Online Appendix for *Increasing Inventories: The Role of Delivery Times*, by Maria-Jose Carreras-Valle

A Increasing Inventories

This section details additional information regarding the inventories to sales ratio. It includes details on the inventory data used in the paper, additional sources, and how they compare. Additionally, it includes the inventory to sales ratio for all the NAICS 3-digit industries. Last, it includes further details on the inventory to sales ratio for manufacturing firms, and the manufacturing sector in other countries.

A.1 U.S. Census Bureau inventory data

The *Manufacturers' Shipments, Inventories, and Orders* survey has monthly data on manufacturing inventories and sales for M3 industries for the period 1992 to today. Additionally, they have data for different types of inventories. The monthly M3 estimates are based on information obtained from most manufacturing companies with $500 million or more in annual shipments. In order to strengthen the sample coverage in individual industry categories, the survey includes selected smaller companies. The sources from which companies are identified for inclusion in the survey panel are the quinquennial economic censuses (manufacturing sector) and the Annual Survey of Manufactures (ASM).

They define three different types of inventories:

- Materials-and-Supplies Inventory: All unprocessed raw and semi-fabricated commodities and supplies for which you have title.
- Work-in-Process Inventory: Accumulated costs of all commodities undergoing fabrication within your plants and long-term contracts where the inventory costs are for undelivered items and the value of work done that has not been reported in sales.
- Finished Good Inventory: The value of all completed products ready for shipment and all inventories and goods bought for resale requiring no fur-

ther processing or assembly. No accumulation of finished goods inventories should occur with long-term contracts unless the total sales receipts are not recorded until the time of delivery.

The survey defines inventories in their instruction manual as the value of total inventories of the end of the month stocks, regardless stage of fabrication. Inventories reported include the following goods:

1. current cost of total inventory of all good owned by the firm located anywhere in the U.S. and at all stages of fabrication,
2. inventories held in U.S. Customs warehouses that have not cleared customs as an export from the U.S.,
3. inventories being transported to or from the U.S., owned by the U.S. manufacturer,
4. inventories held in U.S. Customs warehouses or Foreign Trade Zone warehouses
5. inventories held at sales branches if the firm holds title
6. inventories in transit only if the firm own title to them
7. values for long-term contracts funded on a flow basis consistent with sales or receipts, such as: If work done during the month is included in your monthly sales, the inventory should be reduced consistent with the sales report; or if total receipts are expected at the time of delivery, the value of work done should be accumulated in the inventory

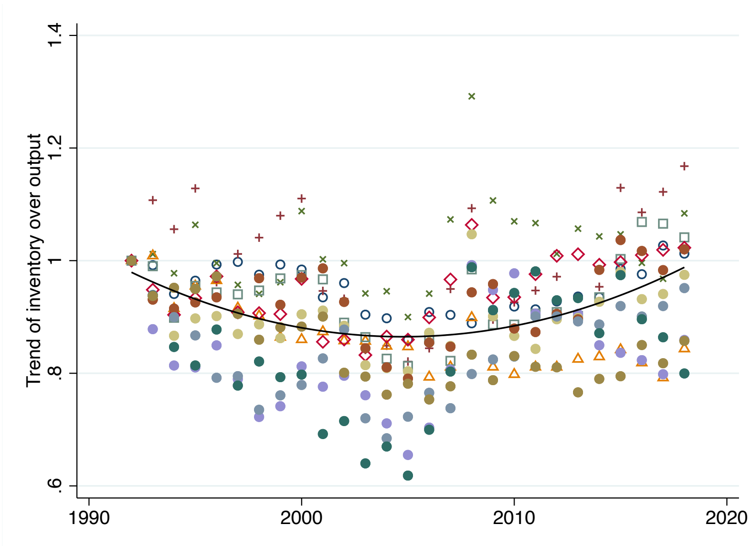
Inventories reported exclude the following goods:

1. Inventories held at foreign subsidiaries,
2. goods for which you do not hold title such as government or customer-owned goods,
3. the value of equipment used in the manufacturing process

A.2 Increasing inventories across manufacturing industries

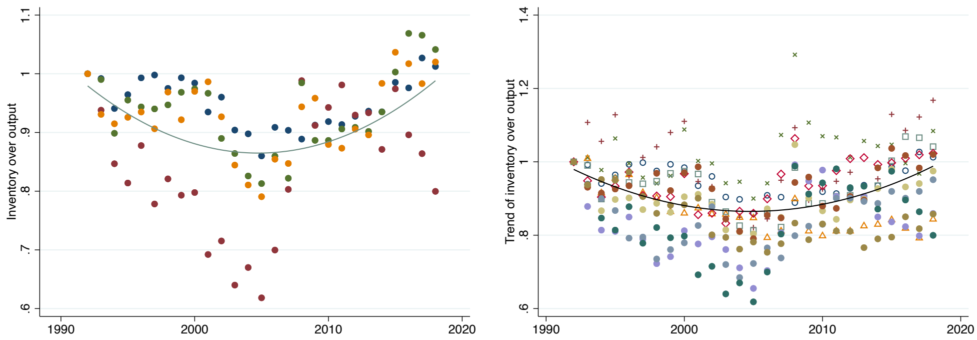
This section shows the trend for NAICS three-digit manufacturing industries, using monthly data from 1992 to 2018 for inventory over monthly sales from the U.S. Census Bureau. The sectors are presented in Figure 18. The only manufacturing industry whose inventory over sales ratio continue to decrease throughout the period is industry 322, *Paper Manufacturing* which represents 3% of total inventory and 4% of total output on average for the period 1997 to 2018. For the reminder of the manufacturing industries, inventory over sales ratio observe an increase or in some cases, the decline of inventories stops around 2005. Figure 18 shows the trend of inventory to sales across industries, and the quadratic fitted line. Last, Figure 20a shows the overall trend in inventories to sales holds when we include the Petroleum and Coal sector (NAICS 324). Figure 20a also shows how the aggregate trend remains present when I leave out the Transportation sector (NAICS 336), which tends to stock a higher amount than average of final goods as inventories.

Figure 18: Increasing inventories across industries



Note: The Figure shows the trend of inventory-to-sales ratio for the NAICS 3-digit industries (excluding Petroleum and Coal Products). It includes the quadratic fitted line of the trend, showing the initial decrease and following increase after 2005.

Figure 19: Increasing inventories across manufacturing sectors

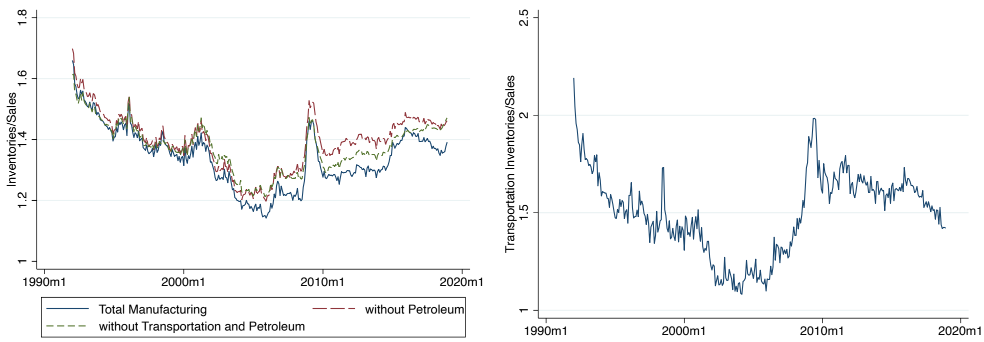


(a) Four largest sectors

(b) All sectors

Note: The Figures show the trend of inventories over sales. Panel a shows the rise in inventories after 2005 for the three types of inventories, as defined by the U.S. Census Bureau. Panel b shows a scatterplot and a quadratic fitted line of the index of inventories to sales ratio for the four largest NAICS 3 digit industries, in terms of output. Industries are Food and Beverage, Transportation, Chemicals, and Machinery. They represent 47% of total manufacturing output, and 48% of inventories.

