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Shipping Prices and Import Price Inflation

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August 30, 2022

Abstract

During the pandemic there have been unprecedented increases in the cost of shipping goods accompanied by delays and backlogs at the ports. At the same time, import price inflation has reached levels unseen since the early 1980s. This has led many to speculate that the two trends are linked. In this article, we use new data on the price of shipping goods between countries to analyze the extent to which increases in the price of shipping can account for the increase in U.S. import price inflation. We find that the pass-through of shipping costs is small. Nevertheless, because the rise in shipping prices has been so extreme, it can account for between 3.60 and 5.87 percentage points per year of the increase in import price inflation during the post-Pandemic period.

1 Introduction

After the first months of the pandemic passed and the economy began to re-open, two things became central to the national discussion—supply chain disruptions and price increases. The supply chain disruptions took many forms from delays and backlogs at ports ([reference](#)) to low inventory in key sectors ([Leibovici and Dunn \(2021\)](#)). The April 2022 Economic Report of the President featured a chapter on supply chains, stating "[t]hese highly publicized disruptions and product shortages made the public painfully aware of the many steps involved in getting a product produced, transported, and placed on shelves or doorsteps." [PDF](#) These supply chain issues can be seen in the stark increase in the price of shipping goods between countries (Figure 1), which has increased almost 7-fold during the Pandemic. Meanwhile, the U.S. has experienced some of the highest annual rates of inflation since the 1980s. [reference](#)

Figure 1 shows the sharp increase in import prices, as measured by an import price chain index from the Bureau of Labor Statistics, and the sharp increase in shipping costs, measured with the Freightos Freight Chain Index (found [here](#)). The simultaneous increase in the price of shipping goods and inflation has led to speculation that the two issues are linked. Pete Buttigieg, Secretary of Transportation, noted in late 2021 that "[t]here's no question that when you have a scarcity of access to shipping, you're going to see upward pressure on prices, and that's going to be part of our challenge when it comes to inflation" [reference](#).

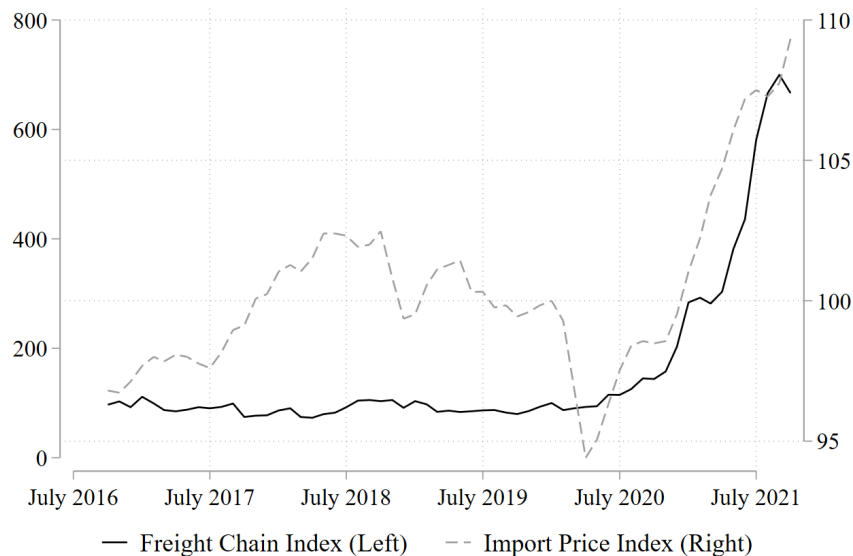


Figure 1: Freight Price Index and Import Price Index

The figure above displays two chain indexes with January of 2020 as the base month. The solid line, graphed on the left axis, displays the price of freight shipping and the dotted line, graphed on the right axis, displays import prices over time.

In this article, we will examine the relationship between shipping costs and price inflation. The main exercise is an examination of the pass-through of shipping costs to import price inflation using variation across products in exposure to shipping price increases.

Our analysis proceeds in two steps. First, we create a commodity-level measure of exposure to the increase in

shipping prices. To do so, we leverage a new dataset on the cost of shipping goods by sea between trade partners and the U.S. We merge the shipping prices with data from Comtrade which gives the share of a commodity imported from each partner country. Then, for each commodity, we average shipping price growth across trade partners, weighted by the import share of each trade partner.

Second, we merge our commodity-level measure of shipping prices with commodity-level import price data from the BLS. Finally, we use our dataset to examine the relationship between import price inflation and our measure of exposure to the increase in shipping prices.

In general, we find a modest amount of pass-through from shipping price growth to import price inflation. After the pandemic, we estimate that a 1 percentage point increase in shipping price growth leads to an increase in import price inflation of 0.064 percentage points. While this is a fairly modest number, the increase in shipping prices has been so extreme during the Pandemic that the implications for import price inflation are large. On average, shipping price growth increased by 86 percent which implies an increase in import price inflation of 5.87 percentage points per year.

We then look at the heterogeneity of this pass-through over time and across commodity types. We find a more significant pass-through after 2020 and for product types that ship a higher share of goods by sea than other types of transportation as well as for products with a higher ratio of the cost to ship by sea to the cost of the good. We also find more pass-through in Food and Materials goods as opposed to Consumer Goods and in Machines, Electronics and Parts. This pattern seems to suggest that whether the type of good is perishable and whether it is an intermediate good versus final good might matter for the pass-through.

