Increasing Inventories: The Role of Delivery Times

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Abstract

Inventories mitigate the risk of global sourcing. I present new evidence of the rise in U.S. manufacturing inventories after 2005, reversing a declining trend that lasted for decades. I examine this trend in a model of delivery times and inventories. The rise in global sourcing lead to longer and more volatile delivery times, which increase firm's exposure to risk. Thus, firms hold more inventories. I find the rise in global sourcing accounts for 81% of the rise in inventories. Further, a globalized economy that uses more foreign inputs trades-off the increase in output at the cost of increased macroeconomic volatility.

Keywords: Inventories, global sourcing, global supply chains, delivery times

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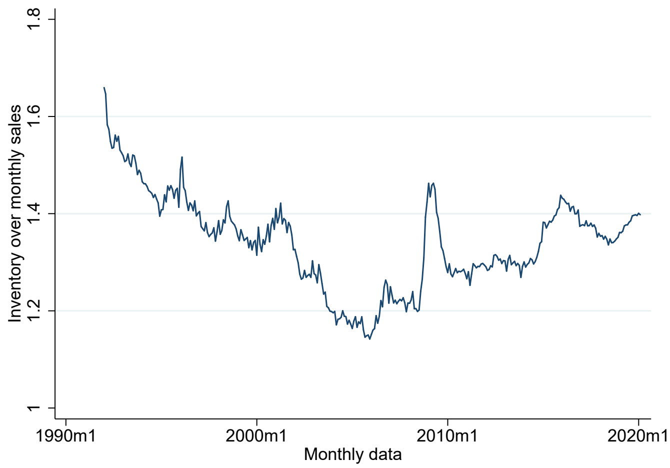
Global sourcing, where firms source inputs from distant locations around the globe, is an increasingly common feature of the modern production process. Whereas the efficiency gains of global sourcing are well documented, a growing literature emphasizes the risks and vulnerabilities of international input trade (e.g., Baldwin and Freeman (2022)). The formation of global networks increases the distance and the delivery times of inputs (Wong and Ganapati (2023)), which reduces a firm's ability to meet demand, respond to productivity changes, and mitigate supply shocks. Despite recent interest in resilient networks, the role of inventories in reducing the risk of global sourcing has received little attention.

I study the role of inventories in allowing firms to assume the additional risk of forming global supply chains by absorbing shocks and smoothing out production. First, I show new evidence of the change in the inventory trend: After a 25-year decline, U.S. manufacturing inventories-to-sales ratios have been steadily increasing since 2005. The average firm held 1 month and 4 days of sales as inventories in 2005. By the end of 2018, manufacturing firms were holding an additional week of sales as inventories, and by 2019 this had increased by another 5 days. Second, I explore the inventory trend in a model of global sourcing, centered on the trade-off between the relative price and the delivery times of inputs across suppliers. It features a new, tractable way of modeling stochastic delivery times. With globalization, firms substituted away from domestic inputs and toward cheaper, foreign inputs, which face longer and more volatile delivery times. Longer delivery times increase firms' exposure to underlying shocks–e.g., demand or productivity shocks–since they hinder a firm's ability to respond to shocks within the period. To mitigate this additional risk, firms raise their inventories. Last, I find that the increase in global sourcing accounts for 81% of the rise in U.S. manufacturing inventories after 2005. Regarding the aggregate economy, I show that the rise in the use of foreign inputs increases output at the cost of the rise in macroeconomic volatility. An economy that uses a higher share of the cheaper foreign inputs sets lower final prices, and produces higher output. Yet, given the longer delivery times of the foreign inputs, firm's are more exposed to both demand and delivery times shocks. Thus, prices and output are more volatile, even when accounting for the rise in inventories.

Figure 1: Increase in U.S. manufacturing inventories



Note: This Figure shows the trend in inventory-to-monthly sales for the aggregate manufacturing industry from 1992 to 2018, where inventories decrease from 1992 to 2004 and began to rise in 2005. Data source: U.S. Census Bureau.

First, I provide new and robust evidence of the rise in inventories. I show that after the well-documented and important decline in the inventories-to-sales ratio that started in the 1980s, inventories for aggregate U.S. businesses across the retail, wholesale, and manufacturing sector have been steadily increasing. The reversal of the long-term decline is sharpest for the manufacturing sector, as shown in Figure 1, which is the main focus of this paper. Within the manufacturing sector, the trend appears across industries and types of inventories. Intermediate-input inventories show the steepest decline and rise, highlighting the importance of sourcing choices in inventory dynamics.

Contemporaneous to the rise in inventories, I show an increase in the use of foreign inputs in production. As countries source from locations farther away, the distance imports travel, and thus the delivery times for inputs, increases. For the U.S. manufacturing, the share of foreign inputs over total inputs used in production increased from 13.3% in 1997 to 16.5% in 2018, largely driven by the 3 percentage point rise in inputs from China (see Schott (2008) and Heise, Pierce, Schaur, and

Schott (2019)). With this change comes longer and more volatile delivery times, since nearly 80% of imports from China arrive via ocean transportation, taking around a month to arrive, and are subject to frequent and long delays. Then, I show U.S. industries that use more foreign inputs also tend to stock more inventories. The relationship is strongest for intermediate input inventories, in which a 10% increase in foreign inputs is associated with a 7% rise in input inventories.

In the second part of the paper, I quantify the role of delivery times in shaping the long term inventory dynamics in a model of global sourcing and delivery times. The decrease in the inventories-to-sales that started in the 1980s has been studied in the context of *just-in-time* practices and inventory management (Ohno (1988); Feinberg and Keane (2006); Pisch (2020)). Advances in transportation and information technology (*technology*) enabled firms to build their inputs right before they were needed in the production process. This process decreased the delivery times of inputs, and thus reduced the need for inventories. While the continuous advances in technology maintain the downward pressure on inventories, here I show the change in the production process that came with the rise in global sourcing (*trade*) creates incentives to hold additional inventories. Both forces, technology and trade, interact and shape the inventory trend observed in the data.

To quantify these concurrent forces, I build on work by Khan and Thomas (2007) and Alessandria, Kaboski, and Midrigan (2010a), and depart from the literature that uses a fixed, one-period delivery lag by introducing different and stochastic delivery times for inputs in an environment with idiosyncratic demand risk. Here, a stochastic share of the inputs is delivered in the current period, and firms do not have access to the rest of the order until the next period. This new assumption allows me to match delivery time data across different suppliers and to quantify how marginal changes in the distribution of delivery times affect a firm's sourcing and inventory choices.