Figure 20: Increasing inventories: transportation and petroleum sector



(a) Inventories without petroleum and transportation sector

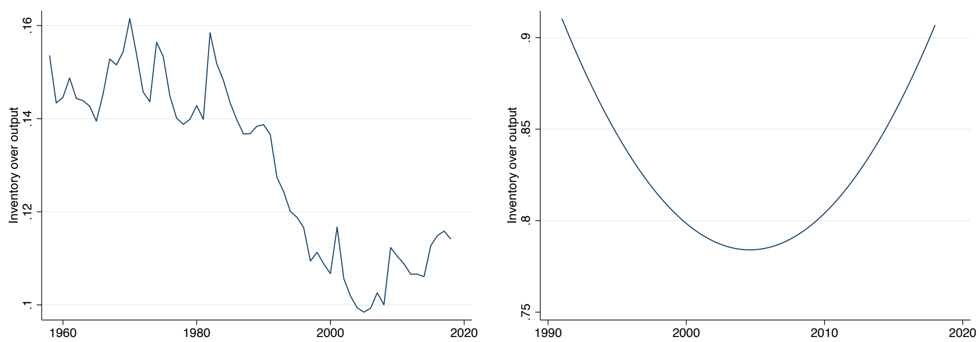
(b) Transportation (336) sector

Note: The Figures show the trend of inventories over sales. Panel a shows the trend for total manufacturing industry, and how that compares to the trend without the Petroleum and Coal sector (324), and the Transportation sector (336). Panel b shows the trend for the Transportation sector only.

A.3 Increase in inventories across sectors using NBER-CES database

An additional source that includes data on inventories is the NBER-CES Manufacturing Industry Database. They include yearly data from 1958-2018 for NAICS 6-digit industries. The key disadvantage of the dataset is that they do not include information on the different types of inventories, so I can only see the trend for the total inventories across industries. Figure 21a shows the long term term trend of inventory-to-sale ratio for the total manufacturing industry. It shows the steep decline that starts in the 1980's, and the more recent rise in inventories. Figure 21b shows the quadratic fit of the index of the inventories-to-sales ratio across the six digit industries, showing as well the initial decrease and increase after 2005. Additionally, Table 5 shows the results using a time series regression with fixed effects for the period 1990 to 2005 (column 1), and for 2006 to 2018 (column 2). Results show an initial annual decrease in the ratio of inventories-to-sales of 1%, and an increase of 1% after 2005.

Figure 21: Increasing inventories: NBER-CES database



(a) Long term trend for total manufacturing sector

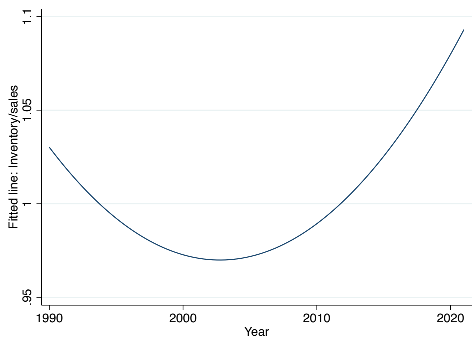
(b) Rise in inventories across six-digit NAICS industries

Note: The Figures show the trend of inventories over sales. Panel a shows the long term trend for the total manufacturing industry. Panel b shows the quadratic fit of the scatter plot of the trend (index) of the inventories-to-sales for all the six-digit manufacturing industries.

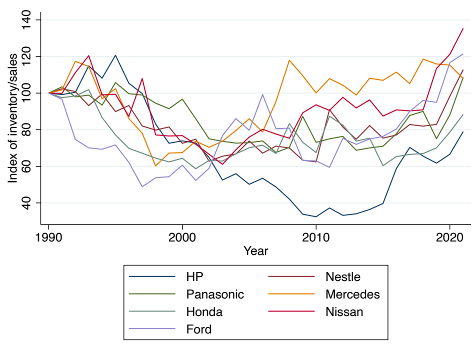
A.4 Increase in inventories across firms using Compustat

The rise in inventories is also observed across firms, using the Compustat North America database. [7] For the analysis, I constraint the dataset to manufacturing firms that have available inventory and sales data for the period 1990-2021, which gives me a total of 478 U.S. public firms. Figure 22a shows the quadratic fit of the trend of inventories-to-sales for all the firms in the sample. It shows the very similar trend documented in the aggregate data, an initial decrease followed by a rise in inventories. Figure 22b shows the trend for the seven largest firms in the dataset. Last Table 5 shows the results using a time series regression with fixed effects for the period 1990 to 2005 (column 3), and for 2006 to 2018 (column 4). Results show an initial annual decrease in the ratio of inventories-to-sales with the negative coefficient, and the coeficient turns positive showing the rise after 2005.

Figure 22: Increasing inventories: Compustat firm-level data



(a) Quadratic fit of the trend across firms



(b) Trend for the seven largest firms

Note: The Figures show the trend of inventories over sales. Panel a shows the long term trend for the total manufacturing industry. Panel b shows the quadratic fit of the scatter plot of the trend (index) of the inventories-to-sales for all the six-digit manufacturing industries.

A.5 Increase in manufacturing inventories across countries

In this section, I document the rise in inventories for Australia, Canada, Japan, and Korea. Data on inventories and sales was collected in each of the countries

[7] Compustat North America is a database of U.S. and Canadian fundamental and market information on active and inactive publicly held companies. Data comes from the Fundamentals Annual database, retrieved from WRDS Wharton Research Data Services reported by Standard and Poor's Global Market Intelligence.

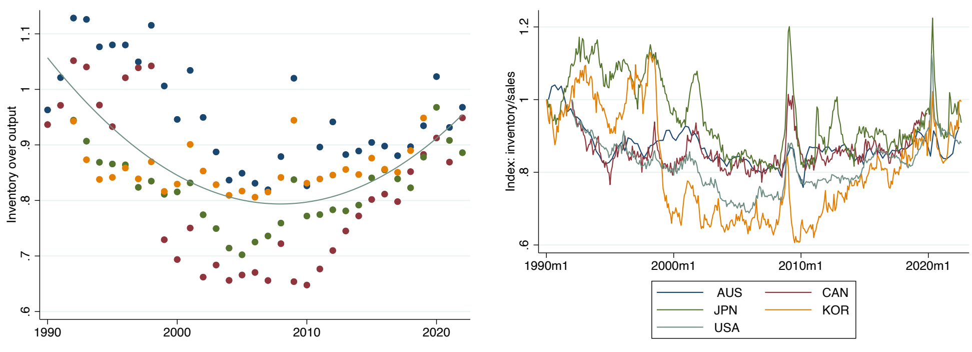
Table 5: Inventories increase across sectors and firms in 2005

	Inventory/sales			
	Sectors		Firms	
	1990 – 2005	2006 – 2018	1990 – 2005	2006 – 2021
	(1)	(2)	(3)	(4)
Year	−0.0101	0.0093	−0.0010	0.0018
	(0.0011)	(0.0012)	(0.0002)	(0.0001)
Constant	20.900	−17.8109	2.1857	−3.422
	(2.1880)	(2.5080)	(0.3769)	(0.2490)
Fixed effects	sector-level	sector-level	firm-level	firm-level
N	5,415	4,682	6,972	7,436

Note: The Table shows the results for the regression $y_{i,t} = \beta t + \delta_i + \epsilon_{i,t}$ where $y_{i,t}$ are the inventories over sales for a sector of firm every year, and δ_i is the fixed effect for each sector or firm. First two columns report the results using the NBER-CES dataset for the 6-digit industries, and the last two report the regression results using the WRDS Compustat dataset for North America annual information.

statistical website for the manufacturing sector. Figure 23a shows the decline and rise in inventories around 2005, which provides evidence that the increasing trend of inventories might be a global phenomenon. As globalizations develops, and as countries start trading with countries that are farther away, the average delivery times for inputs increases. With this increase in delivery times, comes the rise in inventories.