Finally, we use our estimates of the pass-through from shipping costs to import prices to create an upper and lower bound on the impact on inflation. We find that the rise in shipping costs during the Pandemic can account for between 68 and 111 percent of the increase in import price inflation and 15 and 25 percent of the increase in PPI. The lower impact on PPI is because of the modest impact that import prices have on domestic inflation as found by [Amiti et al. \(2021\)](#) and [Amiti et al. \(2019\)](#). We conclude that while the disruptions in the shipping industry played a large role in import price inflation, other factors such as demand shocks ([Guerrieri et al., 2021](#)), fiscal stimulus ([de Soyres et al. \(2022\)](#)), and other supply shocks ([Leibovici and Dunn, 2021](#); [LaBelle and Santacreu, 2022](#)) are necessary to generate the extreme rise in domestic prices.

The literature on the relationship between supply chain disruptions and inflation is small, but growing. The theoretical literature shows that trade fluctuations and supply chain disruptions will impact U.S. inflation with important implications for monetary policy. [Leibovici and Santacreu \(2015\)](#) develop a small open economy model with trade and show that policymakers should take trade fluctuations into account when developing monetary policy. [Wei and Xie \(2020\)](#) show that as supply chain complexity increases over time, monetary policy targeting PPI inflation yields lower welfare losses than monetary policy targeting CPI inflation. Finally, [Comin and Johnson \(2021\)](#), using a New Keynesian model with a small open economy, find that firm-level constraints (e.g. temporary capacity limits for foreign firms) increase import price inflation.

In the empirical strand of the literature, papers attempt to measure the pass-through from supply chain disruptions to prices. [LaBelle and Santacreu \(2022\)](#) find that exposure to foreign shocks through global value chains has a negative and significant effect on output and employment—increasing month-over-month backlogs by 1 percent increases the industry inflation rate by 0.24 percentage points, while the same increase for delivery

times causes an increase of about 0.26 percentage points. In their report from November 2021, [Amiti et al. \(2021\)](#) find that a 10% increase in import prices leads to a 2.6% increase in PPI post-COVID versus a 1% increase pre-COVID. Finally, using their Global Supply Chain Pressure Index (GSCPI), which combines information on maritime and air freight costs with country-level manufacturing, [Abbai et al. \(2022\)](#) show that there is correlation between the GSCPI and different international consumer price indexes and producer price indexes. We build on this work by using a novel dataset of shipping prices by source country to build commodity-specific measures of exposure to the increase in shipping costs.

The rest of this paper is organized as follows. Sections 2 and 3 explain our data and methodology. Section 4 presents our main findings analyzing the pass-through from shipping costs to import prices. Section 5 uses results from the previous sections to calculate a range for the impact of shipping costs on import price inflation and producer price inflation. Finally Section 6 concludes.

2 Data

In this section, we describe the various data sources we use and how we combine them. A key limitation to our approach is that the data on import price inflation varies at the commodity level while the data on shipping prices is at the country level. Therefore, it is not obvious how to combine the two sources of information. Ideally, we would like to know the extent to which a commodity is exposed to the increase in shipping costs, but we only know the extent to which imports from a given country are exposed to the rise in shipping costs. To circumvent this problem, we use additional data on trade flows available at the commodity by country level.

After discussing the details on the various data sources in this Section, we define our measure of shipping costs in Section 3.

2.1 Shipping price data

An important contribution of this project is to use a novel dataset on the price of shipping goods to the United States. The data on shipping costs comes from [Drewry Shipping Consultants](#), who produce monthly or bimonthly time series on shipping costs between major port pairs across the globe since 2006. Their Container Freight Rate Index represents an all-in spot-market rate that includes all maritime charges at the origin and destination ports. These charges include the base rate, fuel surcharge, and the terminal handling charge for a 40 foot-equivalent dry container of goods.

The list of port pairs included in this article are found in Appendix B.1. For countries without ports in the dataset, we use our best judgment to match them with neighboring ports. For example, we map Ireland to the U.K. port. The port-to-country crosswalk is found in Appendix B.1 in Table 16. Then, for all the ports, we collapse to a quarterly level by taking the mean of all the shipping costs in that quarter before mapping each series from a destination country to the United States over time.

Figure 2 shows the growth in shipping costs between 2020 and 2021 between various countries to the United States. The change in shipping costs varies substantially across countries, with Brazil and Thailand experiencing the largest growth in 2021 and Mexico, Australia, and South Africa seeing very small increases. The cross-country variation in the change in shipping costs will allow us to examine the impact of shipping costs on

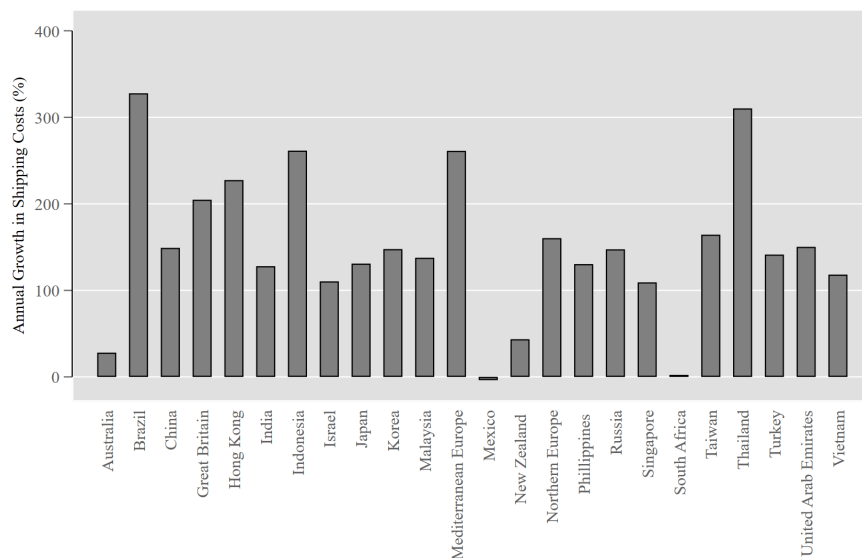


Figure 2: Annual Growth in Shipping Costs by Country

The figure above shows the annual increase in shipping costs for all the ports in our data set in 2021Q4.

commodity prices based on the countries from which those commodities are imported.

