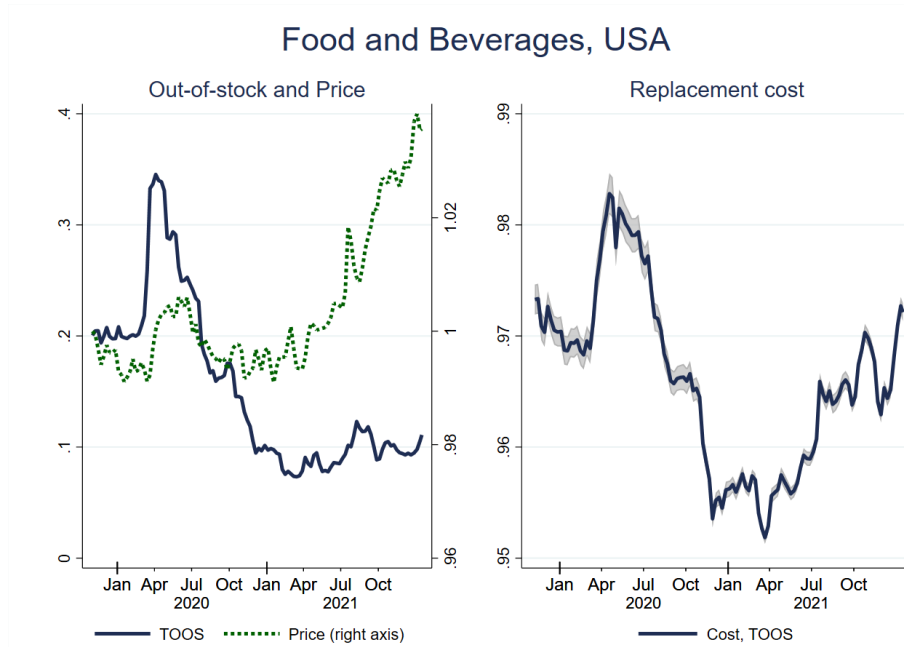


Figure 10: Stockouts, Prices, and Estimated Costs in Food & Beverages, United States

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 January 17, 2022. Shaded areas provide 95% confidence bands for estimated replacement cost.

6.6 Inflation Responses to 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 ε_{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 3-digit sectors in 7 countries. Figure 11 provides the estimated impulse responses.