Figure 23: Increasing inventories across countries



(a) Inventories across countries and the quadratic fit

(b) Manufacturing inventories trend

Note: The Figures show the trend of inventories over sales. Panel a shows the long term trend for the total manufacturing industry. Panel b shows the quadratic fit of the scatter plot of the trend (index) of the inventories-to-sales for all the six-digit manufacturing industries.

B Rise in Imported Inputs

This section details additional information regarding the rise in foreign inputs used in production, driven by the rise in inputs from China. Further, it shows that inventories of import-intensive industries observe the sharpest decrease and increase in inventories. It includes details on data sources, and methodology of the analysis presented, and supports the claims by including additional analysis using data from the (i) World Input Output Database, (ii) OECD Input-Output Database, and (iii) U.S. Census Bureau using the end-use classification. Further, it shows evidence of the growth in inputs from China across manufacturing sectors. Then, I provide evidence of the rise in the use of foreign inputs across countries. Last, I include details of the increase in the distance imports travel.

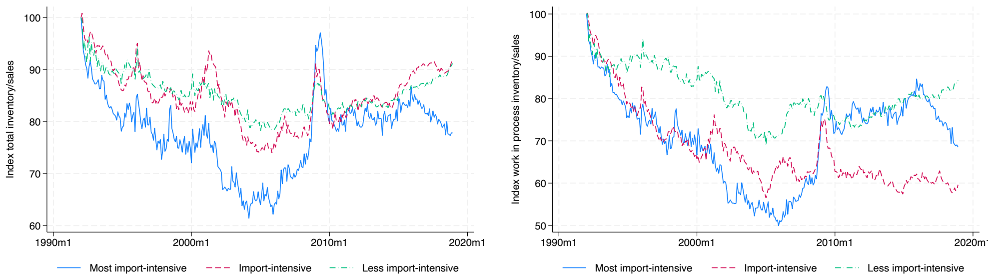
B.1 Rise in the share of imported inputs

Import data comes from the U.S. Census Bureau, and it was retrieved from Schott (2008) (dataset available in their website). It includes annual 10 digit HS industry data for imports, by method of transportation and country of origin, from 1989 to 2018. Data on domestic and foreign intermediate inputs used in production by industry used are published by the BEA Input-Output tables. They include annual data from 1997 to 2020 on output, domestic intermediate input use by industry, and foreign intermediate input use by industry, for almost NAICS 3 digit industries. They aggregate industries 311 and 312, 313 and 314, and 315 and 316 to form three industries. I adopt this aggregation in my analysis as well, and obtain 18 total manufacturing industries. Then I drop the sector 324, *Petroleum and Coal Products* from the analysis in this paper due to its volatile nature.

I compute data on the intermediate inputs used in production by country of origin by following a similar methodology used by the BEA for the *Import Matrices*. To report the total foreign intermediate inputs by industry, they assume that imports are used in the same proportion across all industries and final uses. To obtain foreign intermediate inputs by country of origin, I assume the ratio of imported inputs over total inputs from a given country is proportional to the share of imports from that country over total U.S. imports. The following equation details the share of imported inputs from country i in industry j:

$$\frac{\text{Country } i \text{ imported inputs in } j}{\text{Total inputs used in } j} = \frac{\text{Imports from } i \text{ in } j}{\text{Total imports of } j} \frac{\text{Imported inputs from } j}{\text{Total inputs used in } j} \tag{11}$$

Figure 24: Inventories of import-intensive industries show the sharpest trend



(a) Total inventory

(b) Intermediate input inventory

Note: The figure shows the trend in total and intermediate input inventory over output across U.S. manufacturing industries. Industries are sorted by their imported input intensity, using the average from 1997 to 2018. The levels are chosen such that each group represents around 33% of the average total manufacturing output. The figure shows the positive relationship between the imported input intensity and the growth in inventories across manufacturing sectors. Import intensive industries show the largest increase in inventories.

Inventories of import-intensive industries observe the sharpest decrease and increase in inventories. Figure 24a shows the trend of the total inventory to output ratio for the U.S. manufacturing industries, sorted by their imported input intensity. The three levels are sorted using the average of imported inputs over output from 1997 to 2018 and each level represents $\sim 33\%$ of the total average output. The inventory trend is most pronounced for the more import-intensive industries, and the least pronounced trend for the less import-intensive industries. A similar pattern emerges for the intermediate input inventories in Figure 24b. Not only do import-intensive industries tend to stock more inventories (level), but also their inventories show the largest growth over the period of analysis.

B.2 Other sources of imported inputs

Additional data sources are considered for the analysis of the share of imported inputs across countries of origin. The key findings are observed across data sources: the rise in the share of foreign inputs, driven in part by the rise in inputs from China.

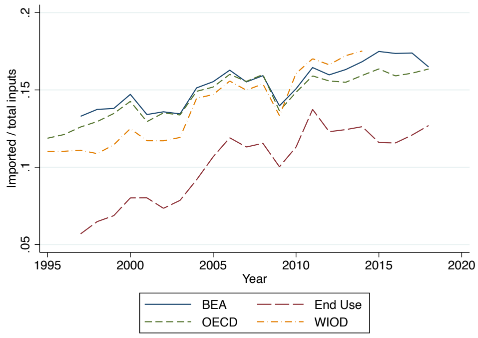
The **World Input Output Database** reports the share of imported inputs for each manufacturing sector across countries of origin. It additionally shows the amount of domestic and foreign inputs used in production, and reports annual data for the period 1995-2014. A similar data source are the **OECD Input Output Tables**, which report inputs used by each sector across countries of origin and show domestic inputs used. The tables are reported annually, from 1995-2018. Last, I include data from the U.S. Census Bureau using the **end-use classification system** for industrial supplies. To compute the share of imported inputs, I rely on the imports by country of origin from the U.S. Census Bureau, and use the concordance from NAICS to the end-use classification. For this source I do not have data on domestic inputs, so I rely on the BEA to obtain the shares of total inputs reported in the following figures.

Figure 25a shows the substitution away from domestic inputs and toward foreign inputs across data sources. The BEA, WIOD, and OECD data follow a similar level and trend, whereas the U.S. Census Bureau industrial supplies (end-use) show the increasing trend, but at a lower level. This is most likely because industrial supplies are a subset of inputs used in production. Figure 25c similarly shows the rise in inputs from China across data sources. The largest rise is observed in the WIOD data, which grows 3.5 percentage points from 1995 to 2014. Following is the data from the BEA, which grows 3 percentage points from 1997-208, and the OECD data which grows 2.4 percentage points. Last are the industrial supplies from China, which not only show the lowest level, but also grow only 1.5 percentage points. Figure 25b shows that inputs from Mexico and Canada remain relatively stable for the period of analysis across data sources.