2.2 Import Data

We use several data sources to gather information on import prices, shipping methods, and import volumes. Annual import volumes by commodity type and partner country come from the United Nations Commodity Trade Statistics Database (Comtrade). We use this data to create our measure of exposure to increases in shipping costs by commodity type.

We then supplement our dataset with information on the quantity and cost of goods shipped by sea from the United Nations Conference on Trade and Development ([UNCTAD](#)), which is available only in 2016. The UNCTAD has information at the HS6 level about the volume and the cost of goods shipped between countries by different methods of transport, including air, rail, roads, and sea. For each country-good pair, we sum the value of goods shipped by all methods and create the share of the value for that good that is shipped by each method. In Section 4, we use these shares to test whether shipping prices are more important for goods that are more reliant on sea transportation. We also use the UNCTADstat data to calculate a ratio of the cost of transport to the value of the good. Each good has information on the cost of transport and the value of the good shipped by that transport type once it reaches its destination.

Table 1 shows summary statistics across HS6 commodities on the share of value shipped by each transport type. On average across product types, about 53% of value is shipped by sea compared to 27% by plane, 11% on the road, and 9% via railroads. Table 2 lists the commodities with the highest and lowest value shipped by sea. The highest value shipped by sea includes beverages and spirits, packaged meats and coffee. These generally non-perishable items that are sourced from countries with which we do not share a border such as Brazil for coffee and Russia for iron. The bottom 5 include things like fresh fruits and vegetables for whom are biggest

Table 1: Shares Shipped by Different Transport Types

Average Share of Goods Shipped by Transport Type					
	Mean	Median	SD	Minimum	Maximum
Sea	0.529	0.510	0.154	0.010	0.902
Road	0.113	0.019	0.166	7.10e-08	0.849
Air	0.269	0.275	0.166	0.0002	0.688
Railway	0.089	0.047	0.107	1.57e-07	.491
Commodity Types	86				

The shares are calculated using the final merged data set described below in Section 3.2. For each HS6-level product type, we sum the value of that product type shipped by each of the transport types to create an overall measure of the value of goods shipped for commodity. The value for each transport type is then divided by the sum.

Table 2: Top and Bottom 5 Product Types, by Share Shipped by Sea

Top 5 Product Types		Bottom 5 Product Types	
Product Type	Share Shipped by Sea	Product Type	Share Shipped by Sea
Beverages and spirits	0.886	Vegetables	0.0998
Meat	0.883	Medical Instruments	0.281
Iron and steel	0.859	Edible fruit and nuts	0.317
Coffee, tea, and spices	0.781	Pharmaceutical products	0.418
Inorganic chemicals	0.779	Copper and copper goods	0.437

The table above shows the HS2-level products with the highest and lowest share shipped by sea across the final merged dataset. The mean share shipped by sea across the top 5 commodities is approximately 84%, versus 53% in the overall dataset.

trade partner is Mexico with whom other options such as truck and rail exist.

2.3 Import Prices

Finally, data on import prices at the HS-code level comes from the Bureau of Labor Statistics Import Price Indexes. The import prices are monthly unadjusted import prices at the HS2 or the HS4 level, representing prices at the level of a product or a category of commodities. The data is then collapsed to a quarterly level for HS2 and HS4 commodities. Table 3 displays summary statistics for the annual growth in import prices before and during the COVID-19 Pandemic for three different samples. The import price data is merged with the UNCTADstat data on the share of value shipped by different transport types, as described in subsection 2.2. The first sample includes all of the commodities that appear in the UNCTADstat data and the BLS import price series. The second sample includes all commodity types with a share shipped by sea above the 75th percentile, and the third has a share shipped by air above the 75th percentile. The mean, median, and standard deviation of all categories increased during the pandemic. However, commodities shipped by sea increased in price by 5.6 points while commodities shipped by air only increased by about 2.1 points.

Table 3: Import Price Inflation Pre-Pandemic versus Pandemic

Import price inflation			
Mean	All Commodities	75th Percentile Sea	75th Percentile Air
Pre-pandemic	1.304	2.233	-0.098
Pandemic	6.680	7.843	2.143
Median			
Pre-pandemic	0.264	0.995	-0.254
Pandemic	1.761	2.203	0.755
Standard Deviation			
Pre-pandemic	10.852	12.056	4.388
Pandemic	18.267	16.859	10.608

The statistics are calculated using the raw UNCTADstat merged with raw import prices from the BLS , described below. Pre-Pandemic is defined as 2011Q1 to 2020Q1, while the pandemic period is from 2020Q2 to 2021Q4. The data is at the HS2 and HS4 levels.

2.4 Combining the data sources

To measure pass-through of shipping costs to prices in the United States, we need to combine the shipping cost index, import prices, import volumes, product-level shares shipped by sea, and oil prices. To begin, we merge the quarterly HS4 import prices with the shipping cost exposure index described above. We also linearly interpolate any missing shipping cost index values, if the preceding and following shipping cost index values are non-missing. Then we merge in the share of value shipped by different transport types and annual import volumes from Comtrade. After saving the data that merges at the 4-digit level, the process is repeated for 2-digit sectors and any commodities that don't merge for 4-digit values. Finally, we drop any sectors in chapter 27, which represents fuel products, and merge in quarterly Brent crude oil price per barrel. Regression results controlling for oil prices are in Appendix A.1.