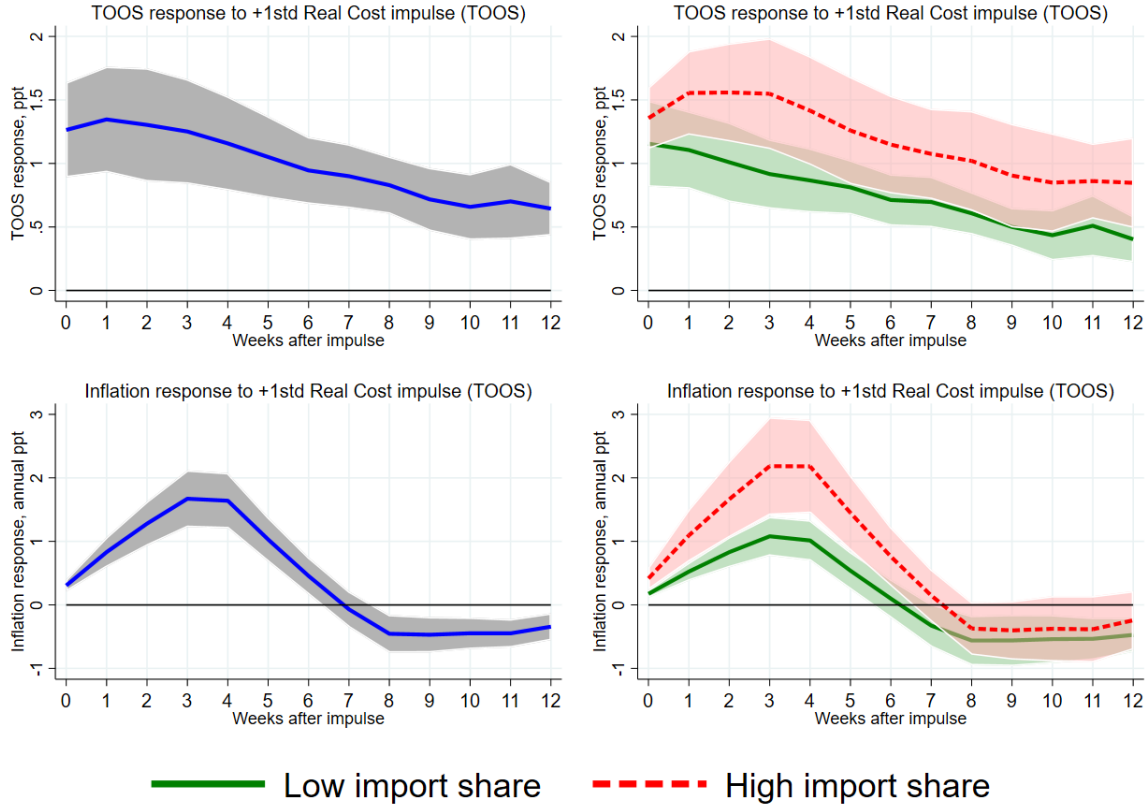


Figure 11: Responses to Real Replacement Cost Shocks in 3-Digit Sectors, in 7 Countries

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 (≥ 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 1.7 ppt (annualized rate) three weeks after the cost impulse (left panels in Figure 11). 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 0.63 ppt after three weeks, and the inflation response is higher by 1.17 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 shortages and price increases.

7 Conclusion

Rising inflation in 2021 spurred a lively debate on its causes. Covid supply disruptions and cost pressures are often mentioned by policy-makers and economists as playing a role, 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 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 shortages 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 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 1.6 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 shortages likely reflect emergent cost pressures due, in part, to supply bottlenecks. Unexpected shortages are quickly followed by inflation. During a protracted event, such as a global health pandemic, the shortages 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. As cost pressures dissipate, the inflation outlook will increasingly depend on other factors, such as the effect of the fiscal stimulus, the adjustment of inflation expectations, geopolitical shocks, and the diffusion of cost pressures via domestic and international production networks.

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A Additional Tables and Figures

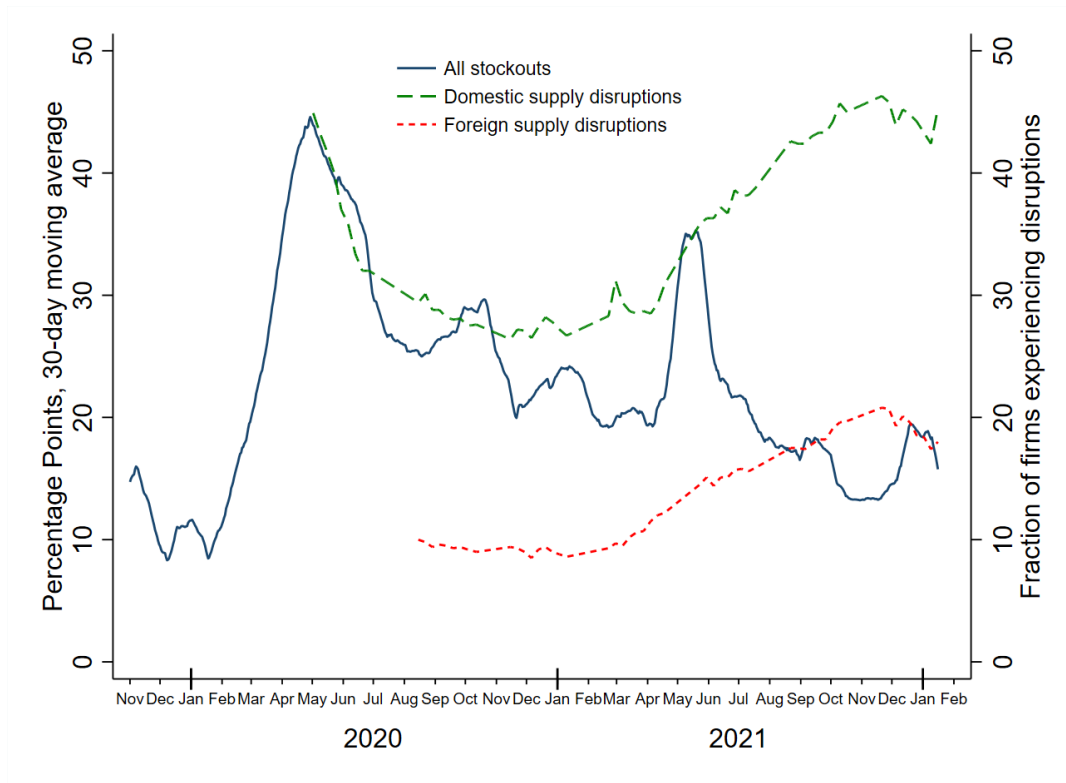


Figure A1: Stockouts (AOOS) vs. U.S. Census Survey of Small Business Disruptions

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 2010 and February 2022. See <https://portal.census.gov/pulse/data/#about>.

