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 to construct a direct high-frequency measure of consumer product shortages during the 2020–2021 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 cost of replenishing inventories and higher exposure to trade.

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

"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 implications of the global COVID-19 pandemic is the severe disruption of the supply of goods to final consumers in a context of a quick recovering demand. Globally, these forces caused bottlenecks in shipping networks and disrupted the flow of goods along international supply chains. Domestically, the pandemic increased the cost of business operations, undercutting retailers' efforts to manage inventories amid swings in consumer demand.[2] 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.[3] Although there is evidence of these disruptions for some products in manufacturing, there is no systematic evidence on shortages of consumer products.[4] Furthermore, the degree of inflationary pressures associated with such shortages has been widely debated and remains unknown.[5]

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 by PriceStats 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,

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

[2]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.

[3]In Appendix Figure A4 we show that the U.S. annual inflation rate in March and April 2021 has been at the highest level recorded for those calendar months in the past ten years. See Foster, Meyer, and Prescott (2021) for survey results that connect firm-level concerns about supply disruptions to rising expectations of inflation.

[4]See Krolikowski and Naggert (2021) for an analysis of shortages in car manufacturing. Mahajan and Tomar (2021) provide evidence of food supply chain disruptions in India.

[5]Alessandria, Khan, Khederlarian, Mix, and Ruhl (2021) study the effect of supply-chain frictions on COVID recovery in a heterogeneous firm model of international trade.

Electronics, and Personal Care products, covering between 62% and 80% of the goods consumption weights in the CPI baskets. The dataset also contains product-level prices, allowing us to exploit the dataset's rich time and cross-section details to assess the inflationary effects of shortages.

The paper consists of three parts. We first document the dynamics of unavailable products ("temporary stockouts") and discontinued products ("permanent stockouts") across sectors and countries over the course of the pandemic. We then establish the degree to which stockouts co-move with prices. 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 particular, in the United States, total stockouts rose from a pre-pandemic level of around 10% in 2019 to over 40% in early May 2020. The stockouts rose first for health and personal care goods, but quickly spread to other categories, with increases ranging from 23 percentage points (ppt) for "Furnishings and Household" goods to above 60 ppt for "Food and Beverages." Total stockouts recovered gradually over time, with another spike of about 30 ppts in May 2021. By January 2022, U.S. stockouts were about 15 ppts above their pre-pandemic levels.

Second, the composition of shortages changed significantly over time. Temporary stockouts, which are more visible to consumers because they are flagged by retailers, rose sharply in most sectors and countries early on and then recovered gradually over time. By the end of 2020, they had fallen even below pre-pandemic levels for most countries in our sample. By contrast, permanent stockouts, which had also increased quickly, remained elevated or continued growing in some countries after July 2020. They recovered halfway in late 2021 before rising again during the Omicron wave of the pandemic. By early 2022, the share of discontinued products remained elevated in the U.S., at roughly half of the peak of May 2021.

Third, over time stockouts became increasingly concentrated in fewer categories. For example, in the United States, stockouts remained persistently high for "Food and Beverages," but returned roughly to pre-pandemic levels in other major categories of goods.

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

and countries. The magnitude of the average 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% brings 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 inflationary effects are associated with global supply bottlenecks, we compare evidence for imported products and import-intensive sectors with domestic products and sectors. First, according to micro evidence from one large U.S. retailer, 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. Second, when we compare sector responses to temporary stockout disturbances, import-intensive sectors experience larger and more persistent inflation responses, with roughly twice the impact of domestic goods after six weeks. By contrast, we do not find a strong link between trade exposure and inflation responses to fluctuations in discontinued products. Altogether, 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 explicitly account for the endogeneity of stockouts by incorporating the cost of replenishing inventory stocks. 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. We use the model to derive an empirical specification for estimating the cost behind the observed dynamics of temporary stockouts and prices at a sector level. We then construct empirical responses of sector stockouts and inflation to estimated cost shocks.[6]

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 stockouts 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. When we split the responses

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[6]Studies of inventory management and pricing include (Deaton and Laroque, 1992; Aguirregabiria, 1999; Hall and Rust, 2000). 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, 2010).

for high- and low-import-share sectors, we document that both inflation and stockouts are more responsive in trade-intensive sectors. This evidence suggests that retailers more exposed to international trade experienced higher cost pressures that resulted in both temporary stockouts and higher prices.

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. 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 in a 3-digit COICOP classification, covering five major categories 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.

Using 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]

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

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

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

	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.
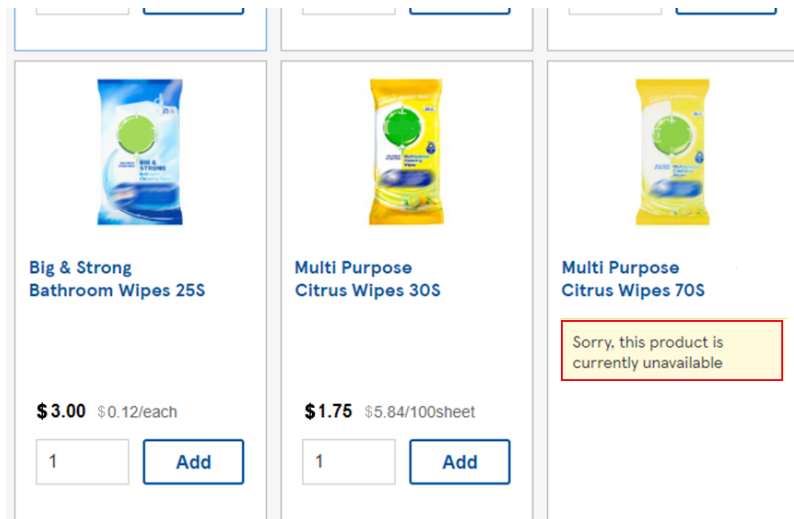

Figure 1: Identifying Stockouts on a Retailer's Website

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 high-frequency 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:

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

The second type of stockouts accounts for the fact that retailers discontinued many products

and removed them from their websites. Although some discontinued goods were replaced with new varieties, the total number of products available to consumers declined significantly in most countries. We therefore compute a complementary stockout measure, "Permanent Stockouts" (POOS), as the percentage decline in the number of available products in a sector relative to their average level in January 2020:

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

Finally, we define a broad measure of stockouts, all stockouts ($AOOS_{jc,t}$), as the sum of temporary and permanent stockouts.

To obtain aggregate 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:

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

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

3   Stockout Dynamics

Stockouts experienced substantial variation over the course of the crisis. In particular, three main patterns stand out. First, there was a large increase in temporary and permanent stockouts in the wake of the pandemic, affecting most countries and sectors. Second, after a year and a half, temporary stockouts returned to normal levels. By contrast, permanent stockouts still remain elevated in some countries and sectors. Third, stockouts are increasingly concentrated in fewer sectors, suggesting a gradual return to normalcy is under way.

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 14% in 2019 to over 35% in early May 2020. They recovered partially in the summer of 2020, but rose to reach nearly peak levels again by May 2021. This pattern is consistent with the percentage of firms reporting some kind of supply disruption in the "Small Business Pulse

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Survey" conducted by the U.S. Census Bureau between May 2020 and February 2022 (see Figure A1 in the Appendix).[10] By January 2022, all stockouts are still almost double their normal levels.