3 Methodology

3.1 Measure of exposure to shipping price increase

We are trying to determine the impact of shipping costs on price inflation for an average product. To do this, we need a measure of shipping cost exposure by product. We combine the quarterly country-level shipping cost data with the annual Comtrade data on import volumes. For each commodity ω , we calculate a measure of shipping cost exposure as

$$S_{t,\omega} = \sum_j \frac{R_{j,t} - R_{j,t-1}}{R_{j,t-1}} \gamma_{j,t-1}(\omega) \quad (1)$$

where $R_{j,t}$ is the price of shipping from country j to the U.S. at time t and $\gamma_{j,t-1}(\omega)$ is country j 's import share of good ω . We use the lagged values for import shares so that substitution between routes does not bias the

Table 4: Shipping Cost Exposure Pre-Pandemic versus Pandemic

Shipping Cost Exposure	Mean	Median	SD	Min	Max	Commodities
Pre-pandemic	4.313758	2.140413	21.84416	-51.40384	112.6588	1316
Pandemic	85.85074	79.43548	66.8617	-23.56436	327.7778	1311

The statistics are calculated using the shipping cost exposure measure from Comtrade before it is merged into the other pieces of the dataset. Pre-Pandemic is defined as 2011Q1 to 2020Q1, while the pandemic period is from 2020Q2 to 2021Q4. The shipping cost growth is at the HS2 and HS4 levels combined.

price increase. $S_{t,\omega}$ is intended to measure a commodity’s exposure to a shipping price shock. Next, we merge our data on the commodity-level shipping exposure measure with import price data from the BLS to create a quarterly dataset of shipping cost exposure and price increases.

Table 4 shows summary statistics for the pre-pandemic and pandemic values of shipping cost exposure as measured in Equation 1. Pre-pandemic the typical annual growth in shipping costs was around 4 percent. In the pandemic, shipping costs spiked– on average across commodity types, companies saw an 85% growth in the cost of shipping goods in 40 foot dry container with one type of product experiencing a maximum 327% growth in shipping cost exposure.

Figure 3 displays the growth rate in shipping costs for all HS2-level commodities between the fourth quarter of 2020 and the fourth quarter of 2021. All product types have seen increases in shipping cost exposure throughout 2021. The smallest growth in shipping costs have been seen for meat, fruits and nuts, and vegetables. Both fruits and nuts and vegetables have a large portion of their value coming to the US from Mexico, a country that mainly sends goods to the US by roads and by railway. Meat, instead, has imports mostly from Australia and New Zealand- Australia and New Zealand, in turn, saw some of the lowest shipping cost increases in 2021, as seen in Figure 2. In contrast, meat and fish products, such as caviar, sausages, and canned products, and coffee, tea, and spices saw the largest increase in shipping cost exposure. Meat and fish products come largely from Thailand and Indonesia while coffee, tea, and spices come from Vietnam and Brazil.

3.2 Measuring pass-through of shipping costs to prices

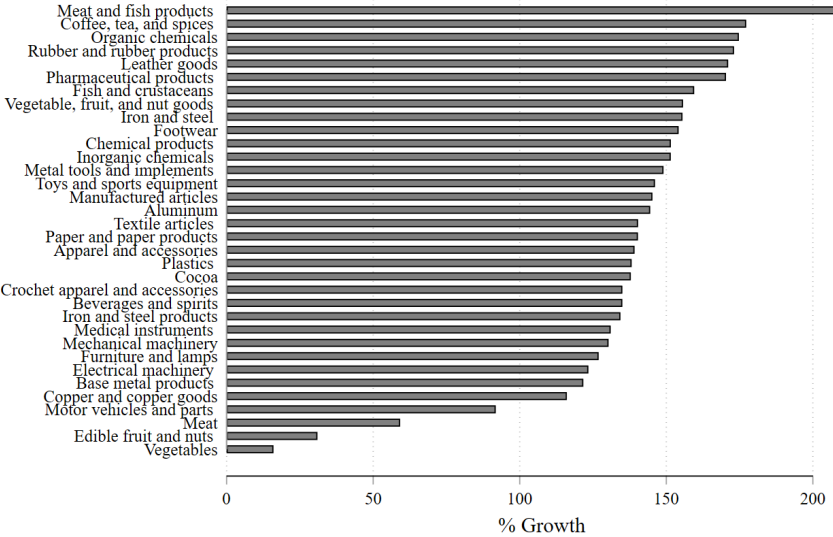
Next, we run an OLS regression of import price inflation on our measure of shipping cost exposure. We estimate the following equation

$$\pi_{it} = \beta S_{it} + f_i + \epsilon_{it} \tag{2}$$

where π_{it} is the annual growth in import prices, S_{it} is the annual growth in shipping cost exposure defined in Equation 1, and f_i is a set of commodity-level fixed effects. Our coefficient of interest is β , which gives the percentage point increase in import price inflation associated with 1 percentage point increase in our measure of exposure to shipping price growth.

One concern is that the error term will be correlated over time if changes to import prices and shipping costs are persistent. To address this issue, we adjust the standard errors for panel-specific AR1 auto-correlation. Panel-specific AR1 errors adjust the standard errors for correlation between a period and the period before within a

Figure 3: Annual Growth in Shipping Cost Exposure by Commodity in 2021Q4



The figure displays the annual growth in shipping cost exposure for all HS2-level commodities in our data set in 2021 Q4.