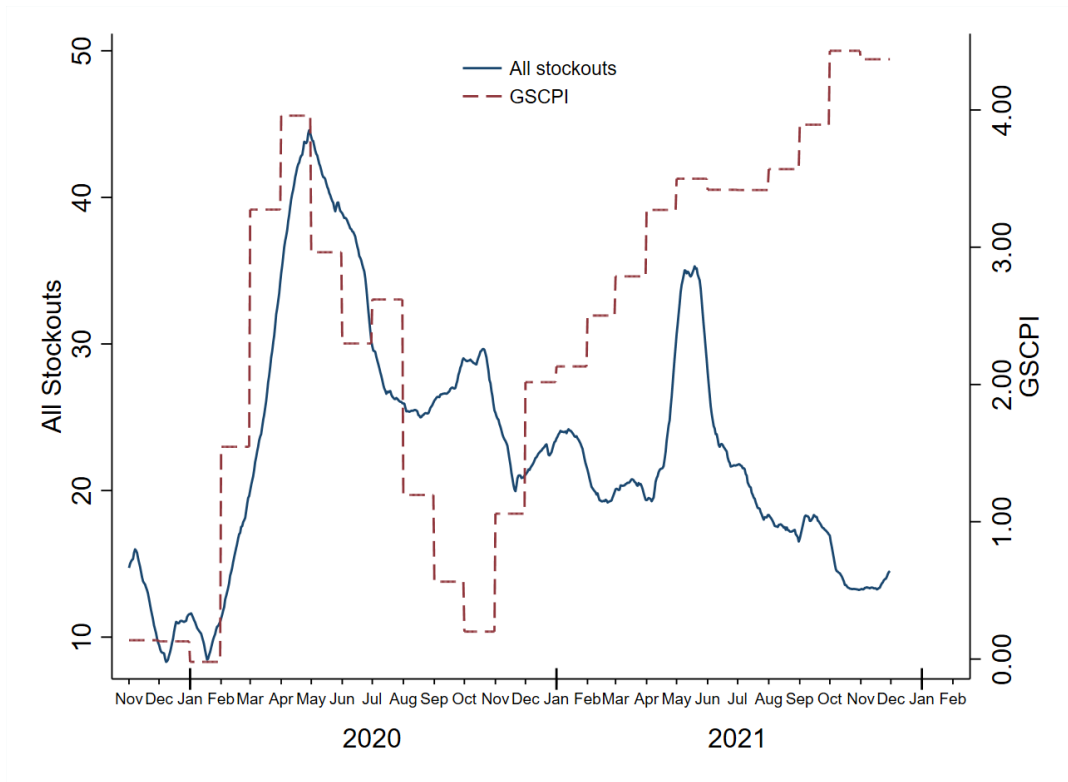


Figure A2: Stockouts (AOOS) vs. Global Supply Chain Pressure Index

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).