In the model, firms stock inventories to mitigate demand and delivery time shocks. The interaction between the volatility of demand and the mean of delivery times creates incentives to hold inventories. When firms have to wait for an input to arrive and their demand changes every period, they need to store some of the inputs as inventories to ensure that they will be able to meet their demand. As delivery times increase, the firm's ability to respond to demand shocks in each period decreases. Thus longer delivery times increase the value of holding an extra unit of inventories. Further, since holding inventories is costly, firms run the risk of stock-outs when they face high demand or a low delivery time shock. In this case, firms will raise their price until demand is met. Longer delivery times increase the probability of stock-outs, which increases price and output volatility.

I calibrate the model to study the consequences of global sourcing and the rise in delivery times that resulted. I analyze the period from 1992 to 2018 using import data by country of origin and method of transportation from the U.S. Census Bureau (Schott (2008)) and domestic and foreign input and output data reported by the Bureau of Economic Analysis Input-Output Tables. First, I model the improvements in transportation and information technology as a decrease in the mean and variance of the distribution of domestic delivery times, using data on lead times from the Institute of Supply Management. As domestic inputs become more readily available firms' incentives to hold domestic inventories decrease. Second, I model the productivity rise in China during this period, that lead to the fall in the price of their inputs. This endogenously leads to the rise in the use of foreign inputs. As firms increase their reliance on foreign inputs, the longer and more volatile delivery times increase firms' incentives to hold foreign inventories. I estimate foreign delivery times using data on average lead times for ocean transportation between the U.S. and China as reported by the logistics company Freightos.

I find that an important share of inventory dynamics is accounted for by changes in the delivery times of inputs. Advances in transportation and information technology, together with the rise in global sourcing, generate in the model an untargeted pattern in inventories similar to that observed in the data. The model accounts for 50% of the initial decline in the inventories-to-output ratio and 81% of the rise in inventories after 2005. Further, the model shows that a globalized economy that uses more foreign inputs trades-off an increase in output at the cost of the rise in macroeconomic volatility. As firms use more of the cheaper foreign inputs to produce, the price of the final good decreases and output rises. However, foreign inputs increase a firm's exposure to demand shocks, via the longer and more volatile delivery times. While inventories partially shield the firm from the added risk, firms are still more frequently constrained in the amount of inputs they have to produce. Thus, prices rise and output declines more often, which causes higher volatility in prices and output in the stationary distribution.

Further, I require both the technology and trade channels to explain the inventory dynamics. At first, inventories decrease because firms stock lower domestic inventories. Then, the rise in inventories is driven by the rise in foreign inputs, which are inventory-intensive, and compensate for the constant decline in domestic inventories. Finally, I use the model to decompose firms' incentives to hold inventories. Most of the incentives come from the interaction between the mean of the delivery times and the variance of demand, since they determine a large share of the *level* of inventories. Firms stock inventories primarily because delivery times expose them to demand shocks. However, as firms increase their reliance on inputs subject to volatile delivery times, the variance of delivery times determines an important share of the growth of inventories over time. Thus, the additional risk implied by possible delays for inputs accounts for the later rise in inventories.

Related Literature. This paper builds on and contributes to three strands of the literature. The paper advances the literature of inventory management and long-term inventory trends by providing the first evidence of the rise in inventories. I build on the work by Ohno (1988), Feinberg and Keane (2006), and Dalton (2013) who study the role of the improvements in transportation and information technology on the decline in inventories that began in the 1980s. For instance, Shirley and Winston (2004), Li and Li (2013), and Cui and Li (2018) document the negative relationship between inventories and improvements in transportation technology. Yet, here I focus on the relationship between the improvements in technology and the decline in delivery times.

Second, the paper contributes to the literature on inventory dynamics. Here, I differentiate from this rich literature by focusing on the role of delivery times in inventory dynamics. I build on the work by Khan and Thomas (2007) and Alessandria, Kaboski, and Midrigan (2010b), and include a new way of modeling stochastic delivery times, which allows me to study how changes in delivery times across time and suppliers affect firms' sourcing choices and their incentives to hold inventories. The paper relates to the studies of inventories and the business cycle (e.g., Iacovello, Schiantarelli, and Schuh (2007); Kryvtsov and Midrigan (2009); Novy and Taylor (2014); Tamegawa (2014); Alessandria, Khan, Khederlarian, Mix, and Ruhl (2023)), and the relationship between inventories and imported inputs (e.g., Jain, Girotra, and Netessine (2014); Vieira Nadais (2017)). Here, I show that U.S. inventories increase with imported input intensity, building on the work by Alessandria, Kaboski, and Midrigan (2013), who estimate that Chilean manufacturers hold more inventories of foreign inputs than of domestic inputs, and Khan and Khederlarian (2020b) document a similar relationship for India's manufacturing firms.

Last, the paper contributes to the growing literature on the risks of global sourcing (see Baldwin and Freeman (2022) for review on the literature) and the importance of delivery time frictions in trade (e.g., Evans and Harrigan (2005); Hummels (2007); Leibovici and Waugh (2019)). I expand our understanding on these topics by highlighting the role of inventories in reducing the risk of global sourcing, and further quantifying the costs of delivery time frictions.

Layout. The paper is organized as follows. The next section documents the rise in inventories, the increase in reliance in foreign inputs, and the positive relationship between inventories and imported inputs. In Section II, I develop a dynamic trade model with stochastic delivery times and demand shocks. Section III presents the calibration strategy and details how I calibrate the model to quantify the two opposing forces of delivery times. Section IV presents quantitative findings on the role of delivery times in inventories, and Section V concludes.

I Increasing inventories and the rise in global sourcing

In this section I provide evidence of the concurrent rise in inventories and the rise in global sourcing. After a sharp decline in U.S. manufacturing inventories that started in the 1980s, the ratio of inventories over sales has been increasing since 2005. At the same time, U.S. firms increased the share of foreign inputs over total inputs used in production. I show that the rise is driven by the sourcing of inputs from China after China joined the World Trade Organization in 2001. Inputs from China are subject to particularly long delivery times and lengthy delays, since 80% of the goods arrive via ocean transportation. I then show the positive relationship between foreign inputs and inventories across manufacturing industries.