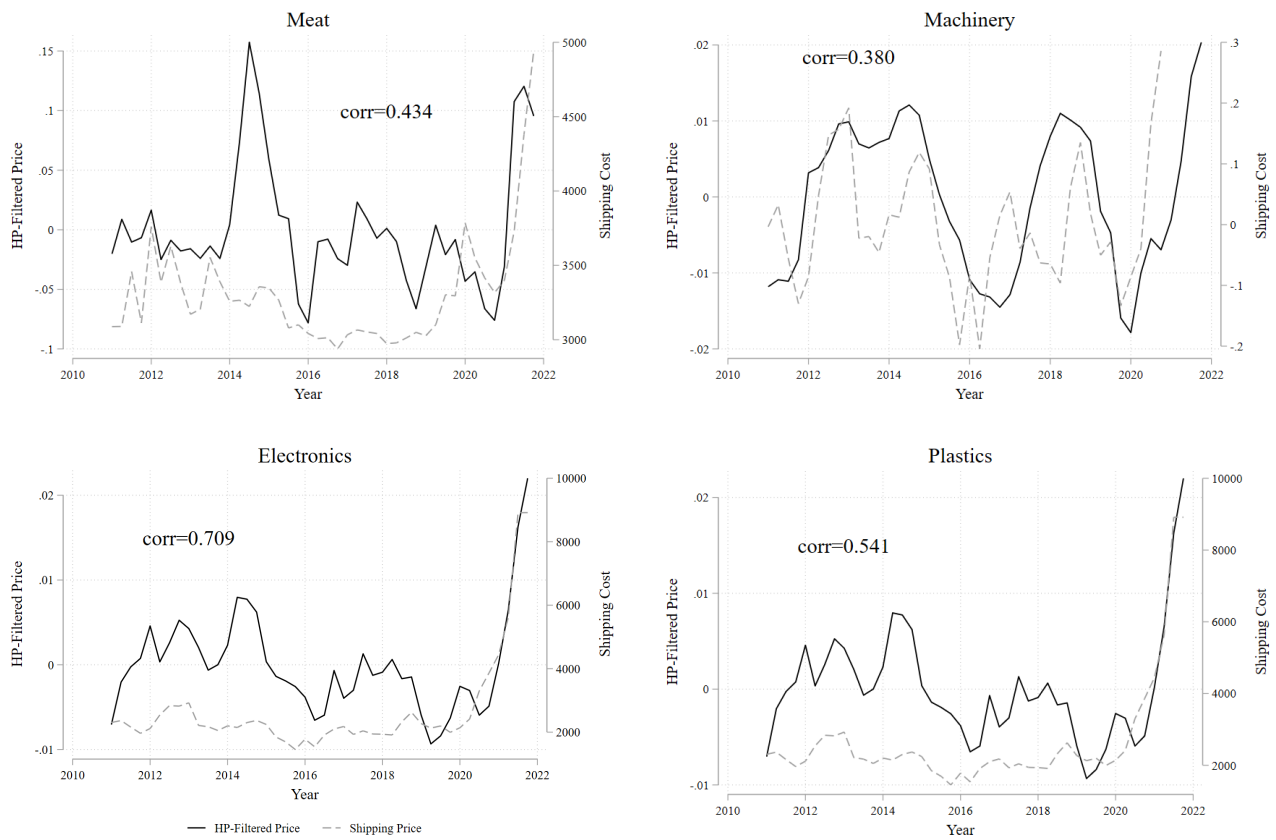
specific commodity. We also adjust the standard errors to allow for within-period correlation across goods.

One possibility is that the measure of shipping cost exposure is capturing broader pandemic disruptions such as factory closures due to COVID-19 outbreaks. This would be the case if countries that experienced the biggest increase in shipping costs also had the most stringent lock-down measures or the most severe outbreaks. Looking at Figure 2, there does not seem to be a pattern between the growth in shipping costs and other pandemic factors. For example, Brazil experienced the largest increase in shipping costs while also enacting very few pandemic related shutdowns. On the other hand, Australia had very stringent COVID-19 policies, but a much smaller increase in shipping costs. However, we exploit heterogeneity in the share of the value of each commodity shipped by sea and heterogeneity across the types of commodities to provide suggestive evidence that the role of shipping costs is particularly important.

4 Results

Before we turn our attention to the regression results from estimating Equation 2, we first examine the time series correlation between import prices and our measure of shipping price exposure for a few select HS2 commodities. Figure 4 displays time series plots of shipping price exposure (in gray) and the cyclical component of the HP-filtered import prices (in black) for each of the four good types. Each plot also displays the correlation between the two values over the entire period in the figure. In each case, the shipping cost exposure and import prices are correlated from 2010 to 2021, the period on which we’re focused. For each commodity, import price inflation and shipping cost exposure both increase around the same time in the middle of 2020. One concern is that this correlation might be driven by the spike in both import prices and shipping costs during the pandemic. The figure note gives the correlation for the time period before the pandemic and in each case there is a still

Figure 4: Time Series of Prices and Shipping Costs for Specific Commodities



The figure shows the value of HP-filtered import prices as a solid line while the dotted gray line displays the value of shipping cost exposure for specific HS2 and HS4 level commodities. The correlation displayed in the figure is the overall correlation, but the pre-pandemic correlation levels for meat, machinery, electronics, and plastics are 0.238, 0.514, 0.397, and 0.277 respectively.

Table 5: Baseline Regression Results

	Import Price Inflation		
	Baseline (1) Price Growth	Before 2020 (2) Price Growth	After 2020 (3) Price Growth
Shipping Cost Growth	0.0247*** (0.00557)	0.00708 (0.00617)	0.0684*** (0.0142)
Observations	2950	2334	308
R^2	0.035	0.062	0.860
Commodity FEs	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

a significant correlation between the two series. Electronics has the highest correlation over the entire period, while machinery saw the highest pre-pandemic correlation values.