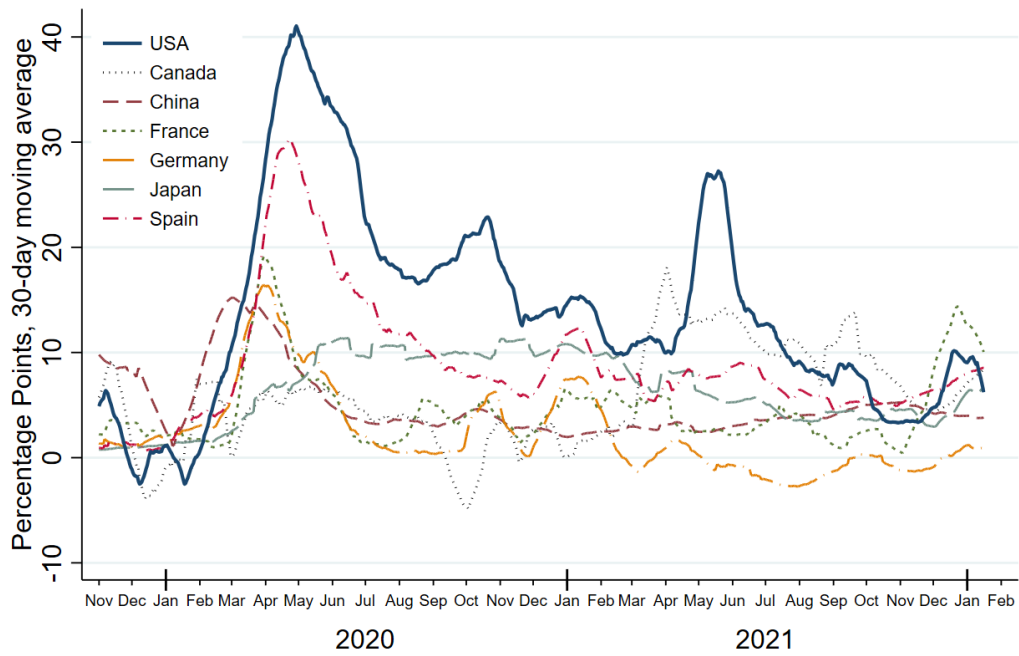
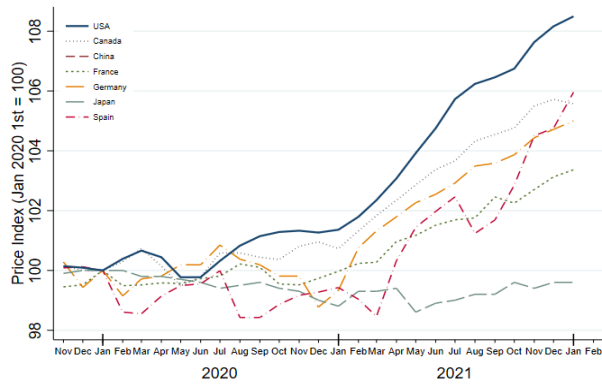
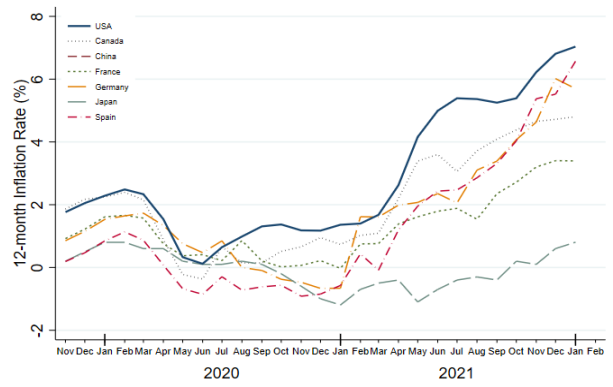


Figure A3: All Stockouts in 7 Countries

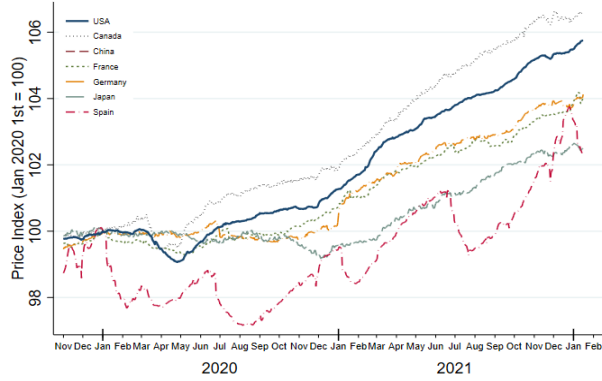
Notes: The initial level of $AOOS$ varies greatly by country, so in order to facilitate the comparison, here we plot the change relative to pre-pandemic levels, given by $AOOS_{t,c} - AOOS_{Jan2020,c}$.