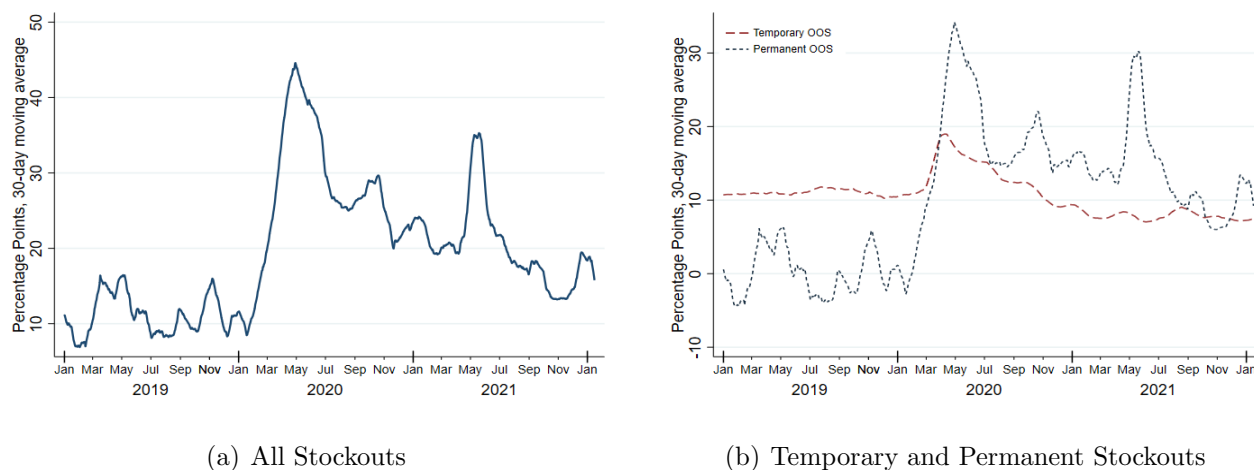(a) All Stockouts

(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 12% to 22% 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, they were once again peaking around 30% over pre-pandemic levels. They fell recovered again, but by early 2022, during the Omicron wave of the pandemic, the share of discontinued products remained at roughly half 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.
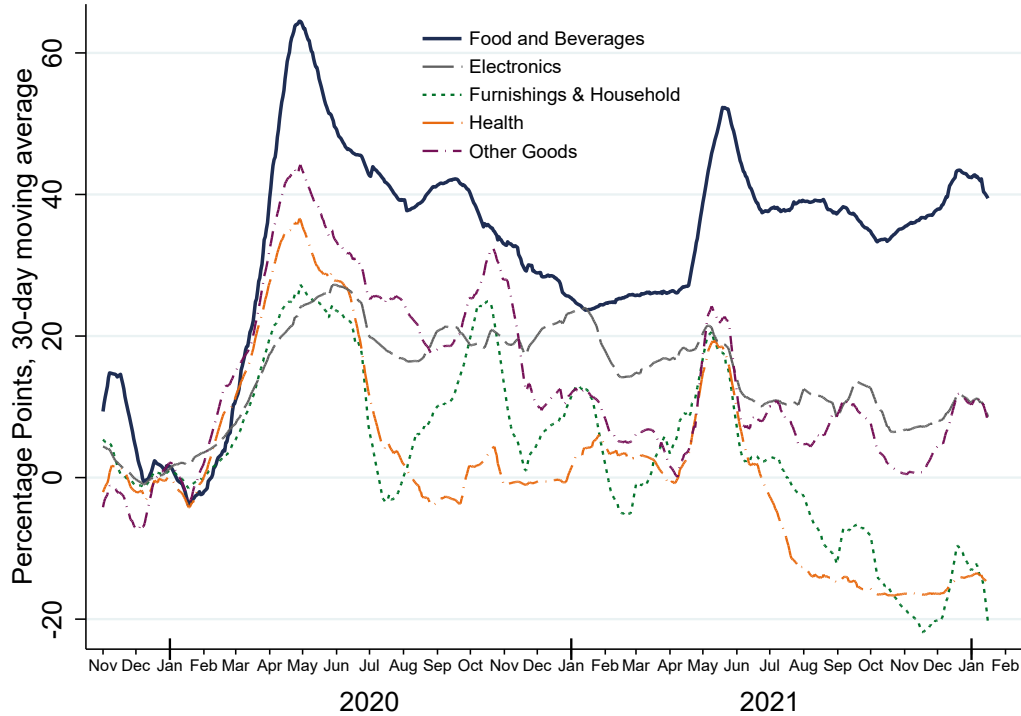
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[10]U.S. Census Bureau (2021).

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

As expected in a health crisis, stockouts rose first for health and personal care goods. Thereafter, stockouts quickly spread to other categories. In May 2020, the stockout increase ranged from 23 ppt for "Furnishings and Household" goods to above 60 ppt for "Food and Beverages." Some categories recovered gradually over time, and by May 2021 stockouts were finally back to normal in "Health," "Furnishings and Household," and "Other Goods." However, the disruptions were more persistent for "Food and Beverages," where stockouts remained above 30 ppt above pre-pandemic levels, and "Electronics," where they have risen over most of 2021. These findings are consistent with U.S. media reports on these two sectors, where supply problems in electronics are linked to global computer-chip shortages, and those in food to labor and raw material shortages.[11]

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

3.2 Other Countries

Stockout patterns identified in the U.S. data are broadly similar to those in other countries, but there are also important differences. Figure 4 shows both temporary and permanent stockouts for all seven countries. To facilitate the comparisons of temporary stockouts, in Figure 4(a) we plot the incremental change relative to the pre-pandemic levels, given by $TOOS_{c,t} - TOOS_{c,Jan2020}$.

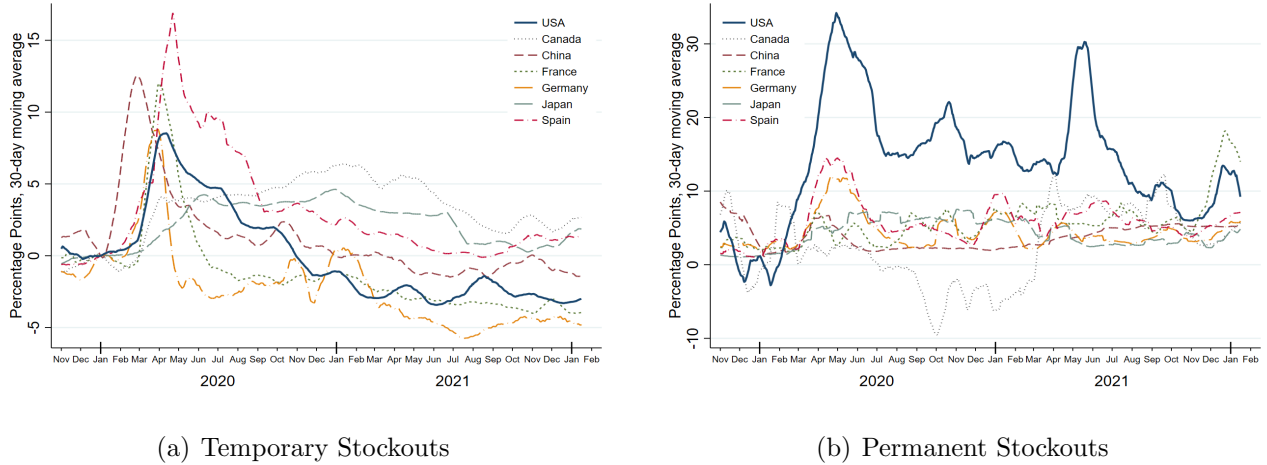|	
(a) Temporary Stockouts	(b) Permanent Stockouts