Data. Data on inventories and foreign inputs are from the U.S. Census Bureau and the Bureau of Economic Analysis (BEA). Aggregate inventory and sales data are from the *Manufacturer's Shipments, Inventories, and Orders* survey from the U.S. Census Bureau. I match sectors in the survey to North American Industry Classification System (NAICS) three-digit industries. Inventories reported by the U.S. Census Bureau include the value of all inventories the firm owns if they are located within the U.S., in a customs warehouse, or being transported to or from the U.S., as long as they are owned by a U.S. firm. I exclude the *Petroleum and Coal Products* sector (NAICS code 324) from the analysis, since the petroleum sector is volatile by nature and only accounts for 5% of total manufacturing inventories.[1] Firm-level data on inventories for public U.S. firms are from WRDS Compustat. The U.S. Census Bureau reports imports by country of origin and method of transportation, which I obtain from Schott (2008). Data on domestic and foreign inputs and output are reported by Bureau of Economic Analysis Input-Output Tables. In Appendix B I present similar findings using imported input data from the World Input-Output Database, OECD Input-Output Tables, and the end-use classification by the U.S. Census Bureau. Imported input data is available from 1997 to 2019 for

[1] In Appendix A I show robustness checks for the inventory-to-sales trend, which holds when I include the petroleum sector and when I exclude the transportation sector.

three-digit NAICS industries.

1.1 Increasing Inventories

The reversal of the long-term decline in inventories is observed across U.S. businesses, manufacturing industries, types of inventories, and public firms, and in other countries' manufacturing sectors. Figure 2a shows the rise in inventories to monthly sales for aggregate U.S. businesses. The average U.S. business, including the manufacturing, retail, and wholesale, stored 1 month and 1 week of sales as inventories at the end of 2005, and by the end of 2019 they were storing an additional 5 days of sales as inventories. Across businesses, it is the manufacturing sector who observes the largest rise starting in 2005,[2] as depicted in Figure 2b, and the wholesale and retail sector observe an increase in inventories starting around 2010. In 1992, manufacturing firms held 1 month and 20 days of sales as inventories. Inventories reached the lowest point in December of 2005, where the average firm held one month and 4 days of sales as inventories. By the end of 2019, firms were holding additional 12 days of sales as inventories.

Within the manufacturing sector, the decrease and subsequent increase in inventories is present across industries and types of inventories, as shown in Figure 3. The U.S. Census Bureau reports three types of inventories: finished goods; materials and supplies, which are raw materials used in production; and work-in-process inventories, which are commodities undergoing fabrication within firms. I refer to the sum of materials and supplies and work-in-process as intermediate input inventory.

Whereas inventories rise across all types, panel a shows that input inventory has the steepest decrease and increase, which reflects the importance of input sourcing choices for firms' inventory holdings. Further, the trend in inventories is observed across all NAICS three-digit manufacturing sectors. Panel b shows a

[2] A longer time series for the manufacturing inventories-to-sales ratio, from 1958 to 2018, is reported in Appendix A using the NBER-CES manufacturing industry database.

Figure 2: Reversal of the long-term decline in U.S. inventories

(a) Business inventories (b) Types of businesses

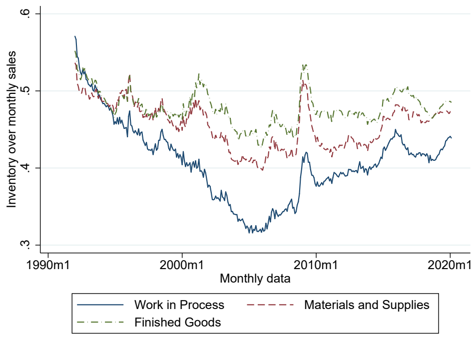
Note: The figures show trends for inventories over sales. Panel a shows the rise in inventories for total businesses in the U.S. and panel b shows trends for the three types of businesses; as defined by the U.S. Census Bureau: manufacturing, wholesale, and retail. The sharpest trend is observed in the manufacturing sector.

scatterplot of the inventories-to-sales time-series trends for all industries and their quadratic fit. Individual series for each industries can be found in Appendix A. Next section shows that, while all industries observe an increase in inventories, its the import intensive industries that observe the largest growth. Last, Appendix A shows the reversal of the long-term decline in inventories is also observed across U.S. manufacturing public firms and in other countries' manufacturing sectors: Australia, Canada, Japan, and South Korea.

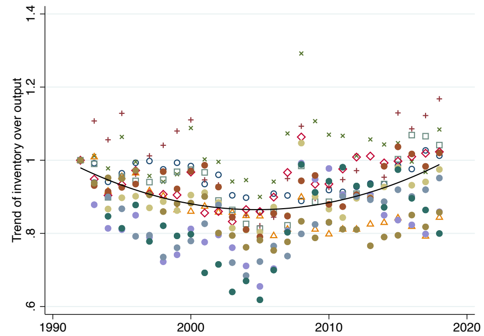
1.2 Rise in global sourcing

With the rise in inventories, there has been an increase in the use of foreign inputs in production and thus in the distance imports travel. Figure 4 shows that with the rise in global sourcing, as countries trade with partners farther away, the distance traveled by imports increases across countries. Following Wong and Ganapati (2023), I compute a measure of distance using the dollar value of imports by country of origin and the population-weighted as-the-crow-flies distance in kilometers, provided by CEPII Gravity dataset. The distance of imports increased at an average annual rate

Figure 3: Increasing inventories across industries and types of inventories



(a) Types of inventories



(b) Manufacturing sectors and their quadratic fit

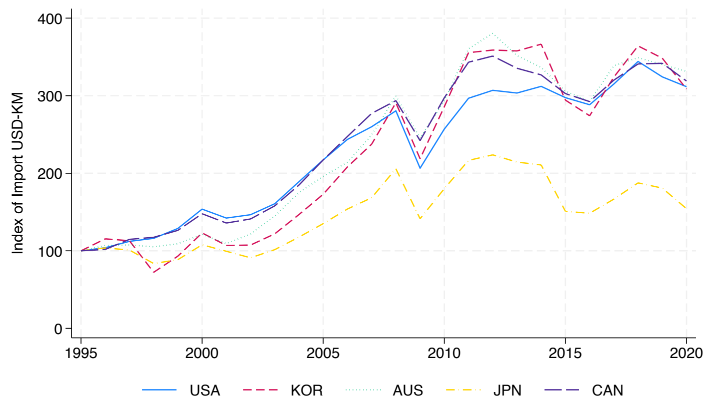
Note: Panel a shows the rise in inventories after 2005 for the three types of inventories, as defined by the U.S. Census Bureau: finished goods, material and supplies (raw goods used in production), and work-in-process inventory (goods undergoing fabrication). Panel b shows a scatterplot and a quadratic fitted line of the index of inventories-to-sales ratio for NAICS three-digit manufacturing industries.

of 6% from 1995 to 2018, for the U.S., South Korea, Australia, Japan, and Canada. As the distance traveled by imports increases, so does their delivery times.