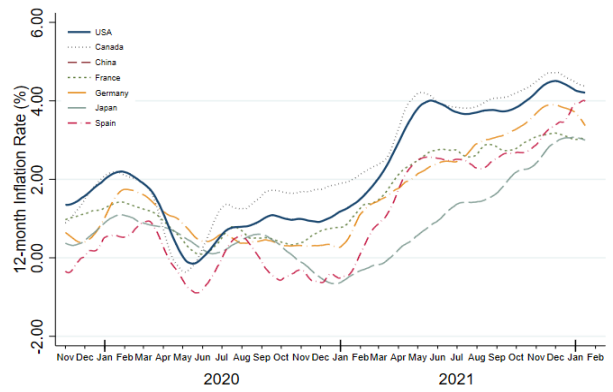
(a) CPI - Price Index



(b) CPI - Annual Inflation



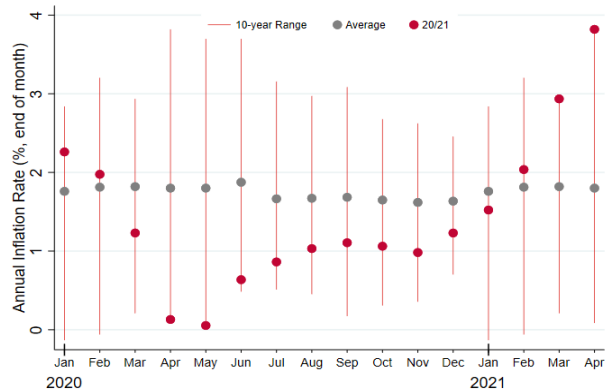
(c) Online - Price Index



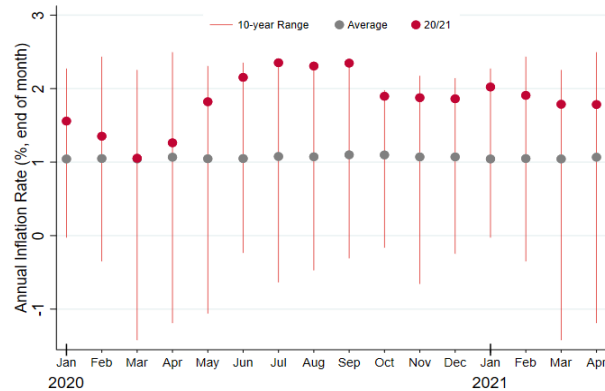
(d) Online - Annual Inflation

Figure A4: 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.



(a) All Items



(b) Electronics

Figure A5: U.S. Online Inflation in 2020–21 versus 10-year Averages

Notes: In these plots we compare the annual inflation rate in online prices during the pandemic to the average and range of values in the past 10 years. We use price indices computed by PriceStats, both at the aggregate “All Items” level (left) and for “Electronics” (right). The plot on the left shows that the annual inflation rate in March and April 2021 has been at the highest level recorded for those months in the past 10 years. The plot on the right shows that the annual inflation for electronics has been roughly 1 ppt above normal levels since June 2020.

	Food & Bev.	Electronics	Household	Health	Other Goods
Monthly inflation					
OOS (%)	0.008 (0.001)	-0.004 (0.000)	-0.004 (0.001)	-0.007 (0.001)	-0.014 (0.001)
Obs.	5,357	5,204	3,896	974	1,461
Annual inflation					
OOS (%)	0.004 (0.001)	0.023 (0.001)	0.007 (0.001)	-0.031 (0.005)	-0.109 (0.004)
Obs.	5,346	5,192	3,888	972	1,458

Table A1: Impact of Stockouts on Inflation Rates in the United States - with Time FEs

Notes: This table shows the coefficient of a regression at the 3-digit category level in the United States. The dependent variable is either the monthly (top panel) or annual (bottom panel) inflation rate, in %. The independent variable is the level of stockouts (both temporary and permanent), in %. All regressions are run using daily data and include 3-digit category dummies and time fixed effects. Robust standard errors are shown in parentheses.

	USA	Canada	China	Germany	Spain	France	Japan
Annual inflation							
OOS (%)	0.031 (0.001)	0.026 (0.003)	0.015 (0.002)	0.012 (0.002)	-0.009 (0.001)	-0.011 (0.003)	-0.045 (0.003)
Obs.	16,856	17,120	14,094	15,552	16,302	17,010	16,454

Table A2: Impact of Stockouts on Inflation Rates by Country - with Time FEs

Notes: This table shows the coefficient of a regression at the 3-digit category level in the United States. The dependent variable is the annual inflation rate. The independent variable is the level of stockouts (both temporary and permanent). All regressions are run using daily data and include 3-digit category dummies and period fixed effects. Robust standard errors are shown in parentheses.