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. Yet, there are noteworthy differences in the timing and magnitudes of the changes. Temporary stockouts peaked first in China, where the pandemic started. Stockouts there rose by 12 ppt from their pre-pandemic levels during the month of February 2020 and then gradually declined back to normal around July 2020. European countries were next, peaking in April 2020 with an increase between 10 and 15 ppt. 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 the end of 2020. The two outliers here are Canada and Japan, where temporary stockouts rose only gradually, by around 5 ppt, and remained elevated.

The behavior of permanent stockouts differs a lot more across countries, as shown in Figure 4(b). At one end, countries such as China and Japan had no significant increase in permanent stockouts during the pandemic, and in Canada they decreased. This means that retailers in those

countries managed to continue offering roughly the same (or even higher) number of products for sale. By contrast, all other countries experienced substantial losses in product varieties. The increase in permanent stockouts was particularly large in France and United States. All in all, heterogeneity in stockout patterns, which we also document at a sector level, can be used to identify the effects of product unavailability on inflation rates across countries and sectors.

3.3   Evidence on imports from one U.S. retailer

To provide some evidence on temporary stockouts at the retailer and individual product levels, we examine micro data for one large U.S. retailers selling a total of 16,953 individual products (see Table 2).[12] This retailer specializes in household products, with stockouts levels that averaged 5.6% and lasted about 28 days. About 75% of its products are imported.

	U.S. Retailer
Number of products	
imported	12,275
domestic	4,678
Fraction of stockouts, %	5.6
imported	5.5
domestic	4.1
Stockout duration, days	27.6
imported	26.3
domestic	18.2
Product inflation, ann %	0.86
imported	2.19
domestic	-1.53

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

Imported goods have more stockouts and they last over a week longer than those for domestic goods. This suggests that global supply factors are influencing product availability. Imported goods also exhibited higher average inflation during this time period. In the next Section, we examine the links between stockouts and inflation for both imported and domestic goods more systematically.

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

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. Price indices constructed with online data exhibit similar inflation dynamics, as shown on the graph on the right.

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). We first study the relationship between stockouts and inflation at disaggregate levels (3-digit sector and retailer levels). Next, we break down the results by sectors according to their import intensity, or at the micro level by distinguishing goods that are domestically produced from those that imported. To the extent that the supply of imported goods was more costly during the pandemic, we expect more stockouts and higher prices for imported goods.

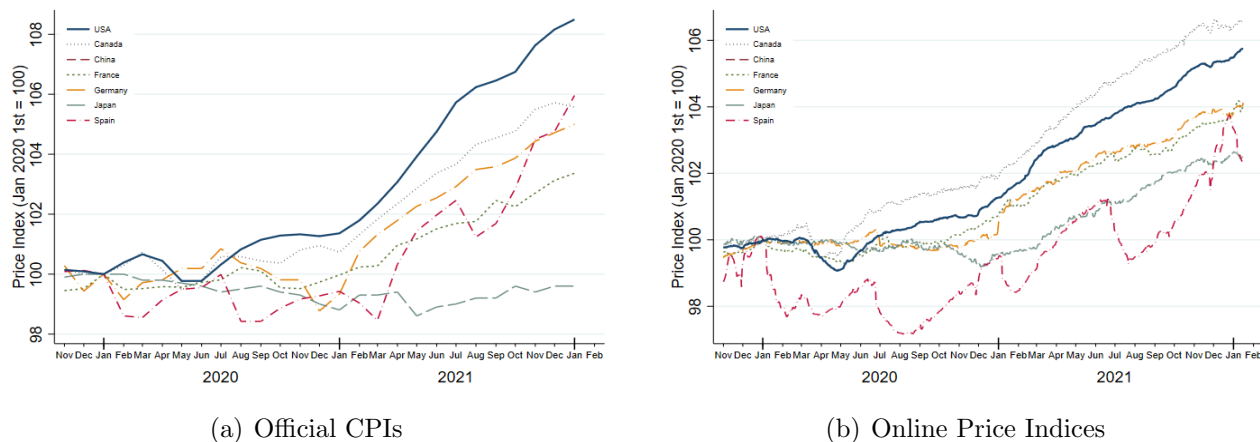

(a) Official CPIs

(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.

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4.1 Sector-level evidence

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 connection between stockouts and prices is not clear. 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.

The effects of shortages on inflation are likely to take several weeks or months, 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 across seven countries. For now, we treat such stockout disturbance as exogenous, and we relax this assumption in the next section.

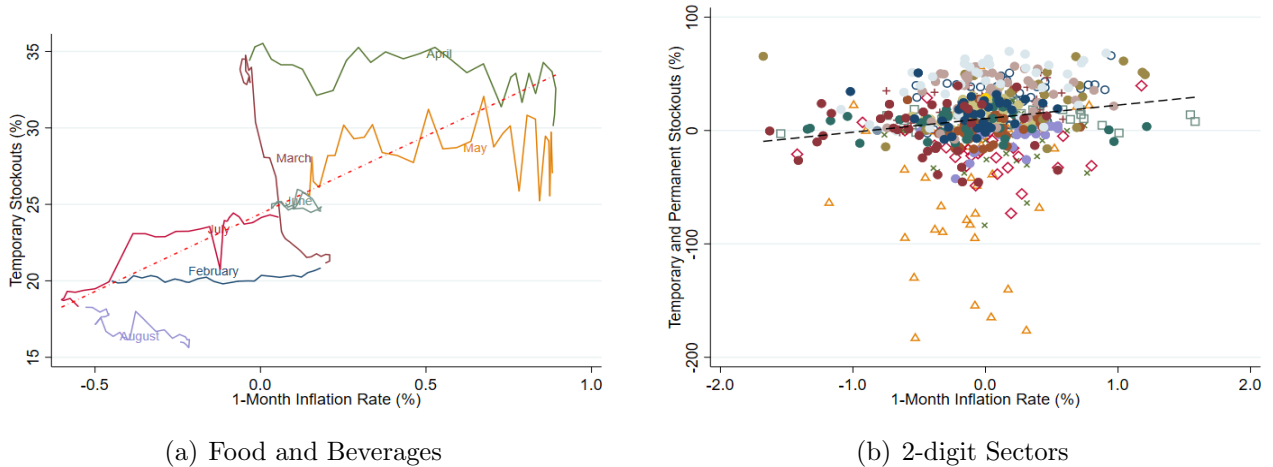| (a) Food and Beverages | (b) 2-digit Sectors |

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 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.