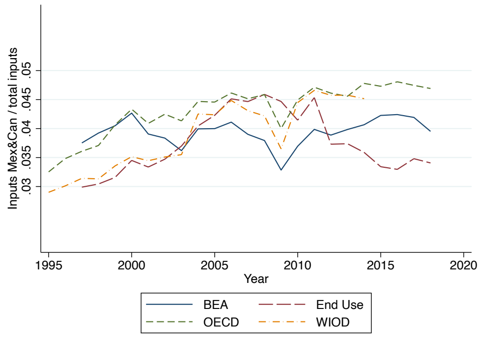
B.3 Rise in inputs form China across manufacturing sectors

Figure 26 shows the rise in imported inputs across NAICS 3-digit manufacturing sectors, using data from the BEA and the U.S. Census Bureau, with the exception of industries that do not import at all from China, such as *Transportation* and *Primary Metals*. Note this fact has been well-documented in the

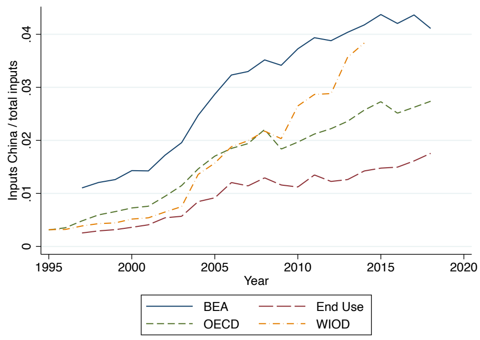
Figure 25: Rise in foreign inputs driven by inputs from China: across data sources



(a) Rise in the share of imported inputs



(b) Inputs from Mex and Canada relatively constant



(c) Rise in inputs from China

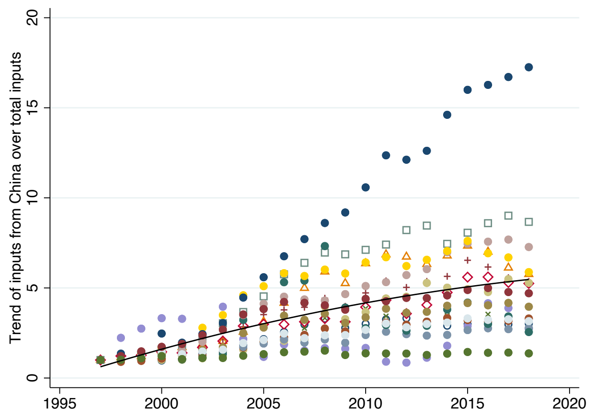
Note: The Figures shows evidence that the rise in the share of imported inputs has increased across data sources, and the same for the rise in inputs form China as well. Data denoted as ”BEA” correspond to the series used in the main section of the paper.

literature.

B.4 Inventories increase with imported input intensity: WIOD data

Industries that choose to use more imported inputs tend to stock more inventories, and following I replicate the analysis in the main text using imported input data from the WIOD. Figure 27a shows the positive relationship between imported inputs and total inventories across the NAICS three-digit manufacturing sectors. The relationship is strengthened when considering intermediate input inventory (work-in-process inventory), as shown in Figure 27b. Furthermore,

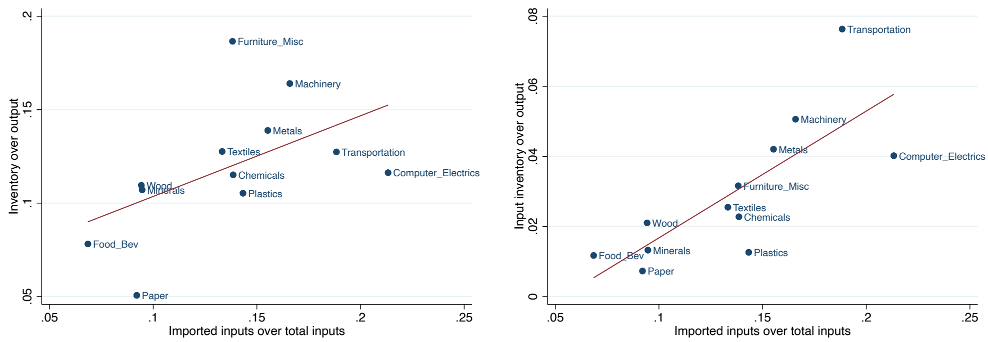
Figure 26: Rise in inputs from China across industries



Note: The Figures show the trend (index) of the growth in the share of inputs from China over total inputs used in production, for the three-digit NAICS manufacturing sectors, and the associated fitted line.

Table 6 shows the time series results where a 10% increase in imported inputs is associated with a raise in inventories of 8.5% and a raise of 10% in input inventories (column 3). When controlling for industry's value added, column 4 shows that a 10% increase in imported inputs increases inventories 7.5%, and input inventories 9.0%. The estimates using WIOD data are higher than the results using BEA and U.S. Census Bureau data included in section 1.3.

Figure 27: Inventories increase with imported input intensity: WIOD inputs

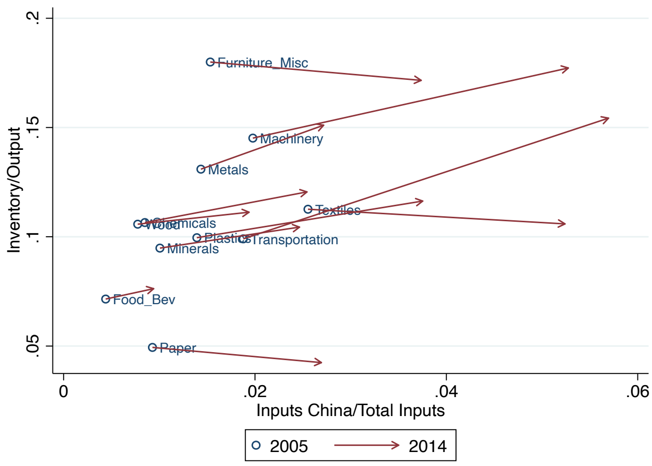


(a) Total inventory (b) Intermediate input inventory

Note: The Figure shows the average of imported inputs over total inputs and the inventory-to-output share for each NAICS 3 manufacturing industry from 1997 to 2018. The line represents the fitted line for each scatter plot. Correlation equals 0.52 for total inventory, and 0.77 for input inventory.

Moreover, the positive relationship between inputs from China and inventories stocked across industries is also present using the WIOD. Table 6 shows that a 10% increase in the use of inputs form China is associated with a raise of 6% in total inventories and 7% in input inventories (column 7). The relationship remains when controlling for value added, where the increase of 10% in inputs from China increases total inventory by 5% and input inventory by 6%. Additionally, Figure 28 shows the conteporaneus rise in inputs form China and total inventory from 2005 to 2014 across industries. The bullet points mark the initial level in 2005, and the arrows point toward the growth experiences until 2017.

Figure 28: Industries use more inputs from China and hold more inventories: 2005 to 2014 (WIOD)



Note: The Figure shows the value of the share of imported inputs over total inputs and the inventory-to-output ratio across NAICS 3 manufacturing industries for 2005. Then the arrow shows the change in the values for the year 2014, showing a contemporaneous increase in inventories and inputs from China across industries.