At the same time, there has been a substitution away from domestic inputs and toward foreign inputs used in production. Here, I explore the rise across the U.S. manufacturing sectors, and Appendix B shows a similar trend across countries. Figure 5a shows the rise in the share of imported inputs, which represented 13.3% of total inputs used in production in 1997 and increased to 16.5% in 2018. The rise is driven by the increase in inputs from China. Figure 5b shows the share of imported inputs for the main trade partners of the U.S.: Canada, Mexico, and China. The share of inputs from Mexico and Canada remain relatively constant, whereas inputs from China grow around 3 percentage points during this period. Further, the substitution of domestic inputs for inputs from China is observed across all manufacturing sectors (details in Appendix B).

Import data by country of origin is reported by the U.S. Census Bureau. Data on domestic and foreign inputs are published by BEA Input-Output tables. I compute the share of imported inputs by country of origin following a methodology

Figure 4: Increase in distance imports travel across countries

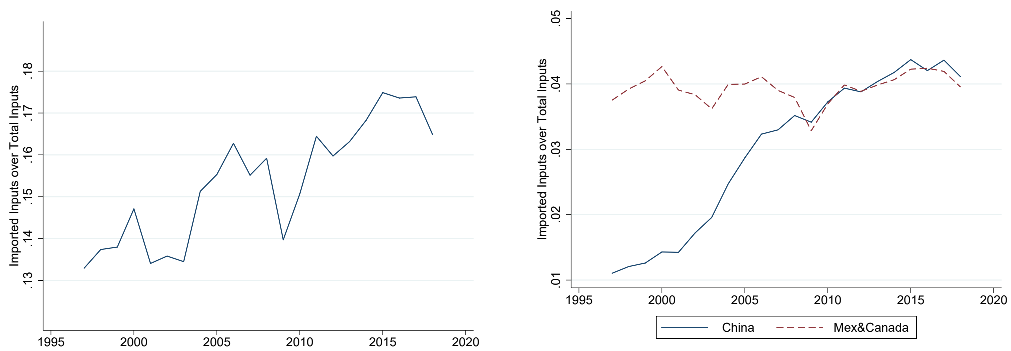


Note: The figure shows the index of the measure of distance imports travel by each country, U.S., Australia, Canada, Japan, and South Korea. The measure uses the USD value of imports by country of origin and the population-weighted as-the-crow-flies distance, from the CEPII Gravity dataset. It follows: Import distance$_d$ = $\sum_o$ imports$_o$ $\times$ distance$_{od}$ where o is the country of origin, and d the country of destination. Distance imports travel, as a proxy for delivery times, has increased across countries, and increased at an average annual rate of 6% from 1995 to 2018 across countries.

similar to that used by the BEA for the Import Matrices. To obtain foreign intermediate inputs by country of origin, I assume that 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. Note that the trend is robust to using data from the (i) WIOD, (ii) OECD , and (iii) U.S. Census end-use classification, all of which show similar trends in Appendix B.

Imports from China are subject to longer and more volatile delivery times than domestic inputs or foreign inputs sourced from Mexico and Canada, which are transported mainly by land via truck and rail. In contrast, 80% of imports from China arrive via ocean transportation and the remainder 20% of imports via air. Notably, these transportation proportions are common across manufacturing industries (see Appendix D). As firms substitute away from domestic inputs, which are mostly transported via land, for inputs from China–which have especially long and volatile delivery times–average delivery times for their inputs rise. Ganapati, Wong, and Zic (2020) document the time-intensity of ocean transportation, in which the

Figure 5: Substitution toward imported inputs driven by the rise in inputs from China



(a) Imported inputs over total inputs

(b) Imported inputs over total inputs: China and Mex/Can

Note: The figures show trends for imported inputs over total inputs. Panel a shows the increase in the share of total imported inputs. Panel b shows the share of imported inputs over total inputs for the three main trading partners with the U.S.: Mexico, Canada, and China. Data are from the U.S. Census Bureau and BEA Input-Output Tables, and imported inputs by country of origin follow the methodology used by the BEA for computing import matrices. I assume imports are used in the same proportion across all industries and final uses to obtain the country of origin's share of imported inputs.

majority of trade arrives via U.S. ports indirectly because ships go through specific hubs before reaching their final destinations. Imports from China via ocean take around 25 days to arrive at the West Coast and 35 days for the East Coast, according to Freightos. Further, Blaum, Esposito, and Heise (2023) document the historical volatility of ocean shipping times. According to Sea Intelligence and eeSea, delivery delays occur more frequently in ocean transportation due to port congestion, customs delays, and weather conditions.[3]

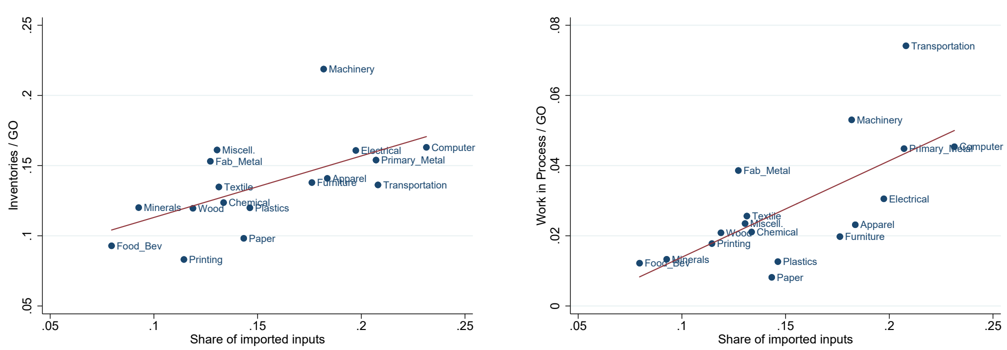
[3]Sea Intelligence and eeSea specialize in the study of carrier reliability, transit times, and vessel delays for ocean container transportation. According to the *Global Liner Performance* 2018 report from Sea Intelligence, on average 30% of all shipments from China to U.S. arrive more than one day after or before the original delivery day. Also, around 10% of all arrivals were more than 3 days delayed, according to the *Schedule Reliability* 2020 report from eeSea.