We first 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): $OOS_{cj,t} = c_j +$

$\beta_{cj}OOS_{cj,t-1} + \epsilon_{cj,t}$.[13] The residual term $\epsilon_{cj,t}$ is the measure of the stockout shock. We then estimate the simultaneous response 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:

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

Specification (4) conditions on the history of shocks $\epsilon_{cj,t-l}$, where $l = 0, ..., L$, lags of endogenous variable $X_{j,t-n}$, $n = 1, ..., N$, and country-sector dummies D_{cj}. In both estimations, we use $L = N = 4$. We estimate (4) independently for each dependent variable X by weighted OLS regression. We conduct 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 $h = 0, 1, ...$

Figure 7 shows that stockout shocks are associated with significant and persistent responses of both sector stockouts and inflation for seven countries in our data. Temporary stockouts respond by around 2 ppt on impact and decrease slowly, with a half-life of roughly 9 months. 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 the temporary stockout impulse, and 0.21 ppt after the permanent stockout impulse. 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 in the United States. Although it takes about a month for inflation to respond to a stockout disturbance, the response is large and protracted. For example, the estimates suggest that a doubling of the 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 within several weeks.

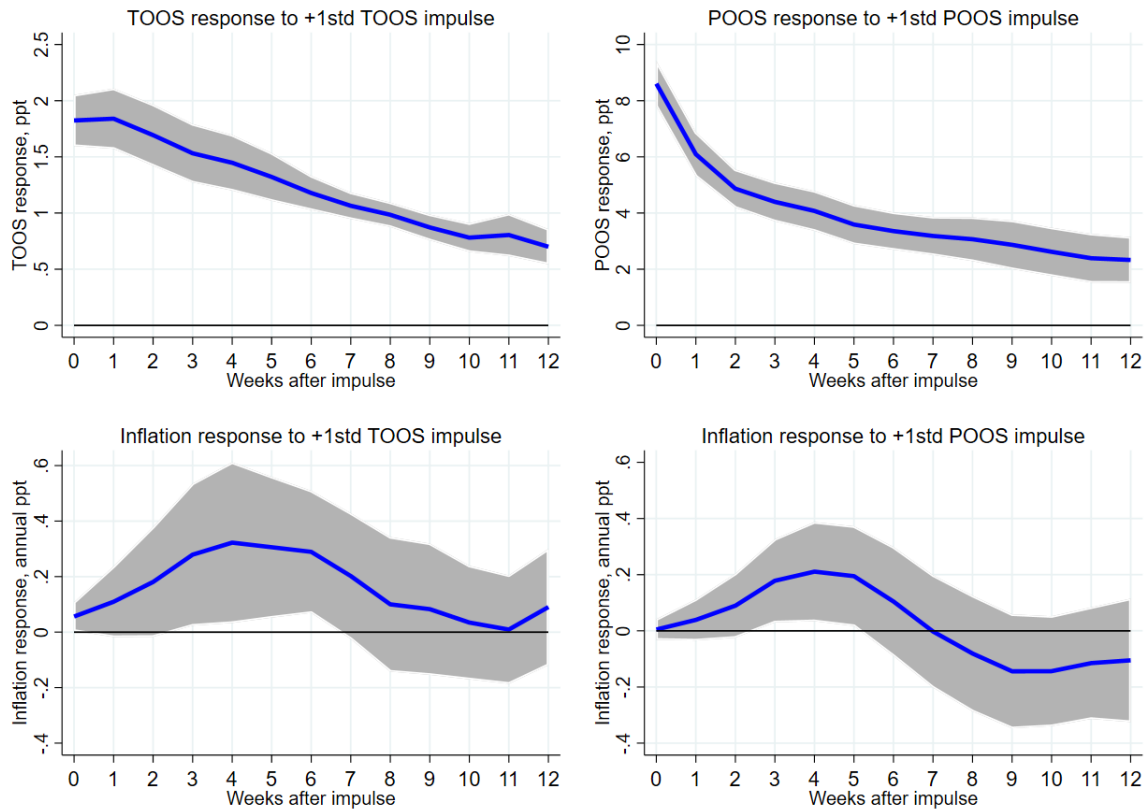[13]Adding higher-order lags does not materially improve the results.

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 inflation (in ppt, annualized rate, bottom). Shaded areas outline 90% bands based on Driscoll-Kraay standard errors.

We extend these results by splitting the 235 subsectors in seven countries into two groups: 109 sectors with a low share of imports in total consumption (share below weighted median across sectors in all countries, at 0.24) and 126 sectors with high share (above 0.24).[14] 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 disturbances, trade-intensive sectors experience higher response of temporary stockouts, by 0.6 ppt on impact, and larger and more persistent inflation responses, with 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

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[14]We obtain measures of trade intensity 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.

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. By contrast, there is no strong link between trade exposure and inflation responses to fluctuations in discontinued products.
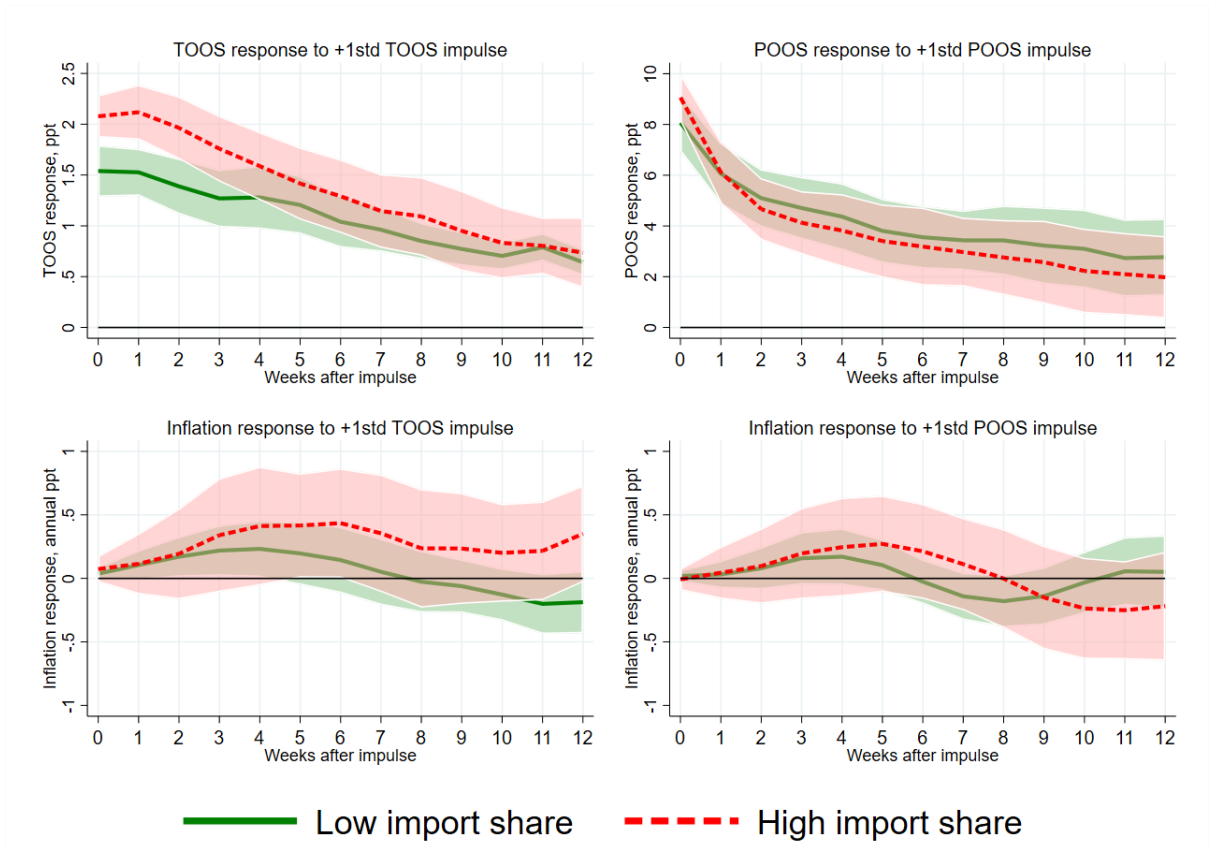