Now we turn to the results of our formal regression analysis. Table 5 shows the results of estimating Equation 2 across several specifications. We use the data from all matched HS commodities, but the tables are repeated for only 2-digit HS codes in Appendix A.3. Our baseline result is in Column 1 which uses the full sample. Import price inflation for goods that were exposed to a 1 percentage point higher increase in shipping price growth was on average 0.0247 percentage points higher.

Next, in Columns 2 and 3, we split the data into the time before and the time after the pandemic. Before the pandemic, we find that the correlation between shipping price growth and import price growth was insignificant. From Figure 4, there is clearly a significant correlation between shipping costs and inflation for a few select commodities even before the pandemic. But, the regression analysis suggests that this does not hold on average across commodity types. This is consistent with the idea that the pass-through is small and that shipping prices were relatively small and stable. After the pandemic, the pass-through has been much larger. Shipping price growth that is 1 percentage point higher is associated with import price inflation that is 0.0684 percentage points higher. Again this might seem modest, but when one considers the magnitude of the shipping price increase post pandemic, the cost of shipping can account for a substantial portion of import price inflation. From Table 4, the average growth in shipping cost was 85.85 percent. This would imply import price inflation of 5.87 percentage points per year during the pandemic.

Then, in Table 6, we restrict the commodities to those in which most of the goods are shipped by sea and those goods where the ratio of transport costs by sea to the overall value of the good is high. Isaacson and Rubinton (2022) find a relationship between the share of goods in an industry shipped by sea and import price inflation. We then replicate our baseline regressions from Table 5 with the smaller samples. The relationship between shipping cost exposure and commodity prices is stronger as we limit the sample to these types of goods. For commodities with above the 75th percentile of value shipped by sea, an increase in shipping prices is associated with 0.117 percentage points higher import price inflation during the pandemic. Meanwhile, having

Table 6: Baseline Regressions with Sample Restrictions

	Import price inflation, %					
	75th Percentile Share Sea			Above Median Cost Ratio		
	Baseline (1) Price Growth	Before 2020 (2) Price Growth	After 2020 (3) Price Growth	Baseline (4) Price Growth	Before 2020 (5) Price Growth	After 2020 (6) Price Growth
Shipping Cost Growth	0.0457*** (0.00873)	0.0237*** (0.00645)	0.117*** (0.0162)	0.0430*** (0.00896)	0.0142* (0.00849)	0.127*** (0.0165)
Observations	730	578	76	1497	1193	152
R^2	0.076	0.073	0.789	0.045	0.059	0.889
Commodity FEs	Y	Y	Y	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms. The first set of results are from those commodities with above the 75th percentile of value shipped by sea and the second set is those with a ratio of transport costs to value of good above the median.

an above-median ratio of transport costs to the value of the good is associated with a pass-through rate of 0.127 in 2021. These results suggest that goods that rely more heavily on shipping saw larger price increases during the COVID-19 pandemic.

Table 7 shows the results of estimating Equation 2, but splitting the sample into four groups based on the type of good. Food and Materials have the strongest relationship between shipping cost and price growth. The Food product types include edible vegetables, dairy products, meats, and others while Materials commodities represent plastics, chemicals, oils, metals, and other raw materials for production. For a 1 percentage point increase in the annual shipping cost growth, the price index increases by 0.056 percentage points for materials and by 0.0719 percentage points for Food. On the other hand for the group of goods classified as Machines, Electronics and Parts which includes wires, conductors, microphones, and other electronic equipment, the pass-through is only 0.011. For consumer goods, which includes miscellaneous items such as shoes, toys, clothes, sports equipment, and lamps, the pass-through is small and insignificant.

There are a number of reasons one would expect different amounts of pass-through depending on the type of good. Essentially this is a measure of how much producers are passing on their costs to their buyers. This pass-through depends on the degree of market competition and price rigidity. Furthermore it might depend on whether goods are being sold to consumers or intermediates. Finally, in the case of shipping, it could depend on whether goods can be stored in inventory or if they are perishable. The higher pass-through in Food and Materials seems to suggest that distinction between final goods and intermediates and whether or not a good is perishable might both be important factors in the extent to which shipping costs are passed through to the price.

In our baseline analysis, we did not include time fixed effects in the specification. In these regressions, the coefficient β measures whether the correlation between import price inflation and shipping costs is, on average across goods, positive. In a final version of our analysis, we add time fixed effects. In this case, we are asking a slightly different question. The coefficient β asks whether within a period, goods that saw higher increases in shipping prices also saw higher import price inflation.

Table 7: Regression Results by Type of Product

	Import price inflation				
	Baseline	Food	Materials	Machines Electronics & Parts	Consumer Goods
	(1)	(2)	(3)	(4)	(5)
	Price Growth	Price Growth	Price Growth	Price Growth	Price Growth
Shipping Cost Growth	0.0247*** (0.00557)	0.0719*** (0.0223)	0.0560*** (0.0129)	0.0105*** (0.00402)	0.00489 (0.00456)
Observations	2950	480	802	1228	440
R^2	0.035	0.047	0.056	0.089	0.058
Commodity FEs	Y	Y	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

Table 8: Import Price Inflation over Time

	Import price inflation		
	Baseline	Before 2020	After 2020
	(1)	(2)	(3)
Shipping Cost Growth, %	0.00585 (0.0122)	-0.0134 (0.0141)	0.0419* (0.0247)
Observations	3250	2562	344
R^2	0.088	0.111	0.858
Commodity FEs	Y	Y	Y
Time FEs	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

The results of adding time fixed effects to Equation 2 are found in Table 8. The baseline measure with both types of fixed effects is not statistically significant- only in the period after 2020 is the relationship significant. An increase of 1 percentage point in the shipping cost exposure measure increases the import price index by 0.042. Before the pandemic, the relationship between shipping cost and import prices could mostly be explained by commodity level effects or by month-specific changes in prices. However, shipping costs became significant in 2021- this is similar to [Amiti et al. \(2021\)](#) who found that the impact of import prices on producer prices more than doubled during the pandemic period.