1.3 Inventories increase with imported input intensity

Industries that use more imported inputs tend to stock higher inventories. Figure 6a shows the positive relation between the average share of imported inputs and inventories over output across NAICS three-digit manufacturing sectors, in which the fitted line has a slope of 0.3. The relationship is strengthened when I consider input inventory, as shown in Figure 6b, in which the slope of the fitted line equals 0.9. Similar results are shown in Appendix B using imported input data reported by the WIOD. Further, to obtain the extent to which importers hold more inventories, I analyze the following linear regression of inventories on foreign imports where i denotes industry, t year, y_{it} inventories, a_{it} value added, x_{it} intermediate inputs, and δ time and industry fixed effects:

$$\log(y_{it}) = \beta_0 + \beta_1 \log(a_{it}) + \beta_2 \log(x_{it}) + \delta_i + \delta_t + \epsilon_{it} \tag{1}$$

Figure 6: Inventories increase with imported input intensity



(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 three-digit manufacturing industry from 1997 to 2018. The line represents the fitted line for each scatter plot. Correlation between total inventories and imported inputs equals 0.59 and 0.68 for intermediate inputs.

I find a strong positive relation between inventories and imports. Table 1 shows the time-series results, in which a 10% increase in imported inputs is associated with a rise in inventories of 6% and a rise of 7% in input inventories (column 3).

When controlling for industry's value added, column 4 shows that a 10% increase in imported inputs increases inventories by 3.5% and input inventories by 4.2%. Moreover, the positive relationship holds when considering only inputs sourced from China. Column 7 shows that a 10% increase in the use of inputs form China is associated with a rise of 4% in total inventories and 5% in input inventories (column 7). The relationship remains when controlling for value added, in which the increase of 10% in inputs from China increases total inventory by 2% and input inventory by 3%, as shown in column 8.

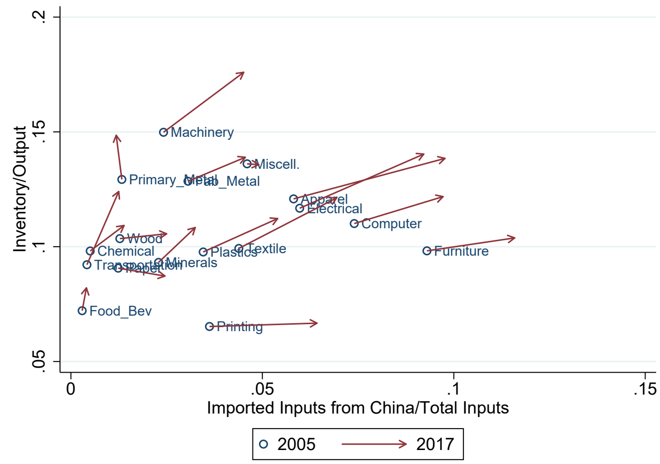
Figure 7 shows the contemporaneous growth of inventories and inputs from China across industries from 2005 to 2017. Bullet points mark the initial levels of inventories over output and the share of inputs from China observed in 2005, and arrows pointing toward the northeast indicate the growth in both variables across industries from 2005 to 2017. While the inventory intensity of sourcing foreign inputs has been documented previously by Alessandria, Kaboski, and Midrigan (2010a) and Khan and Khederlarian (2020a) using firm-level data for Chilean and Indian firms, here I provide evidence of the relationship across U.S. manufacturing industries and tie it with the rise in inputs from China.

II A model of delivery times and inventories

I present a model centered on the trade-off between the price and delivery times of inputs to study the role delivery times play in firm sourcing and inventory decisions. Following the theoretical framework for inventories and trade introduced by Khan and Thomas (2007) and Alessandria, Kaboski, and Midrigan (2010a), I develop a model in which firms stock inventory to insure against demand and delivery time shocks. I depart from the literature that assumes a deterministic one-period delivery lag for all inputs, and introduce different and stochastic delivery times across inputs.[4] In the model, a stochastic share of inputs are delivered this period, and firms

[4] An exception is the work by Alessandria, Kaboski, and Midrigan (2010b), where they introduce a probability of arrival for the orders, where the entire order either arrives immediately or next period. Here, I assume a stochastic share of the order arrives today. I assume the domestic and foreign

Figure 7: Industries source more inputs from China and hold more inventories



Note: The figure shows a scatterplot of the value of the share of imported inputs over total inputs and the inventory-to-output ratio across NAICS three-digit manufacturing industries for 2005. Arrows indicate the change in values for the year 2017, and show a contemporaneous increase in inventories and inputs from China across industries.

do not have access to the rest of the order until the next period. This specification of delivery times allows me to quantify how marginal changes in the distribution of delivery times affect the firm's sourcing and inventory choices. Further, I can use observed lead times to calibrate the delivery times in the model, which adds flexibility to the literature in which delivery times are fixed to the assumed length of the period in the model (e.g., monthly, quarterly).

2.1 Environment

Time is discrete and indexed by $t \in \{0, 1, 2, ..., \infty\}$. The economy is composed of a unit continuum of monopolistic final good producers, a unit continuum of competitive firms that produce domestic and foreign inputs, and a domestic representative consumer. Uncertainty in the model is given by firm-specific, independent, and

inputs are governed by different distributions, which allows the model to calibrate the distributions to the mean and variance of the delivery time data.

Table 1: Positive relation between inventories and imported inputs

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A								
	log(inventory)							
log(imported inputs)	0.86	0.49	0.59	0.35				
	[0.07]	[0.07]	[0.02]	[0.02]				
log(inputs China)					0.17	-0.10	0.41	0.21
					[0.33]	[0.12]	[0.03]	[0.02]
log(value added)		0.48		0.75		0.98		0.86
		[0.11]		[0.03]		[0.09]		[0.04]
Weight by sales	✓	✓			✓	✓		
Year, industry FE			✓	✓			✓	✓
R^2	0.90	0.96	0.89	0.94	0.02	0.89	0.2	0.89
N	17	17	374	374	17	17	374	374
Panel B								
	log(input inventory)							
log(imported inputs)	1.25	1.17	0.72	0.42				
	[0.13]	[0.26]	[0.03]	[0.02]				
log(inputs China)					0.46	0.12	0.52	0.28
					[0.47]	[0.30]	[0.03]	[0.02]
log(value added)		0.10		0.92		1.23		1.03
		[0.30]		[0.04]		[0.24]		[0.05]
Weight by sales	✓	✓			✓	✓		
Year, industry FE			✓	✓			✓	✓
R^2	0.87	0.87	0.85	0.84	0.06	0.68	0.20	0.77
N	17	17	374	374	17	17	374	374

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 regression results for NAICS three-digit industry average from 1997 to 2018, which has a total of 17 observations (one per industry). Columns 3, 4, 7, and 8 report results unsing time series.

identically distributed (*iid*) demand and delivery time shocks for the domestic and foreign inputs.