Figure 8: Responses to a Stockout Shock in a 3-digit sector in 7 countries, by import share in consumption

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 (>0.22). Shaded areas outline 90% bands based on Driscoll-Kraay standard errors.

These results coalesce with analysis in Alessandria, Khan, Khederlarian, Mix, and Ruhl (2021) who point out that inventory management approaches differ for imported and domestic goods. For example, imported goods are held longer in inventory, and inventory investment tends to be more sensitive over the business cycle than for domestic goods. Alessandria, Khan, Khederlarian, Mix, and Ruhl show that transitory changes in shipping delays can raise prices, especially for imported goods.

4.2 Evidence from a large U.S. retailer

So far, we have presented sector-level evidence that shows shortages are associated with economically significant and protracted inflationary effects, and these effects are larger in trade-intensive sectors. We now complement the sector-level evidence with results for individual products within sectors.

We estimate price behavior before and after temporary stockouts using micro data for the large U.S. retailer introduced in Section 3.3. 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. Define a *cumulative price-relative* $\tilde{p}_{ij,t_0,t}$ as the cumulative price change for product i between dates t_0 and t relative to 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 product prices evolved before and after a stockouts, we compute the average price-relative, $\tau = 1, 2, ...$ days before and τ 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, $\sum_{T_0}$, $\sum_T$ are summations over all stockouts, and ω_{ij} are product weights.[15] 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 summations in (5) and (6).

Figure 9(a) plots the average price-relative before and after stockouts. For this retailer, products experiencing stockouts have higher prices relative to other products, especially after stockouts. For returning products, prices are 0.6 ppt higher relative to other products after two weeks. Figure 9(b) shows that higher post-stockout price is driven by imported products, while prices of domestically produced products return to average levels within a couple of weeks.

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[15]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.
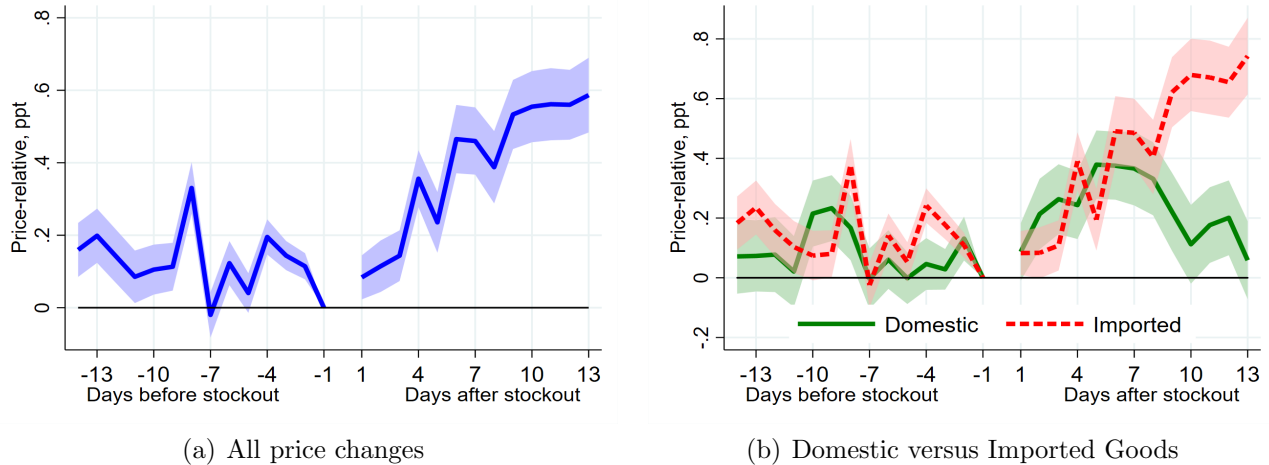
Figure 9: Price Levels Before and After a Stockout For a Large U.S. Retailer

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.

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 large 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 cost over time and lower stockout duration, and/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.

5   Analysis of Costs, Prices, and Stockouts

In Section 4, we treated stockouts as exogenous. This is a strong assumption, of course, because firms decide their inventory levels (and therefore stockout rates) jointly with their prices, and taking into account their market conditions. This means that stockouts are endogenous, and, like prices, depend on the cost of supplying products to consumers and other sector factors. To incorporate such a mechanism in the analysis, we develop a model of a 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, and therefore, this model is not suited for understanding the dynamics of discontinued products. We use the

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model to derive an empirical specification for estimating the cost underlying the joint dynamics of temporary stockouts and prices at a sector level. We then construct empirical responses of sector stockouts and inflation to estimated cost shocks.

This approach provides two additional contributions in this paper. 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 stockouts and inflation, while taking into account the endogeneity of stockouts with respect to prices and the underlying costs.

5.1   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 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 hire labor and produce a homogeneous good using a Cobb-Douglas technology.[16] 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 their 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 assumption here is that retailer i in sector j places its order $q_{jt}(i)$ and chooses its price $P_{jt}(i)$ prior to realization of idiosyncratic demand shock v, but after realization of the sector shocks. This assumption introduces the 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 price decision. Under

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

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 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 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.[17]

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

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

Given its price $P_{jt}(i)$, stock available for sale $z_{jt}(i)$, and 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's problem is to choose $z_{jt}(i)$ to maximize

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

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

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

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:

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

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[17]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.

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.

5.2 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 $\Psi(v_{jt}(i)) = \int \min\left(v, v_{jt}(i)\right) dF(v)$.[18]

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 $(1-\delta_j)E_t\left[Q_{t,t+1}\Omega_{jt+1}(i)\right]$. 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 too 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 do that in the next section.

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

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

j. This yields the following condition:

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

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.

5.3 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 derive its approximation. 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. Coefficient b_j in (B.9) 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 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 rate. The residual term ε_{jt} are zero-mean innovations to period t replacement cost that are uncorrelated with period-$(t-1)$ stockouts.