B.5 Rise in the use of foreign inputs across countries

Figure 29 shows the rise in the use of foreign inputs for production for the U.S., South Korea, Australia, Canada, and Japan. Using data from the OECD Input-Output tables, I compute the index of the use of foreign inputs over total inputs used for production. With the exception of Canada, whose index remains rather flat, the rest of the countries in the sample observe a increase from 1995 to

Table 6: Positive relation between inventories and imported inputs: WIOD inputs

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A								
	log(inventory)							
log(imported inputs)	0.77	0.70	0.85	0.75				
	[0.09]	[0.18]	[0.04]	[0.04]				
log(inputs China)					0.62	0.31	0.57	0.50
					[0.15]	[0.20]	[0.03]	[0.04]
log(value added)		0.11		0.30		0.59		0.20
		[0.24]		[0.05]		[0.28]		[0.06]
Weight by sales	✓	✓			✓	✓		
Year, industry FE			✓	✓			✓	✓
R^2	0.88	0.88	0.85	0.89	0.62	0.75	0.73	0.79
N	12	12	240	240	12	12	240	240
Panel B								
	log(input inventory)							
log(imported inputs)	1.30	1.85	1.01	0.90				
	[0.18]	[0.30]	[0.06]	[0.06]				
log(inputs China)					1.21	1.20	0.67	0.57
					[0.21]	[0.33]	[0.05]	[0.06]
log(value added)		-0.86		0.35		0.01		0.26
		[0.40]		[0.07]		[0.46]		[0.09]
Weight by sales	✓	✓			✓	✓		
Year, industry FE			✓	✓			✓	✓
R^2	0.85	0.89	0.84	0.80	0.77	0.68	0.76	0.77
N	12	12	240	240	12	12	240	240

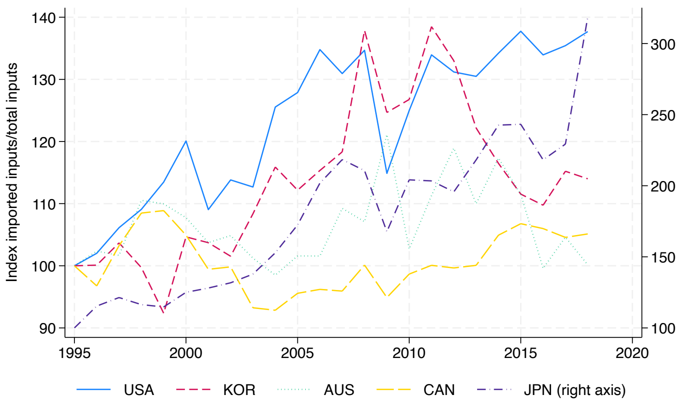
The table reports results for the regression $\log(y_{it}) = \beta_0 + \beta_1 \log(a_{it}) + \beta_2 \log(x_{it}) + \delta_i + \delta_t + \epsilon_{it}$, where i denotes industry, t year, y_{it} inventories, a_{it} value added, x_{it} intermediate inputs, and δ fixed effects. Columns 1, 2, 5, and 6 report the regression results for the NAICS three-digit industry average from 1995 to 2014, which has a total of 12 observations (one per industry). Columns 3, 4, 7, and 8 report results for the time series results across industries.

2018. Note Japan's index grew at a higher rate, so I plot their index on the right axis.

B.6 Increase in the distance traveled by imports across countries

The distance traveled by imports increased at an average annual rate of 6% from 1995 to 2018 across the countries in the sample. Following the work by

Figure 29: Rise in the foreign inputs used in production across countries



Note: The figure shows the rise in foreign inputs used in production for the U.S., South Korea, Australia, Canada, and Japan. The measure uses data on domestic and foreign inputs from the OECD Input-Output tables.

Wong and Ganapati (2023), Figure 4 shows a measure of the distance traveled for imports in each country. I use the USD value of imports by country of origin, based on the CEPII BACI dataset, and distance between countries using the population-weighted as-the-crow-flies distance provided by CEPII Gravity dataset. I construct the measure using the following formula, where o is the country of origin, and d the country of destination.

$$\text{Import distance}_d = \sum_o \text{imports}_{o,d}\text{distance}_{o,d}$$

C Solving and calibrating the model

In this section I provide details on the algorithm used to solve the model, and the calibration strategy. I abstract from denoting specific firms j to simplify the notation.

C.1 Solving for the general equilibrium stationary distribution

Assume values for the parameters of the model $Par = \{\beta, \delta, \alpha, \theta, \epsilon, \sigma, L, \mu_\lambda^f, \sigma_\lambda^f, \mu_\lambda^d, \sigma_\lambda^d, \sigma, p^f\}$. Note I abstract from modeling the foreign input producers, so I take the price of foreign inputs, p^f as a parameter in the model. Then I follow the structure detailed below.

1. I start with an initial guess for the consumption of the representative consumer, the composite good, and consumption price, (C^g, N^g, P^g). I normalize the wage to one, $w = 1$. I create a grid for each of the state variables, $(s^d, s^f, v, \lambda^f, \lambda^d)$.

2. Given the values for $(C^g, N^g, P^g, w = 1)$, I find the implied sectoral output, Y, and the price of the domestic inputs, p^d, according to the equations below.

$$Y = C^g + N^g$$
$$p^d = \frac{P^{g\ \alpha}\ w^{\ 1-\alpha}}{\alpha^{\ \alpha}\ (1-\alpha)^{\ 1-\alpha}}$$

3. Given the parameters, aggregate variables, (C, N, Y), and prices (P, p^d, w), I solve for the problem of the final good firms. I solve for the policy function for the new orders of domestic and foreign inputs, and value function, $(n^d(s^d, s^f), n^f(s^d, s^f), V(s^d, s^f)$ for each of the inventory levels of each input, s^f, s^d. Then I solve for the policy functions for $(s'^d, s'^f, x^f, x^d, \ell, p)$ for a given inventory levels, s^d, s^f, and specific combination of demand and delivery time shocks, $\eta = (v, \lambda^d, \lambda^f)$.

$$V(s^d,\ s^f) = \max_{\{n^d, n^f\}} E_\eta \Big[\tilde{V}(s^d,\ s^f,\ n^d,\ n^f,\ \eta)\Big] \qquad \text{where } \eta = (v,\ \lambda^d,\ \lambda^f)$$
$$\tilde{V}(s^d,\ s^f\ , n^d,\ n^f,\ \eta) = \max_{\{p, x^d, x^f, \ell, s'^d, s'^f\}} \ p\, y(p) - w\, \ell - p^d\, n^d - \ p^f\, n^f + \beta\, V(s'^d,\ s'^f)$$

3.1 **First step** is to obtain the policy functions of $(s'^d, s'^f, x^f, x^d, \ell, p)$ for values of $(s^d, s^f, n^d, n^f, \eta)$. I create a grid for the state variables (s^d, s^f, η). The policy function $(p, x^d, x^f, x, \ell, s')$ will be a function of (n^d, n^f) and defined for each (s^d, s^f, η).[8]

[8] Alternatively, I can create a grid for n^d, n^f, and solve for each point of the grid of the orders, and the choose the order that maximizes the value function.

3.1.1 **Step one:** given $(n^d, n^f, s^d, s^f, \eta)$ I solve for the four cases: both inputs are unconstrained, x^d constrained only, x^f constrained only, and both inputs constrained. To do this, I use the first order conditions of the final good firm problem.