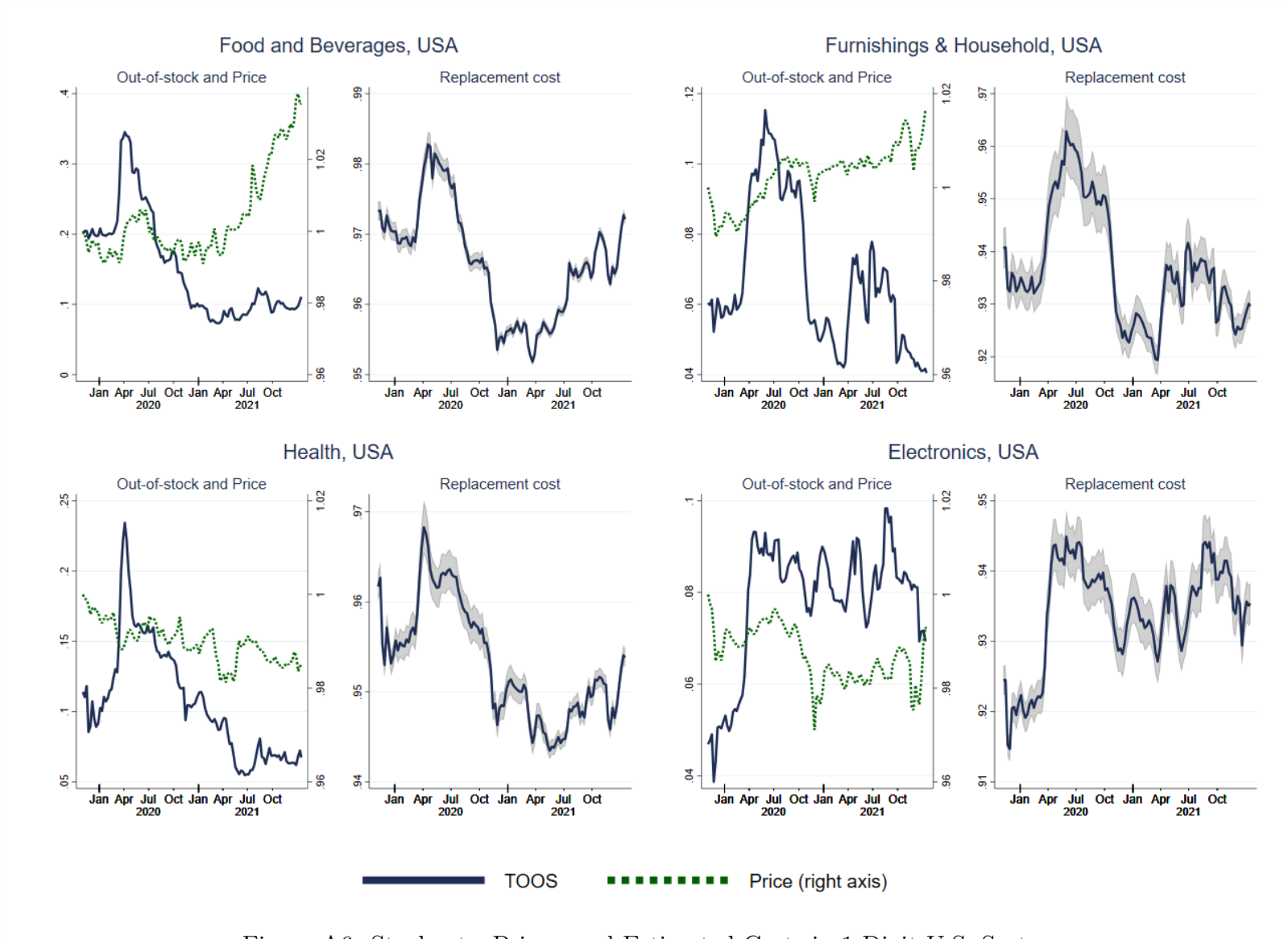


Figure A6: Stockouts, Prices, and Estimated Costs in 1-Digit U.S. Sectors

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.