5.4 GMM Estimation

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

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

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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 $\boldsymbol{Z_t}$ of $N \geq 1$ instruments. We define the following N orthogonality conditions for GMM estimation:

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

where Z_t^i is the ith 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, 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) in the United States and all 7 countries. GMM estimation uses the following instruments: $\boldsymbol{Z_t} = [OOS_{jt-1}, OOS_{jt-2}, p_{jt-1}, p_{jt-2}, p_{jt-3}, \boldsymbol{X_{t-1}}, \boldsymbol{X_{t-2}}]'$, where $\boldsymbol{X_t}$ is a vector of aggregate (monthly) controls. These controls include the change in the lockdown stringency index from "Oxford-Our World in Data,"[19] 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 3-month Treasury bill rates as a measure of the risk-free rate R_t. We compute 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 0.0046% (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.

5.5 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,"

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

"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.[20]

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

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.

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

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[20]When 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.

higher. But if the firm can increase its price, the demand for the firm's 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 2022.[21] 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.

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.

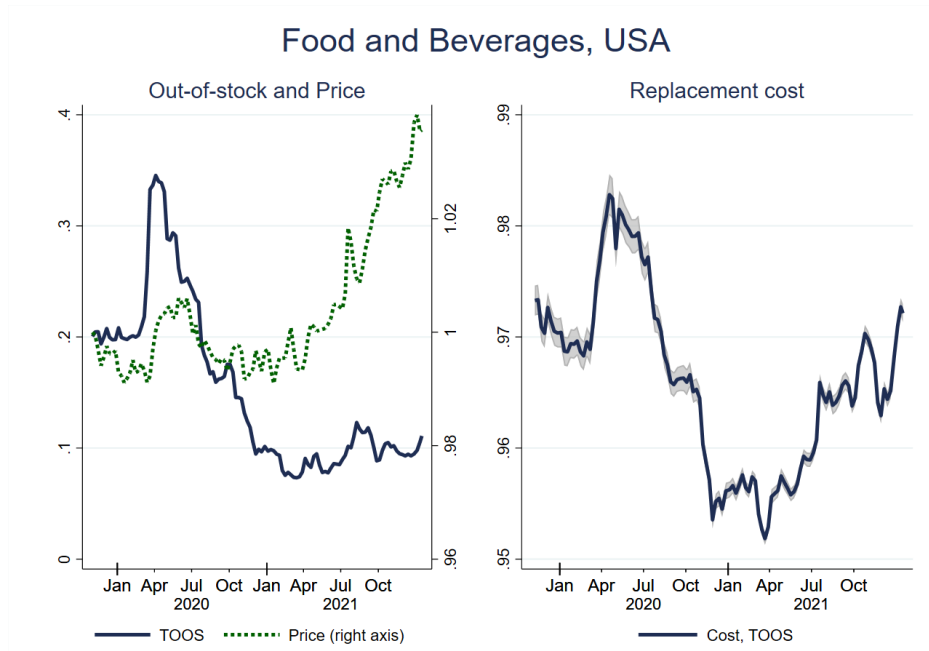[21]See Appendix Figure A5 for details on the changes over time in each sector.

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.

5.6   Inflation Responses to Cost Shocks

In Section 4, we estimated stockout and inflation responses to stockout disturbances, treating those disturbances as exogenous. The model in this section provides a mechanism according to which stockouts and prices respond endogenously to exogenous variation in real replacement cost. We already estimated the replacement cost process using observed variations in sector prices and stockouts. Therefore, we can now estimate dynamic responses of stockouts and inflation at a sector level to that sector's cost 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 estimated responses.
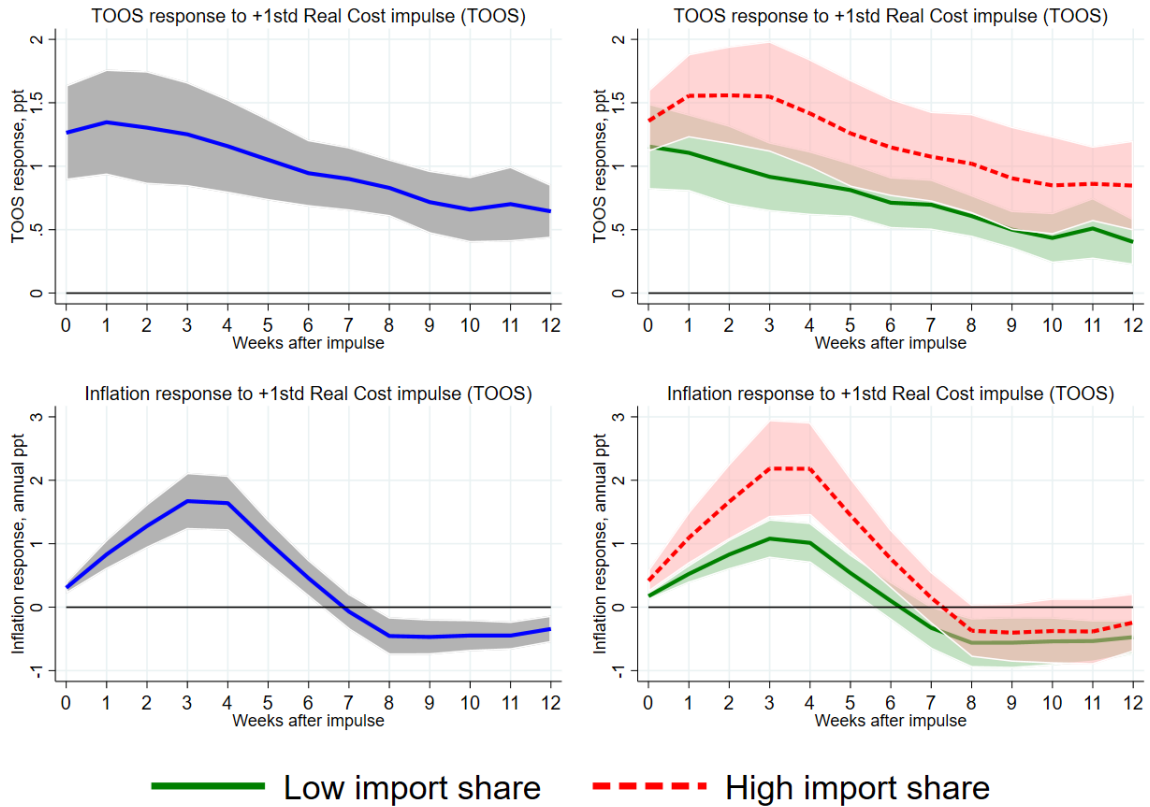
Figure 11: Responses to Real Replacement Cost Shocks in 3-Digit Sectors, in 7 Countries

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.

6 Conclusion

Rising inflation in 2020 amid the COVID-19 pandemic spurred a lively debate on whether the years of low inflation were ending. 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 present product- and sector-level 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, shortages are temporary at first but gradually become more permanent in nature and increasingly concentrated in only 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 factors, and the diffusion of cost pressures via domestic and international production networks.