3.1.1.1 **Both inputs are unconstrained,** x^f_{unc}, x^d_{unc}**.** Note these equation do not depend on the actual orders or stock of inventories, (n^d, n^f, s^d, s^f).

$$\frac{1}{p} = \frac{\epsilon - 1}{\epsilon} \; \frac{\alpha^\alpha \; (1-\alpha)^{1-\alpha}}{w^{1-\alpha}} \; \left(\theta \left(\frac{1-\delta\lambda^d}{1-\delta} \; \frac{1}{p^d}\right)^{\sigma-1}\right) + (1-\theta) \left(\frac{1-\delta\lambda^f}{1-\delta} \; \frac{1}{p^f}\right)^{\sigma-1}$$

$$y = P^\epsilon \; p^{-\epsilon} \; Y \; v$$

$$x = \frac{\epsilon-1}{\epsilon} \; \alpha \; p \; y \left(\theta \left(\frac{1-\delta\lambda^d}{1-\delta} \; \frac{1}{p^d}\right)^{\sigma-1}\right) + (1-\theta) \left(\frac{1-\delta\lambda^f}{1-\delta} \; \frac{1}{p^f}\right)^{\sigma-1} \Bigg)^{\frac{1}{\sigma-1}}$$

$$x^f = \left(\frac{\epsilon-1}{\epsilon} \; \alpha \; p \; y\right)^\sigma \; \left(\frac{1-\delta\lambda^f}{1-\delta}\right)^\sigma \; \frac{1-\theta}{x^{\sigma-1} \; (\tau \; p^f)^\sigma}$$

$$x^d = \left(\frac{\epsilon-1}{\epsilon} \; \alpha \; p \; y\right)^\sigma \; \left(\frac{1-\delta\lambda^d}{1-\delta}\right)^\sigma \; \frac{\theta_a}{x^{\sigma-1} \; p^{d\;\sigma}}$$

$$\ell = \frac{\epsilon-1}{\epsilon} \; (1-\alpha) \; \frac{p \; y}{w}$$

3.1.1.2 **Only** x^d **is constrained.** Note these equations depend on (n^d, n^f, s^d, s^f). To solve this system of equations, I pick a guess for x^f_g and then solve for the values of x^d, x, py, ℓ, p, y. Then I update the value of the guess for x^f_g using the values obtained for py. I create a loop where I update the value of the guess for x^f until I find the fixed point that solves the system.

$$x^d = s^d + \lambda^d \; n^d$$

$$x = \left(\theta^{\frac{1}{\theta}} \; x^{d\;\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\theta}} \; x_g^{f\;\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

$$py = p^f \frac{\epsilon}{(\epsilon-1)\;\alpha} \; \frac{1-\delta}{1-\delta\lambda^f} \left(\frac{x^f_g \; x^{\sigma-1}}{\theta}\right)^{1/\sigma} \quad \text{(Back out py from equation for } x^f\text{)}$$

$$
\begin{aligned}
\ell =& \ \frac{\epsilon - 1}{\epsilon} \ (1 - \alpha) \ \frac{p \ y}{w} \\
y =& \ x^{\alpha} \ \ell^{1-\alpha} \\
p =& \ P \left(\frac{y}{\nu \ y} \right)^{\frac{1}{\epsilon}} \\
x^f_{update} =& \ \left(\frac{\epsilon - 1}{\epsilon} \ \alpha \ p \ y \right)^{\sigma} \ \left(\frac{1 - \delta \lambda^f}{1 - \delta} \right)^{\sigma} \ \frac{1 - \theta}{x^{\sigma - 1} \ (p^f)^{\sigma}}
\end{aligned}
$$

3.1.1.3 **Only x^f is constrained.** Note these equations depend on (n^d, n^f, s^d, s^f). To solve this system of equations, I pick a guess for x^d_g and then solve for the values of x^f, x, py, ℓ, p, y. Then I update the value of the guess for x^d_g using the values obtained for py. I create a loop where I update the value of the guess for x^d until I find the fixed point that solves the system.

$$
\begin{aligned}
x^f =& \ s^f \ + \ \lambda^f \ n^f \\
x =& \ \left(\theta^{\frac{1}{\theta}} \ {x^d_g}^{\frac{\sigma-1}{\sigma}} + (1 - \theta)^{\frac{1}{\theta}} \ {x^f}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\
py =& \ p^d \frac{\epsilon}{(\epsilon - 1) \ \alpha} \ \frac{1 - \delta}{1 - \delta \lambda^d} \left(\frac{x^d_g \ x^{\sigma-1}}{1 - \theta} \right)^{1/\sigma} \quad \text{(Back out py from equation for } x^d\text{)} \\
\ell =& \ \frac{\epsilon - 1}{\epsilon} \ (1 - \alpha) \ \frac{p \ y}{w} \\
y =& \ x^{\alpha} \ \ell^{1-\alpha} \\
p =& \ P \left(\frac{y}{\nu \ y} \right)^{\frac{1}{\epsilon}} \\
x^d_{update} =& \ \left(\frac{\epsilon - 1}{\epsilon} \ \alpha \ p \ y \right)^{\sigma} \ \left(\frac{1 - \delta \lambda^d}{1 - \delta} \right)^{\sigma} \ \frac{\theta_a}{x^{\sigma - 1} \ p^{d \ \sigma}}
\end{aligned}
$$

3.1.1.4 **Both inputs, x^d and x^f, are constrained.** To solve this system of equations, I pick a guess for y_g and then solve for values of p, ℓ. The I update the value of the guess for output and create a loop where I update the values of output until I find the fixed point that solves the system.

$$
\begin{aligned}
x^f &= s^f + \lambda^f n^f \\
x^d &= s^d + \lambda^d n^d \\
x &= \left(\theta^{\frac{1}{\theta}} \, {x^d}^{\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\theta}} \, {x^f}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\
p &= P \left(\frac{y}{\nu \, y_g} \right)^{\frac{1}{\epsilon}} \\
\ell &= \frac{\epsilon - 1}{\epsilon} \, (1-\alpha) \, \frac{p \, y_g}{w} \\
y_{update} &= x^{\alpha} \, \ell^{1-\alpha}
\end{aligned}
$$

3.1.2 **Step two**: Given $(n^d, n^f, s^d, s^f, \eta)$, obtain the feasible values of $(p, x^d, x^f, x, \ell, s')$.

3.1.2.1 Case A. Both inputs are unconstrained, x^f_{unc}, x^d_{unc}: **if** $x^f_{unc} < s^f + \lambda n^f$ and $x^f_{unc} < s^f + \lambda n^f$ are true.

3.1.2.2 Case B. Only x^d is constrained, x^f_{unc}, x^d_c: **if** $x^f_{unc} < s^f + \lambda n^f$ and $x^f_{unc} > s^f + \lambda n^f$ are true.

3.1.2.3 Case C. Only x^f is constrained, x^f_c, x^d_{unc}: **if** $x^f_{unc} > s^f + \lambda n^f$ and $x^f_{unc} < s^f + \lambda n^f$ are true.

3.1.2.4 Case D. Both inputs are constrained, x^f_c, x^d_c: **if** $x^f_{unc} > s^f + \lambda n^f$ and $x^f_{unc} > s^f + \lambda n^f$ are true.

3.2 **Step two**: I start with a guess for the value function $V(s'^d, s'^f)$, and use the policy function to calculate the value function $\tilde{V}(s^d, s^f, n^d, n^f, \eta)$ (function of n^d, n^f, for each value of (s^d, s^d, η)).

$$
\tilde{V}(s^d, \, s^f, n^d, \, n^f, \, \eta) = \max_{\{p, x^d, x^f, \ell, s'^d, s'^f\}} \; p \, y(p) - w \, \ell - p^d \, n^d - \, p^f \, n^f + \beta \, V(s'^d, \, s'^f)
$$

3.3 **Step three**: given the value function $\tilde{V}(s^d,\ s^f,\ n^d,\ n^f,\ \eta)$, I obtain the expected value assuming iid distribution for each of the shocks in η, $E_\eta[\tilde{V}(s^d,\ s^f,\ n^d,\ n^f,\ \eta)]$.