Final good firms. The unit continuum of final good firms, $j \in [0, 1]$, behave monopolistically and produce a unique variety of the final good, y_j. Final good firms maximize profits subject to six constraints. First, each firm faces the demand from the representative consumer, which is a function of the per-period iid firm-specific demand shock, ν_j, total production, Y, and price index, P.

$$y_j(p_j) = \nu_j \, Y \, (P/p_j)^{\epsilon} \qquad \text{where } \nu_j \sim_{iid} G\,(\mu_\nu, \, \sigma_\nu) \tag{2}$$

Second, a firm's technology combines the domestic input, x_j^d, foreign input, x_j^f, and labor, ℓ_j, to produce the final good. I assume domestic and foreign input are combined using a constant elasticity of substitution (CES), with elasticity σ, which allows me to match the increase in reliance on imported inputs observed in the U.S. manufacturing sector. Within the CES aggregator, inputs are weighted using θ. This allows the model to match the initial level of domestic to foreign inputs observed in the data. Then, I assume a Cobb-Douglas function between the intermediate input and labor:

$$y_j = \left(\theta^{\frac{1}{\sigma}} \, {x_j^d}^{\frac{\sigma-1}{\sigma}} \; + \; (1-\theta)^{\frac{1}{\sigma}} \, {x_j^f}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1} \, \alpha} \, {\ell_j}^{1-\alpha} \tag{3}$$

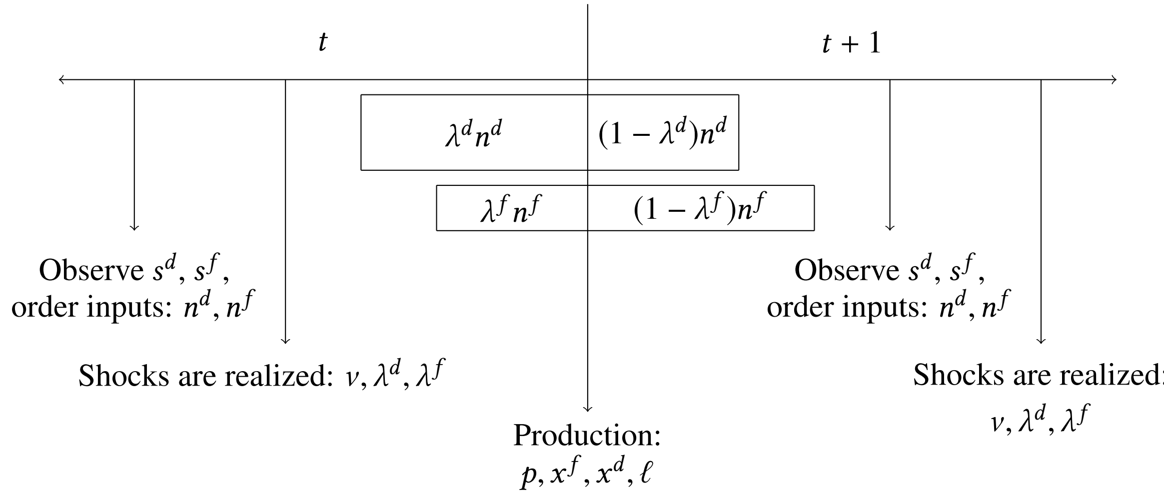
Third, domestic and foreign inputs, $i = \{d, f\}$, face stochastic delivery times. Only a fraction λ_j^i of the order of the inputs, n_j^i, is available for them to produce that period. Thus, inputs used to produce, x_j^i, are constrained to be less than or equal to the initial level of inventories, s_j^i, and the fraction λ_j^i of the order that arrives before production takes place. Each delivery time shock, λ_j^i, is drawn from the input-specific distribution $G^i(\cdot)$. Equation (4) summarizes the third and fourth constraint the final good firm faces. Fourth, firms are able to store inventories of domestic and foreign inputs, which depreciate at rate δ. Equation 5 shows the law of motion of inventories, in which inventories tomorrow, $s_j^{'i}$, are equal to the inputs left after production, $s_j^i \; + \; \lambda_j^i \, n_j^i \; - \; x_j^i$, discounted at rate $(1 - \delta)$, plus the order that arrives next period, $(1 - \lambda_j^i) \, n_j^i$.

$$x_j^i \; \leq \; s_j^i \; + \; \lambda_j^i \, n_j^i \qquad \text{where} \;\; \lambda_j^i \sim_{iid} \; G^i(\mu_\lambda^i, \sigma_\lambda^i) \tag{4}$$

$$s_j^{'i} = (s_j^i \; + \; \lambda_j^i \, n_j^i \; - \; x_j^i)(1 \; - \; \delta) \; + \; (1 \; - \; \lambda_j^i) \, n_j^i \qquad \text{for} \;\; i = \{d, \; f\} \tag{5}$$

Last, Figure 8 shows the timing constraint firms face. Firms must decide how much of the domestic and foreign inputs to order before they know the demand and delivery time shocks for the period. Firms place their orders according to their initial level of inventories and expected shocks. After the firm-specific demand and delivery time shocks are realized, $\{\nu, \lambda^d, \lambda^f\}$, the fraction, λ^d, λ^f, of the orders arrive and can be used for production. Firms decide on the amount of inputs, x^d, x^f,

Figure 8: Timing – firms order inputs before shocks are realized



and labor, ℓ, they will use to produce and set the price, p. These choices and the law of motion of inventories define the inventories for tomorrow. The rest of the order arrives early next period and is added to the next period's inventory.

The recursive problem for the final good producer is given by two Bellman equations, which correspond to the choices made within the timing constraint. For clarity, I drop the subscript denoting the specific firm in the unit continuum, j. The value function, $V(s^d,\ s^f)$, defines the optimal order of inputs, given the initial inventories of each input. Then, after shocks are realized and given the order of inputs, firms decide on the amount of inputs and labor to use in production, and set prices. This problem is described by the value function $\tilde{V}(s^d,\ s^f\ , n^d,\ n^f,\ \eta)$, where firms maximize present and future profits subject to 6 constraints: the demand from the consumer (equation 2), the production function (equation 3), the two constraints for the domestic and foreign inputs used in production (equation 4), and the law of motion for domestic and foreign inventories (equation 5).

$$V(s^d,\ s^f) = \max_{\{n^d, n^f\}} E_\eta\Big[\tilde{V}(s^d,\ s^f,\ n^d,\ n^f,\ \eta)\Big] \qquad \text{where } \eta = (\nu,\ \lambda^d,\ \lambda^f)$$

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

Firms behave monopolistically by setting prices. If a firm is unconstrained in the amount of inventories they need to meet the demand, then the price they set will be equal to a markup times an index of the price of the inputs. However, if a firm is constrained in the amount of inputs and has an inventory stock-out, due to high demand or a low delivery time shock, then the firm will raise the price until it is able to satisfy the demand from the consumer.