5 The Implications of the Shipping Cost Shock on Inflation

In this section, we use our estimates of the pass-through from shipping costs to import prices to produce back-of-the-envelope calculations for the impact on inflation. We find that the pass-through from shipping costs to inflation was much larger during the pandemic. Our estimates of the pass-through after 2020 range from 0.0419

in the specification with commodity and time fixed-effects to 0.0684 in the specification with only commodity fixed-effects. We use these to produce a lower and upper bound on the effect of shipping cost exposure.

During the Pandemic, the shipping cost exposure measure increased by an average of 85.85 percent per year during the period from 2020 quarter 2 to 2021 quarter 4 (see Table 4). This would imply a increase in import price inflation between 3.60 and 5.87 percentage points.¹ During the two year period between 2019 quarter 4 and 2021 quarter 4, year over year import price inflation averaged 5.26 percent in our sample- thus, the increase in shipping costs can account for between 68 and 111 percent of the increase in import price inflation.

However, the literature has found that increases in import prices only have a limited impact on U.S. price inflation [Amiti et al. \(2019\)](#) [Dellmo \(1996\)](#). [Amiti et al. \(2021\)](#) estimate that during the pandemic, the pass-through from a 10% increase in import price inflation to PPI inflation was 2.6 percent. Over the same period from 2019 quarter 4 and 2021 quarter 4, year-over-year producer price inflation averaged 6.13 percent. Thus, shipping cost growth could account for between 15 and 25 percent of PPI inflation.

6 Conclusion

In this article, we investigate the relationship between shipping costs and import price inflation, especially during the COVID-19 pandemic. To examine pass-through, we create a data set combining shipping cost data by country with information on import prices by commodity type and on import volumes by country and commodity type. After creating our measure of shipping cost exposure for different types of goods, we measure the pass-through of shipping costs to import price inflation over time. While the overall impact of shipping costs on import price inflation is modest, the overall growth in shipping costs has been so large that between 3.6 and 5.87 percentage points of import price inflation can be attributed to it. Additionally, product types with greater shares shipped by sea experience a stronger impact of shipping costs than those with a smaller share shipped by sea. Additionally, in 2021, pass-through was larger than in the period from 2010 to 2019, with differential impacts across different good types. Within different broad categories of goods, the impact of shipping costs tends to be larger for more perishable goods. Thus, recent spikes in import prices can be partially, but not entirely, attributed to the rise in shipping costs over the course of the pandemic.

¹We multiply the growth in shipping costs by the estimates of pass-through from Tables 5 and 8, 0.0684 and 0.0419, to get the estimated impact on inflation.

References

- Abbai, B., Akinci, O., Benigno, G., di Giovanni, J., Groen, J. J., Heymann, R. C., Lin, L., Noble, A. I., et al. (2022). The global supply side of inflationary pressures. Technical report, Federal Reserve Bank of New York.
- Amiti, M., Heise, S., Wang, A., et al. (2021). High import prices along the global supply chain feed through to us domestic prices. Technical report, Federal Reserve Bank of New York.
- Amiti, M., Redding, S. J., and Weinstein, D. E. (2019). The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives*, 33(4):187–210.
- Comin, D. A. and Johnson, R. C. (2021). Supply chain constraints and inflation. Technical report, Manuscript.
- de Soyres, F., Santacreu, A. M., and Young, H. (2022). Fiscal policy and excess inflation during covid-19: a cross-country view.
- Dellmo, H. (1996). Relationships between swedish producer and import prices and.
- Guerrieri, V., Lorenzoni, G., Straub, L., and Werning, I. (2021). Monetary policy in times of structural reallocation. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2021-111).
- Isaacson, M. and Rubinton, H. (2022). Inflation and shipping costs. *Economic Synopses*, (5).
- LaBelle, J. and Santacreu, A. M. (2022). Global supply chain disruptions and inflation during the covid-19 pandemic. *Federal Reserve Bank of St. Louis Review*.
- Leibovici, F. and Dunn, J. (2021). Supply chain bottlenecks and inflation: The role of semiconductors. *Economic Synopses*.
- Leibovici, F. and Santacreu, A. M. (2015). International trade fluctuations and monetary policy. *Available at SSRN 2657467*.
- Wei, S.-J. and Xie, Y. (2020). Monetary policy in an era of global supply chains. *Journal of International Economics*, 124:103299.