3.4 **Step four**: I optimize to obtain the policy function of (n^d, n^f) for each value of $(s^d, s^f,\ \eta)$. I use a non linear solver to obtain the corresponding values for the orders. Alternatively, I have a grid for each n^d, n^f, and choose the pair that maximize $E_\eta[\tilde{V}(s^d,\ s^f,\ n^d,\ n^f,\ \eta)]$ for each $(s^d, s^f,\ \eta)$.

3.5 **Step five**: given the policy functions for $n^{*d}(s^d, s^f, \eta), n^{*f}(s^d, s^f, \eta)$ and
$p^*(n^d, n^f, s^d, s^f, \eta), \ell^*(n^d, n^f, s^d, s^f, \eta), x^{*d}(n^d, n^f, s^d, s^f, \eta), x^{*f}(n^d, n^f, s^d, s^f, \eta)$. I use value function iteration to obtain the value function $V(s^d, s^f)$ for the final good firm.

4. Given the policy functions for the final good firm (p_j, x_j^d), I can obtain the analytical solution for the decision variables of the input firm, labor demand and composite input demand, ℓ^d, N^d.

$$\ell_j^d = (1-\alpha)\ p_j\ x_j^d/w$$
$$N_j^d = \alpha\ p_j\ x_j^d/P$$

5. To solve for the stationary distribution, I fix the exogenous random process of η. The I use Monte Carlo simulations to obtain the stationary distributions: I solve for 100,000 firms for 200 periods.

6. Finally I update the initial guess for (C^g, N^g, P^g) using the following equations. If the updates values are different (up to a tolerance level) from the guesses, then I update my guess and go back to step two. Note the representative consumer owns the final good firms, which set prices and thus

have positive profits.

$$P = \left(\int_0^1 v_j \, p_j^{1-\epsilon} \, dj \right)^{\frac{1}{1-\epsilon}}$$

$$N = \int_0^1 N_j^d \, dj$$

$$C = \frac{w \, L \, + \int_0^1 \Pi_j dj}{P}$$

C.2 Transition paths

The initial calibration of the parameters is made according to section 3.1, by computing the general equilibrium stationary distribution. To compute the transition paths I first fix the aggregate variables, (C, N, Y), and prices (P, p^d, w). Then I compute the final good firms policy and value functions using backward induction. Every period firms observe the change in the mean and variance (a proportion of the mean) of the distribution of domestic delivery times and the change in price of foreign inputs, p_t^f. I obtain the partial equilibrium stationary distribution of the economy for each year of the transition path.

C.3 Proposition proof

In this section I show the proof of the proposition for the full model presented in section 2.

Proposition. *Inventories increase with longer delivery times.* If λ decreases, i.e. delivery times increase, the value of holding additional inventories increases.

Proof. I rewrite the problem of the final good firm as follows.

$$\tilde{V} = \max p^{1-\epsilon} \, P^{\epsilon} vY \, - p^d \Big(\frac{s^{d'} - (1-\delta)(s^d - x^d)}{1 - \lambda^d \delta} \Big) \, - p^f \Big(\frac{s^{f'} - (1-\delta)(s^f - x^f)}{1 - \lambda^f \delta} \Big) \, + \beta \, V(s'^d, \, s'^f)$$

$$\text{s.t. } x^d \leq s^d + \lambda^d \Big(\frac{s^{d'} - (1-\delta)(s^d - x^d)}{1 - \lambda^d \delta} \Big) \qquad (\mu^d)$$

$$x^f \leq s^f + \lambda^f \Big(\frac{s^{f'} - (1-\delta)(s^f - x^f)}{1 - \lambda^f \delta} \Big) \qquad (\mu^f)$$

Then I obtain the first order conditions with respect to $\{p, s^{f'}, s^{f'}\}$, where $A = y\, x^{\frac{1-\sigma}{\sigma}}$, $A^d = (x^d/\theta)^{\frac{1}{\sigma}}$, and $A^f = (x^f/\theta)^{\frac{1}{\sigma}}$.

$$\begin{aligned}
&(wrt\; p) && \frac{\epsilon-1}{\epsilon}\, p\, A = \frac{A^d}{1-\lambda^d\delta}\big((1-\delta)p^d + (1-\lambda^d)\mu^d\big) + \frac{A^f}{1-\lambda^f\delta}\big((1-\delta)p^f + (1-\lambda^f)\mu^f\big)\\
&(wrt\; s^{'d}) && (1-\lambda^d\delta)\beta V_{s'^d} = p^d - \mu^d\lambda^d\\
&(wrt\; s^{'f}) && (1-\lambda^f\delta)\beta V_{s'^f} = p^f - \mu^f\lambda^f
\end{aligned}$$

Then I substitute for the lagrange multipliers, μ^d, μ^f, and obtain the following expressions:

$$\underbrace{A^i\, p^i}_{\text{price input}} = \underbrace{(1-\lambda^i)}_{\substack{\text{order}\\ \text{arrives t+1}}}\ \underbrace{A^i\, \beta\, E_{\eta'} V_{s'^i}}_{\substack{\text{discounted value of}\\ \text{extra unit of inventory}}} + \underbrace{\lambda^i}_{\substack{\text{order}\\ \text{arrives t}}}\ \underbrace{A\, \frac{\epsilon-1}{\epsilon}\, p}_{\substack{\text{price}\\ \text{over markup}}} - \underbrace{\lambda^i}_{\substack{\text{order}\\ \text{arrives t}}}\ \underbrace{\frac{A^j}{\lambda^j}\, \big(p^j - (1-\lambda^j)\, A^j\, \beta\, E_{\eta'} V_{s'^j}\big)}_{\substack{\text{marginal discounted value}\\ \text{extra unit input j inventory}}}$$

$$\begin{aligned}
A^d p^d &= (1-\lambda^d)\, A^d\, \beta\, E_{\eta'} V_{s'^d} + \lambda^d\, A\, \frac{\epsilon-1}{\epsilon}\, p - \lambda^d\, \frac{A^f}{\lambda^f}\, \big(p^f - (1-\lambda^f)\, A^f\, \beta\, E_{\eta'} V_{s'^f}\big)\\
A^f p^f &= (1-\lambda^f)\, A^f\, \beta\, E_{\eta'} V_{s'^f} + \lambda^f\, A\, \frac{\epsilon-1}{\epsilon}\, p - \lambda^f\, \frac{A^d}{\lambda^d}\, \big(p^d - (1-\lambda^d)\, A^d\, \beta\, E_{\eta'} V_{s'^d}\big)
\end{aligned}$$

From here I can obtain the derivative of the discounted value of an additional unit of inventory with respect to λ. Note that when λ decreases, the share of inputs that arrives today decreases, meaning that delivery times for the input increases.

$$\frac{\partial\big(A^i\, \beta\, E_{\eta'}\, V_{s'^i}\big)}{\partial \lambda^i} = \frac{-1}{(1-\lambda^i)^2}\Big(A\, \frac{\epsilon-1}{\epsilon}\, p + \frac{A^i}{\lambda^f}\, \big(p^i - (1-\lambda^i)\, A^i\, \beta\, E_{\eta'} V_{s'^i}\big)\Big) \leq 0$$

This there is a negative relationship between the discounted value of an additional unit of inventory and the delivery times parameter, λ. As delivery times increase, (λ decrease), then the value of inventories increases.