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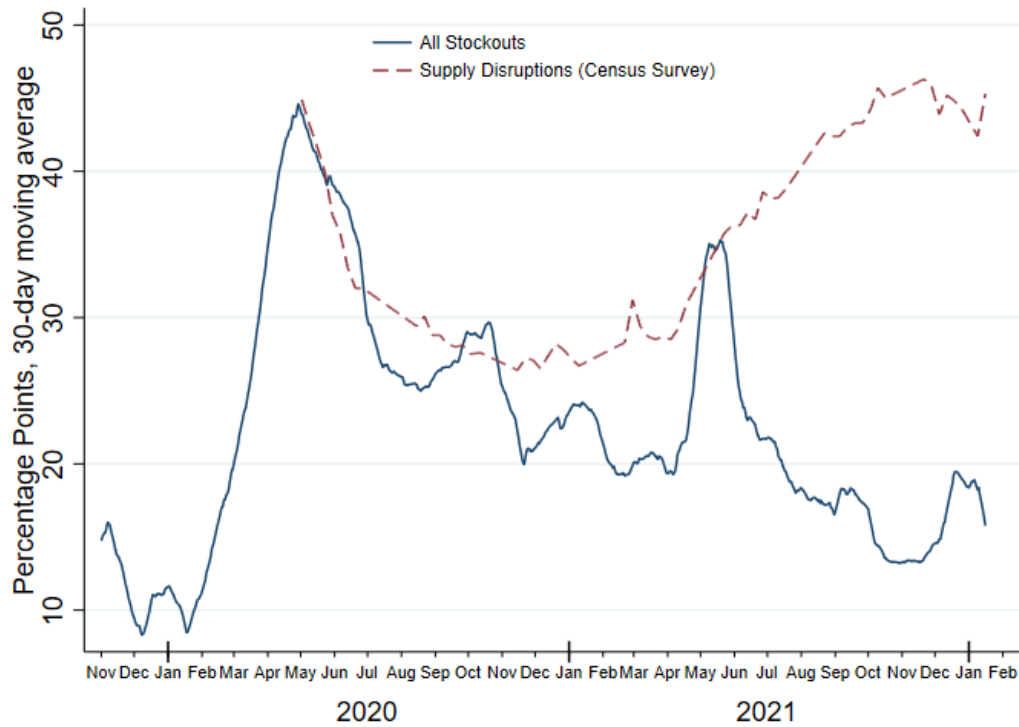# A Additional Tables and Figures

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 supply disruption 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.
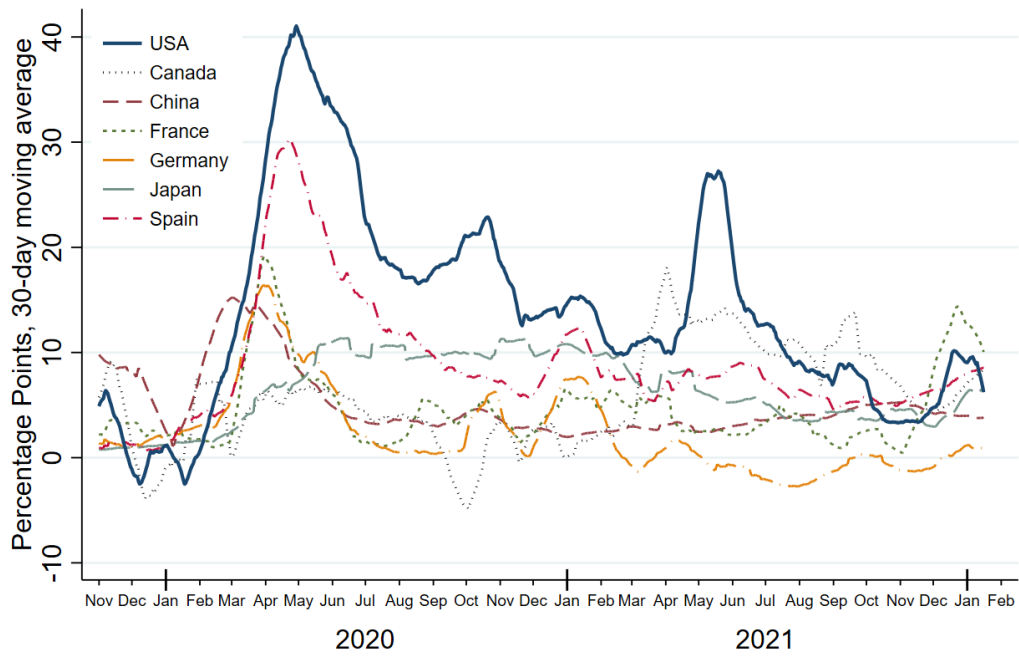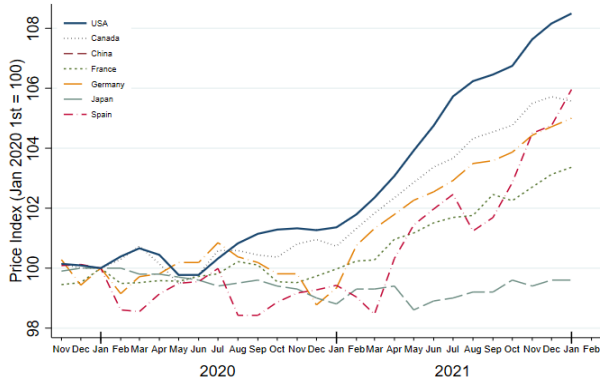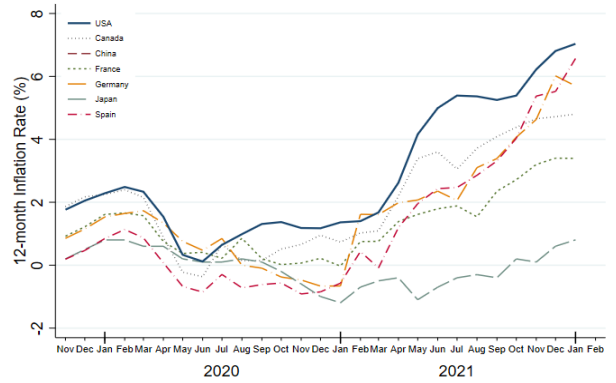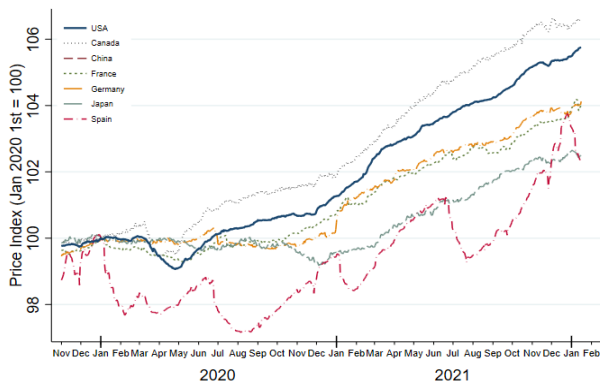
Figure A2: All Stockouts in 7 Countries