A Appendix

A.1 Controlling for oil prices

Table 9: Controlling for oil prices

	Import price inflation				
	Baseline (1)	Before 2020 (2)	After 2020 (3)	75% Percentile Share by Sea (4)	Above Median Cost Share (5)
Shipping Cost Growth	0.0241*** (0.00508)	0.00651 (0.00610)	0.0328** (0.0163)	0.0452*** (0.00845)	0.0421*** (0.00812)
Observations	2950	2334	308	730	1497
R^2	0.042	0.066	0.868	0.079	0.055

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

A.2 Sample Restrictions with Time FEs

A.3 HS2 Commodities Only

Table 10: Baseline Regressions with Sample Restrictions

	75th Percentile Share Sea			Above Median Cost Ratio		
	Baseline (1) Price Growth	Before 2020 (2) Price Growth	After 2020 (3) Price Growth	Baseline (4) Price Growth	Before 2020 (5) Price Growth	After 2020 (6) Price Growth
Shipping Cost Growth	-0.00440 (0.0119)	-0.0187 (0.0124)	0.0594* (0.0313)	0.0117 (0.0200)	-0.0241 (0.0212)	0.0693** (0.0302)
Observations	730	578	76	1497	1193	152
R^2	0.288	0.249	0.821	0.137	0.122	0.899
Commodity FEs	Y	Y	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

Table 11: Baseline Regressions: HS-2 sample

	Import price inflation		
	Baseline (1)	Before 2020 (2)	After 2020 (3)
Shipping Cost Growth	0.0408*** (0.00750)	0.0187* (0.00954)	0.117*** (0.0177)
Observations	1280	1024	128
R^2	0.040	0.065	0.857
Commodity FEs	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

Table 12: Regressions by Product Type: HS-2 sample

	Import price inflation				
	Baseline (1)	Food (2)	Materials (3)	Machines Electronics & Parts (4)	Consumer Goods (5)
Shipping Cost Growth	0.0408*** (0.00750)	0.0720*** (0.0201)	0.0982*** (0.0146)	0.0130*** (0.00283)	0.00378 (0.00428)
Observations	1280	320	480	240	240
R^2	0.040	0.040	0.132	0.243	0.076
Commodity FEs	Y	Y	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

Table 13: Regressions with time FEs: HS-2 sample

	Import price inflation		
	Baseline (1)	Before 2020 (2)	After 2020 (3)
Shipping Cost Growth	0.0239 (0.0197)	-0.0117 (0.0211)	0.0800** (0.0345)
Observations	1280	1024	128
R^2	0.108	0.109	0.852
Commodity FEs	Y	Y	Y
Time FEs	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

Table 14: Baseline Regressions with Sample Restrictions for HS2 Commodities

	75th Percentile Share Sea			Above Median Cost Ratio		
	Baseline (1)	Before 2020 (2)	After 2020 (3)	Baseline (4)	Before 2020 (5)	After 2020 (6)
Shipping Cost Growth	0.0880*** (0.0152)	0.0408** (0.0175)	0.195*** (0.0225)	0.0573*** (0.0119)	0.0290 (0.0181)	0.176*** (0.0250)
Observations	320	256	32	640	512	64
R^2	0.114	0.045	0.828	0.041	0.062	0.833
Commodity FEs	Y	Y	Y	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

Table 15: Baseline Regressions with Sample Restrictions with Time Fixed Effects for HS2 Commodities

	75th Percentile Share Sea			Above Median Cost Ratio		
	Baseline (1)	Before 2020 (2)	After 2020 (3)	Baseline (4)	Before 2020 (5)	After 2020 (6)
Shipping Cost Growth	-0.00606 (0.0181)	-0.0225 (0.0237)	0.0896* (0.0459)	0.0385 (0.0289)	-0.0355 (0.0363)	0.114** (0.0490)
Observations	320	256	32	640	512	64
R^2	0.388	0.298	0.859	0.140	0.118	0.838
Commodity FEs	Y	Y	Y	Y	Y	Y
Time FEs	Y	Y	Y	Y	Y	Y

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors are adjusted for heteroskedasticity, within period correlation, and panel specific serially correlated error terms.

B Port Information

B.1 List of port-pairs

1. Australia (Melbourne) to LA
2. Bangladesh (Chittagong) to NY
3. Brazil (Santos) to Houston
4. Central China (Shanghai) to LA
5. Hong Kong to LA
6. India (Nhava Sheva) to NY
7. Indonesia (Jakarta) to LA
8. Israel (Ashdod) to NY
9. Japan (Yokohama) to LA
10. Korea (Busan) to LA
11. Malaysia (Tanjung Pelepas) to LA
12. New Zealand (Auckland) to LA
13. N. Europe (Rotterdam) to NY
14. Philippines (Manila) to LA
15. Poland (Gdansk) to NY
16. Russia (St Petersburg) to NY
17. Singapore to LA
18. South Africa (Durban) to NY
19. Sweden (Gothenburg) to NY
20. Taiwan (Kaohsiung) to LA
21. Thailand (Laem Chabang) to LA
22. Turkey (Istanbul) to NY
23. U.A.E (Jebel Ali) to NY
24. UK (Felixstowe) to NY

25. Vietnam (Ho Chi Minh) to LA

26. West Mediterranean (Genoa) to NY

Table 16: Crosswalk from Country to Ports

Port	Countries
Australia	Australia
New Zealand	New Zealand
Brazil	Brazil Argentina Uruguay Bolivia
China	China
India	India Bangladesh
Indonesia	Indonesia
Japan	Japan
Korea	Korea
Mexico	Mexico Guatemala Belize Nicaragua
Northern Europe	Austria Belgium Bulgaria Czech Republic Germany Switzerland
Northern Europe (cont.)	Estonia Finland Hungary Lithuania Luxembourg Iceland
Northern Europe (cont.)	Latvia the Netherlands Romania Slovakia Slovenia Sweden
Russia	Russia Ukraine
Taiwan	Taiwan
Turkey	Turkey
Great Britain	Great Britain France Spain Ireland Portugal
West Mediterranean	Cyprus Greece Croatia Italy Malta
Hong Kong	Hong Kong
Vietnam	Vietnam
Singapore	Singapore
Thailand	Thailand
Malaysia	Malaysia
Philippines	Philippines
Egypt	Egypt
South Africa	South Africa
United Arab Emirates	United Arab Emirates
Israel	Israel