I show the derivative is negative, since from the first order condition with respect to final price, p, we know:

$$A\, \frac{\epsilon-1}{\epsilon}\, p + \frac{A^i}{\lambda^i}\, \big(p^i - (1-\lambda^i)\, A^i\, \beta\, E_{\eta'} V_{s'^i}\big) = \frac{A^j}{\lambda^j}\, (\, p^j - \, (1-\lambda^j)\, \beta\, E_{\eta'} V_{s'^j}\,) \geq 0$$

and from the first order condition with respect to s'^{i}, $\mu^i = \frac{1}{\lambda^i}(p^i - (1-\lambda^i)\beta E_{\eta'} V_{s'^i})$, and because the lagrange multiplier, $\mu^i \geq 0$, then $p^i - (1-\lambda^i)\beta E_{\eta'} V_{s'^i} \geq 0$.

D Delivery times of inputs

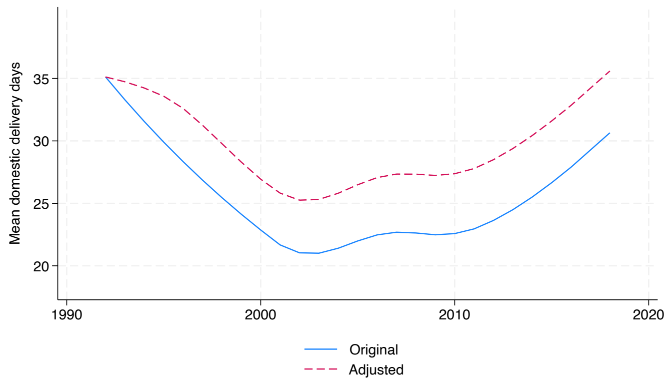
This section provides details on the domestic delivery times, using data from the Institute of Supply Management. Additionally, it details the method of transportation for U.S. imports from China, and the lead times for this route using data from the logistics company Freightos.

D.1 Domestic delivery times

The Institute of Supply Management (ISM), on their *Manufacturing Report on Business* provides monthly data for average commitment lead time for production materials, maintenance and operation supplies, and capital expenditures. They report the average days based on firm's responses to their lead times for each type of input. I then smooth out the averages or each type of products using the Hodrick-Prescott filter with a multiplier of 6.25. To obtain the mean of the distribution of domestic delivery times, I take the average of the smoothed value for production materials and maintenance and operation supplies, which equals 35.1 days. To estimate the variance of the distribution of domestic delivery days, I take the standard deviation of the mean of the averages for production materials and maintenance and operation supplies for the period of 1992 to 2018, which equals to 5 days. Then the variance is such that 95% of the distribution lies within the $+/-5.1$ days.

The ISM data includes lead times for all inputs a firms uses, including foreign and domestic. To estimate the trend of domestic delivery times, I have to adjust the ISM data for the delivery times of foreign inputs. I first take the value for the year of 1992. Second, I adjust the series for the inputs from China starting from 2001. To do so, I subtract the 30 days of the transit time between China and the U.S. multiplied by the share of foreign inputs, shown in Figure 5a. Finally, I smooth out the series using a Hodrick-Prescott filter from 1992 to 2001 to obtain the final series reported in Figure 30.

Figure 30: Mean of domestic delivery times



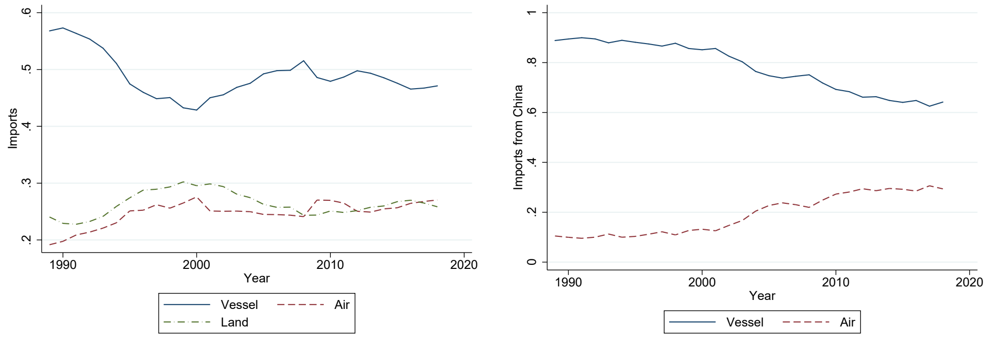
Note: The Figure shows the value of the average reported by the ISM of the delivery times for production materials and maintenance and operation supplies, adjusted by the lead times of foreign inputs.

D.2 Transportation of U.S. imports

This section provides detail on the method of transportation for total U.S. imports and imports that come from China. Figure 31a shows the trend for the method of transportation for all U.S. imports. On average for the period 1997 to 2018, around 50% of imports arrive via ocean. Figure 31b shows that on average, 80% of imports from China arrive via ocean vessel. Additionally, the share of vessel is decreasing, and more goods are shipped via air. Compared to the U.S. average for imports, more imports from China via ocean transportation, and the remaining via air.

The proportions of air vs ocean transportation for the goods coming from China remain relatively constant across manufacturing sectors, with the exception of the computer and electronic manufacturing sector, 334. Figure 32 shows the share of imports from China that arrive via ocean and air transportation across the NAICS 3 digit sectors from 1989 to 2018. Panel a shows that over this period, the proportion of shipments via ocean across sectors is on average 80% across sectors. Panel b shows the share of goods that arrive to the U.S. from China via air across sectors, which is on average around 20%. Over time, excluding the electronic manufacturing sector, there is a trend toward more air transportation.

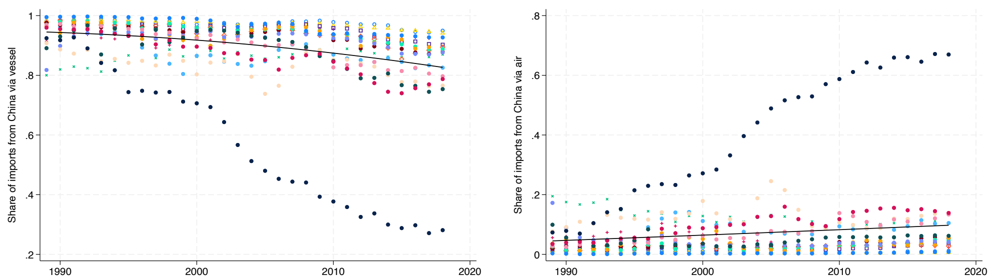
Figure 31: Method of transportation for U.S. imports



(a) Transport method for US imports (b) Transport method for imports from China

Note: The Figure show the share of imports that arrive via land, ocean, and air to the U.S., from 1989 to 2018, using data from the U.S. Census Bureau and retrieved from Schott (2008) website. Panel a shows the share of imports for each method of transportation for all U.S. imports. On average, 50% of imports arrive via ocean. Panel b shows the same share for imports specifically from China. On average, 80% of imports from China arrive via ocean, and the remainder via air.

Figure 32: Imports from China via ocean and air across industries



(a) Share of imports from China via ocean (b) Share of imports from China via air

Note: The Figure shows the share of the goods that arrive from China via ocean transportation (panel a) and air (panel b) for the 3 digit NAICS manufacturing industries. The proportions of ocean (80%) vs air (20%) transportation for the goods coming from China remain relatively constant across industries, with the exception of the computer and electronic manufacturing sector, 334.