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 $AOOS_{t,c} - AOOS_{Jan2020,c}$.
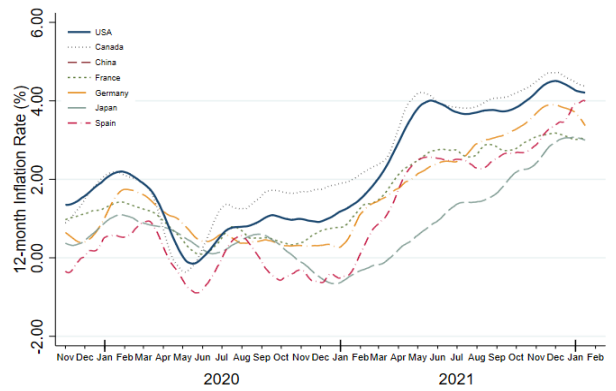
(a) CPI - Price Index
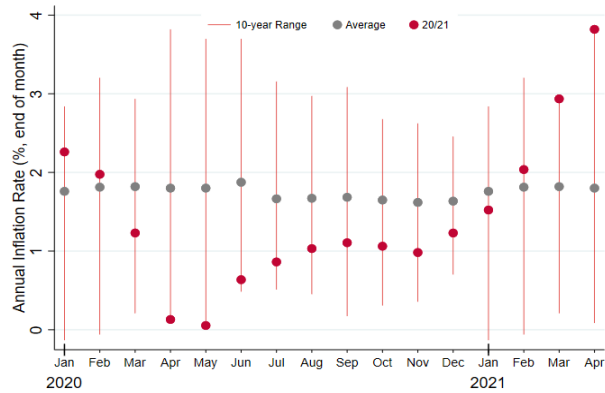
(b) CPI - Annual Inflation
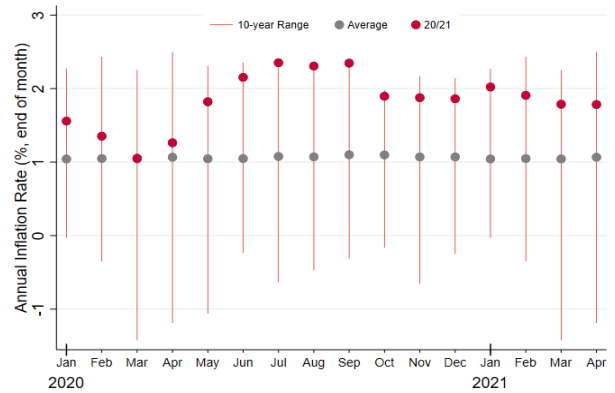
(c) Online - Price Index

(d) Online - Annual Inflation

Figure A3: 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 A4: 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 (right) 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	-0.004	-0.004	-0.007	-0.014
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Obs.	5,357	5,204	3,896	974	1,461
Annual inflation					
OOS (%)	0.004	0.023	0.007	-0.031	-0.109
	(0.001)	(0.001)	(0.001)	(0.005)	(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	0.026	0.015	0.012	-0.009	-0.011	-0.045
	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(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.
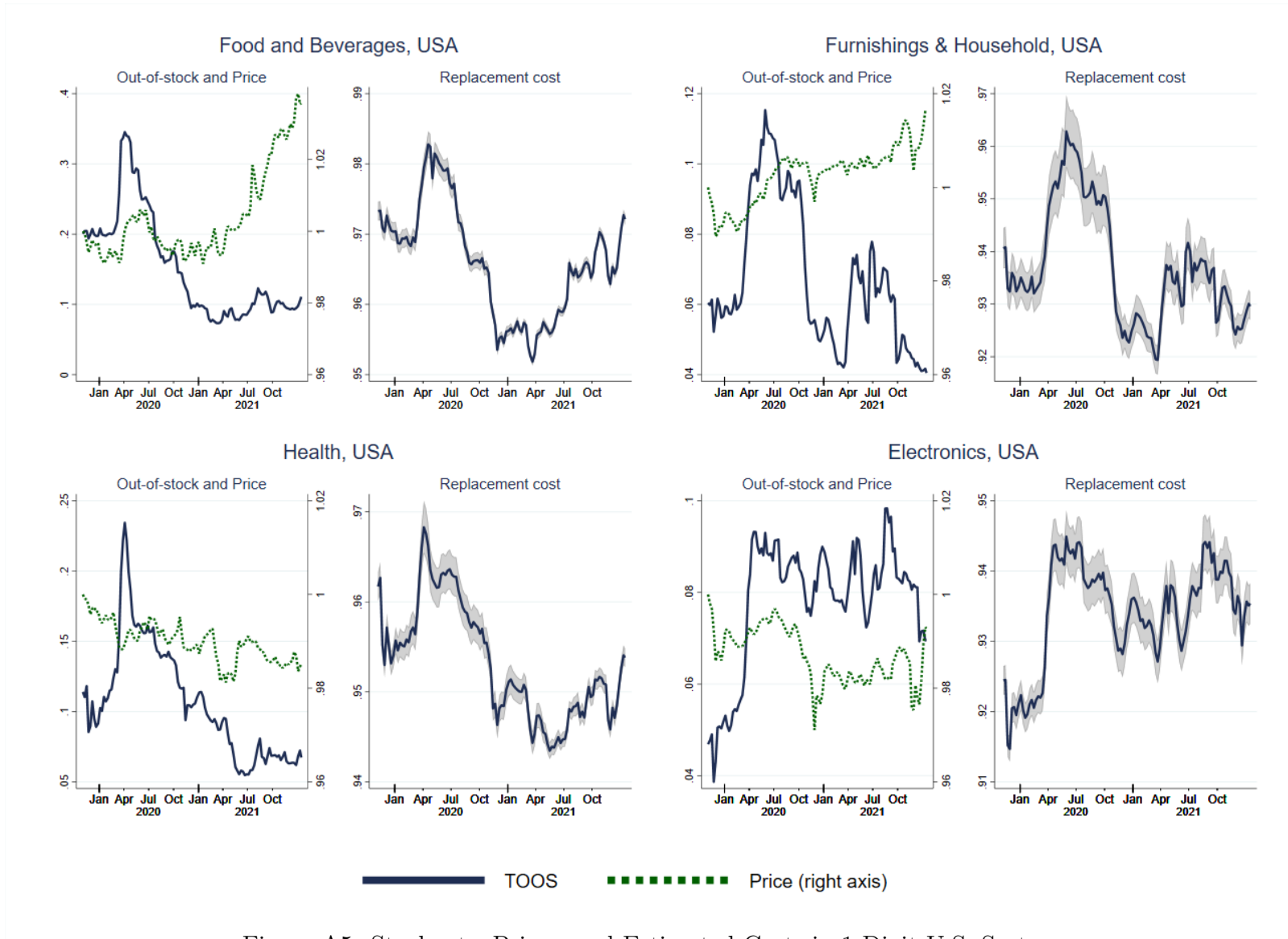
Figure A5: Stockouts, Prices, and Estimated Costs in 1-Digit U.S. Sectors

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:

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

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

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

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

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

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

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

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

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

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 technology[22]

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

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

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

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.[23] 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):

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

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.

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

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

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

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

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

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

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

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 $b_j^+ = \frac{cov(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{var(OOS_{jt-1})}$ 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

$$\tilde{\varepsilon}_{jt} = \triangle\tilde{\varepsilon}_{jt} + \rho_\varepsilon b_j^+ OOS_{jt-1} + \rho_\varepsilon \epsilon_{jt-1}, \qquad \text{(B.8)}$$

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:

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

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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 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, $\rho_\varepsilon \frac{cov(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{var(OOS_{jt-1})}$, 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 $\frac{cov(\tilde{\varepsilon}_{jt-1}, OOS_{jt-1})}{var(OOS_{jt-1})}$. 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 ε_{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.