The interaction between positive delivery times and the demand shock creates incentives for firms to hold inventories. Since firms have to wait for their inputs to arrive, while their demand changes every period, they need to store some of these inputs as inventories to ensure they will be able to meet their demand. Also, firms hold inventories because delivery times are stochastic and firms don't have certainty regarding when they will arrive. On the other hand, inventories are costly; they depreciate at rate δ and firms face a discount rate β. The cost of holding inventories creates a trade-off between the relative price and delivery times across inputs.

Domestic and foreign input firms. There is a unit continuum of competitive domestic inputs firms, j, that produce a specific variety of the input. The variety j is demanded by the final good firm that produces that same variety within the continuum. To produce the domestic input, x_j^d, equation (6) shows that the firm uses a Cobb-Douglas production function using labor, ℓ_j^d, and the composite input, N_j^d. Also, there is a unit continuum of foreign input producers that produce the variety, x_j^f. Similar to domestic inputs, the final good firm j demands the foreign input j. I abstract from modeling the problem of foreign inputs firms, and take as given the input price, p^f.[5] All firms along the continuum have access to the

[5]Alternatively, I can assume a constant returns to scale technology for the foreign firm, where $x_j^f = A^f \ell_j^f$ and thus $p^f = w^f / A^f$. Here, I take as given the productivity changes and normalize the

same technology and don't face any shocks, so there is a unique price for the unit continuum of domestic inputs, p^d, and one for all varieties of the foreign inputs, p^f.

$$x_j^d \;=\; N_j^{d\,\alpha}\;\ell_j^{d\;1-\alpha} \tag{6}$$

Representative consumer. The representative domestic consumer has preferences over the final consumption good, C. The consumer demands the unit continuum of final good varieties, y_j, and uses a CES aggregator with elasticity of substitution ϵ, to produce the final consumption good, C, and the composite good, N, as shown in equation (7). The price index, P, represents the price of the final consumption good and the composite input. To pay for the varieties, y_j, the consumer has access to the income described in equation (8). First, the consumer sells the composite input to the unit continuum of domestic inputs firms that use it as input in their production, PN, where $N = \int_0^1 N_j^d\, dj$. Second, the consumer receives labor income, wL. Third, the consumer owns the final good firms and receives their profits $\int_0^1 \Pi_j\, dj$.[6]

$$C \;+ N = \left[\int_0^1 \, v_j^{\frac{1}{\epsilon}}\; y_j^{\frac{\epsilon-1}{\epsilon}}\; dj\right]^{\frac{\epsilon}{\epsilon-1}} \tag{7}$$

$$\int_0^1 p_j\, y_j\; dj = P\;N \;+\; w\;L \;+\; \int_0^1 \Pi_j\; dj \tag{8}$$

Competitive Equilibrium. The equilibrium is given by the state-contingent policy functions for the final good firms $j \in [0,1]$: $\{n_{jt}^d(s), n_{jt}^f(s), x_{jt}^d(s,n,\eta), x_{jt}^f(s,n,\eta), \ell_{jt}(s,n,\eta), p_{jt}(s,n,\eta)\}_{t=0}^{\infty}$ where $s = (s^d, s^f)$, $n = (n^d, n^f)$, and $\eta = (\nu, \lambda^d, \lambda^f)$; allocations for the domestic input firms $\{N_{jt}^d, \ell_{jt}^d\}_{t=0}^{\infty}$; for the consumer $\{(y_{jt})_{j\in[0,1]}, N_t, C_t\}_{t=0}^{\infty}$; and prices $\{w_t,\; P_t,\; p_t^d\}_{t=0}^{\infty}$ such that:

- The policy functions and allocations solve the final good firm problem, the

wages of the foreign country to one.

[6] Alternatively, I can assume a representative consumer that demand the final consumption good, C, and a representative retailer that produces the goods C and N using the unit continuum of final goods.

domestic input firm problem, and the representative consumer problem;

- The final good market clears, in which the demand of the domestic consumer is equal to the supply of the final good firm for each of the varieties, y_j, $j \in [0, 1]$;
- The domestic input market clears, in which the demand of final good firms is equal to the supply of the domestic input firm for each of the varieties, x_j^d, $j \in [0, 1]$;
- The composite good market clears, in which the supply of the consumer is equal to the demand of the unit continuum of domestic input firms, $N = \int_0^1 N_j^d \, dj$;
- The labor market clears, in which the fixed inelastic labor supply of the consumer is equal to the labor demand of the unit continuum of domestic inputs and final good firms, $L = \int_0^1 \ell_j^d \, dj + \int_0^1 \ell_j \, dj$.

2.2 Discussion of the mechanism of the model

Firm's sourcing decisions and their choice to hold inventories is driven by the trade-off between the price and delivery times for inputs. A firm considers not only the relative price of the inputs, but also their relative delivery times, which imply a different inventory choice. Delivery times expose the firm to demand risk, since firms don't have immediate access to the inputs and thus can't respond to the demand shock within the period. As a result, firms need to store inputs as inventories. Further delivery times are stochastic, and potential delays mean that firms must incur the cost of storing additional inventories. If a firm sources the cheaper foreign input, it faces longer and more volatile delivery times, and stocks more inventories to be able to meet the demand in every period.

The longer the delivery times, the more inventories firms will choose to hold. To show this, assume a simpler model with one input, linear technology, and remove the timing constraint– although Appendix C shows that the same holds for the model presented in this section. First order conditions for the final good firm are rearranged to show equation (9). The price of the input is equal to the discounted value of an extra unit of inventories weighted by the proportion of the order that arrives tomorrow and is added to future inventories, $(1-\lambda)$, plus the price over markup, p/μ, weighted by the proportion of the order that arrives today, λ.

$$p_{input} = \underbrace{(1-\lambda)}_{\substack{\text{order} \\ \text{arrives t+1}}} \underbrace{(1-\delta)\,\beta\, E_{\eta'}\, V_{s'}(s',\eta')}_{\substack{\text{discounted value of an} \\ \text{additional unit of inventory}}} + \underbrace{\lambda}_{\substack{\text{order} \\ \text{arrives t}}} \underbrace{p/\mu}_{\substack{\text{price} \\ \text{over markup}}} \tag{9}$$

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

Proof. From equation (9), it follows that the derivative of the discounted value of an additional unit of inventory with respect to λ is less than or equal to zero (note that as λ increases, delivery times decrease): $\frac{\partial\left((1-\delta)\,\beta\, E_{\eta'}\, V_{s'}(s',\eta')\right)}{\partial\lambda} = \frac{\mu\, p_{input} - p}{(1-\lambda)^2/\mu} \leq 0$. When firms are unconstrained in the amount of inputs they can use to produce, then price equals the markup times the price of the input $p = \mu\, p_{input}$. When firms are constrained in their inventory and they stock-out, they raise their price to meet demand, $p > \mu\, p_{input}$. Thus, there is a negative relationship between the value of inventories and λ.