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 :

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

where $y_{jt}^d(i)$ is the quantity of variety i in sector j , θ 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 $\{y_{jt}^d(i)\}$ to maximize

$$P_{jt}Y_{jt} - \int_0^1 P_{jt}(i)y_{jt}^d(i)di$$

subject to the stockout constraint

$$y_{jt}^d(i) \leq z_{jt}(i) \quad \forall i \tag{B.2}$$

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

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

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

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

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

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

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 technology²⁴

$$M_{jt} = N_{jt}. \quad (\text{B.3})$$

The homogeneous good is sold at the competitive price P_{jt}^I 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

$$E_0 \sum_{t=0}^{\infty} Q_{0,t} [P_{jt}^I M_{jt} - W_{jt} N_{jt}],$$

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 .²⁵ 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:

$$P_{jt}^I = W_{jt}.$$

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):

$$\frac{\Omega_{jt}(i)}{P_{t-1}} = \frac{P_{jt}^I}{P_{t-1}} (1 + \phi_j(q_{jt}(i) - q_j)). \quad (\text{B.4})$$

From equation (7)

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

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.

²⁴It is straightforward to extend this framework to include capital in production technology.

²⁵From 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 $\hat{p}_{jt}^I = \ln \frac{P_{jt}^I/P_j^I}{P_{t-1}^I/P}$, 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

$$\omega_{jt}(i) \approx \omega_j(1 + \hat{p}_{jt}^I + \phi_j dq_{jt}^+(i) + \phi_j OOS_j dz_{0jt}^+(i) + \phi_j(OOS_{jt-1}(i) - OOS_j)z_{0j}^+), \quad (\text{B.6})$$

where ω_j , OOS_j , z_{0j}^+ denote average levels of ω_{jt} , OOS_{jt} , z_{0jt}^+ respectively.

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

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

where

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

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

$$\tilde{\varepsilon}_{jt} = \omega_j(\hat{p}_{jt}^I + \phi_j dq_{jt}^+ + \phi_j OOS_j dz_{0jt}^+), \quad (\text{B.7})$$

The innovation term $\tilde{\varepsilon}_{jt}$ in (B.7) includes deviations of the suppliers real price \hat{p}_{jt}^I 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}_{jt}^I 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 $b_j^+ = \frac{\text{cov}(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{\text{var}(OOS_{jt-1})}$ the conditional correlation of $\tilde{\varepsilon}_{jt-1}$ and OOS_{jt-1} , and $\rho_\varepsilon = \frac{\text{cov}(\tilde{\varepsilon}_{jt}, \tilde{\varepsilon}_{jt-1})}{\text{var}(\tilde{\varepsilon}_{jt-1})}$ serial correlation of average costs $\tilde{\varepsilon}_{jt}$, we can write

$$\tilde{\varepsilon}_{jt} = \Delta \tilde{\varepsilon}_{jt} + \rho_\varepsilon b_j^+ OOS_{jt-1} + \rho_\varepsilon \varepsilon_{jt-1}, \quad (\text{B.8})$$

where $\Delta \tilde{\varepsilon}_{jt} = \tilde{\varepsilon}_{jt} - \rho_\varepsilon \tilde{\varepsilon}_{jt-1}$ is the innovation in the average cost keeping stockouts constant, and $\varepsilon_{jt-1} = \tilde{\varepsilon}_{jt-1} - b_j^+ OOS_{jt-1}$ 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

$$b_j = \omega_j \phi_j z_{0j}^+ + \rho_\epsilon b_j^+, \quad (\text{B.9})$$

$$\varepsilon_{jt} = \Delta \tilde{\varepsilon}_{jt} + \rho_\epsilon \varepsilon_{jt-1}. \quad (\text{B.10})$$

Coefficient b_j in (B.9) reflects two channels through which sector stockouts OOS_{jt-1} influence sector's real replacement cost ω_{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 ϕ_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, $\rho_\epsilon \frac{\text{cov}(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{\text{var}(OOS_{jt-1})}$, is due to persistence ρ_ϵ in average costs (average supplier's price and adjustment cost), keeping sector stockouts constant, and its effect on higher likelihood of stockouts $\frac{\text{cov}(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{\text{var}(OOS_{jt-1})}$. 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 ε_{jt} also consists of two parts. The first term, $\Delta \tilde{\varepsilon}_{jt}$ 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, $\rho_\epsilon \varepsilon_{jt-1}$, 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.