With the improvements in transportation and information technology, delivery times decrease and firms stock lower inventories as the value of an additional unit of inventories decreases. On the other hand, as the price of foreign inputs decrease, due to free trade agreements or productivity increases in foreign countries, U.S. firms substitute away from domestic inputs and toward foreign inputs, given the CES assumption in equation (3). Foreign inputs face longer delivery times than domestic inputs, and the average delivery times for inputs increases. Firms trade off the cheaper input for an increase in their exposure to volatility and, in response, firms increase their inventories.

Moreover, inventories increase if the variance of the distribution of delivery times increases. As delivery times become more volatile, firms increase their level of inventories to adjust to the increase in risk. Similarly for the variance of demand shocks, where if demand volatility is higher, firms will need to increase their inventories to insure against the additional risk they face.

III Quantifying frictions

To study the role of delivery times in inventory dynamics, I start by calibrating the model to match moments of the U.S. manufacturing industry in 1992. Then, I use data on delivery times and imported inputs to calibrate the two opposing forces of delivery times, technology and trade, for the period from 1992 to 2018. I use the model to study the frictions related to delivery times and the macroeconomic implications of sourcing inputs from abroad.

3.1 Benchmark calibration

I describe the calibration strategy to match the U.S. manufacturing economy in 1992. I set the length of the period to be a quarter, $T = 90$ days. The discount factor, β, is set to $0.96^{1/4}$, which corresponds to a 4% annual interest rate. Following Alessandria, Kaboski, and Midrigan (2010a), I set the storage costs, δ, equal to 7.5%, which implies a 30% annual rate. The elasticity of substitution between domestic and foreign inputs, σ, equals 0.8, following Boehm, Flaaen, and Pandalai-Nayar (2017). The elasticity of demand for a firm's variety, ϵ, is equal to 1.5, which is a common value in the international business cycle literature. The share of inputs used in production, α, is set to 0.63, and it is estimated using data on the value of inputs over output in 1992 reported in the Input-Output Tables published by the Bureau of Economic Analysis. A summary of the model parameters is provided in Table 2.

I assume the demand distribution is log normal with mean zero. The variance of demand, σ_v, and the weight of domestic inputs, θ, are jointly calibrated to match the sum of work-in-process and material inventories over output and the share of total foreign inputs used in production in 1992. As a result, the variance of demand equals $\sigma_v = 0.38$ and the weight $\theta = 0.13$. The variance of demand can be interpreted as a parameter that summarizes all the different sources of uncertainty the firm faces–e.g., demand and productivity shocks. The exception is delivery time risk, which is estimated directly from the data.

The introduction of delivery times to the model is the main theoretical contribution, and allows the model to study how marginal changes in delivery times change firms' inventory and sourcing choices. Further, it allows the model to match different lengths of delivery times for different inputs, in contrast to the literature which assumes a fixed one-period lag.

Interpreting delivery times, λ. Given the number of days in a given period, T, the parameter λ represents the proportion of days within the period the firm is able to use the order to produce. Equation (10) shows the relationship between the delivery days observed in the data and the parameter λ. The parameter λ is equal to the proportion of days of the period the firm has the input in its warehouse and can use it to produce, $1 - \text{delivery days}/T$. If the delivery time is longer than the length of the period, then λ is capped at a one-period delay, which is commonly used in the literature. Here, there is an implicit assumption that the order is made on the first day of the period. This could be thought of as a normalization, regardless of when the firm orders within the period. Alternatively, I could assume there is a continuum of firms that order throughout the period. In this case, λ represents the share of firms for which the order arrives before the period ends and they are able to use the inputs to produce.

$$\lambda_j^i = \max(\,0,\ 1\ -\ \text{delivery days}_j^i/T\,) \qquad \text{for } i = \{d, f\} \text{ and firm } j \tag{10}$$

The number of domestic and foreign delivery days are drawn from two different log normal distributions estimated using the mean and variance of delivery days in the data. For domestic delivery days, I use data from the Institute for Supply Management's Manufacturing PMI on average lead times for production materials and supplies. I set the geometric mean of the log normal distribution to equal the average days observed in the data in 1992, which is 35 days. To estimate the variance of the distribution, I calculate the standard deviation for the average days for 1992, which equals 5 days. I then estimate the variance such that 95% of the distribution lies within the observed 5-day variation (30 to 40 days).

To estimate the distribution of delivery times for foreign inputs, I use data on average delivery days and delays for ocean shipping in the U.S.-China trade route. On average, from 1992 to 2018, 80% of goods coming from China are transported via ocean and the remaining 20% via air. For simplicity, I assume that all goods are transported via ocean. I use ocean transit times and delays, reported by the shipping platform Freightos. Ocean transportation from China takes around 25 days to arrive at the West Coast, and 35 days for the East Coast. Assuming half of the goods arrive on the East Coast and the other half the West Coast, I set the geometric mean of the log normal distribution equal to the 30 days of the U.S.-China route plus the 35 days of domestic transit. Observed variation in ocean delivery times is around 10 days. The standard deviation is estimated such that around 95% of the distribution lies within the sum of the reported average delays of foreign and domestic transit.

3.2 Delivery time trends: technology and trade

To examine to what extent delivery times can explain the reversal in the U.S. manufacturing inventory trend, I calibrate the model for the two opposing forces of delivery times. First, I model improvements in transportation and information technology (*technology*) as a direct decrease in delivery times. Second, delivery times increase with the rise in global sourcing (*trade*). I model improvements in technology as a decrease in the mean and variance of the distribution of domestic delivery times. From 1992 to 2018, I estimate the decrease using data on lead times for production materials and operating supplies reported by the ISM. I adjust the data series for foreign transit times[7] and smooth it using the Hodrick-Prescott filter. As

[7]The ISM reports average delivery times, including both domestic and foreign inputs. This requires me to adjust the series to obtain domestic delivery times, using the share of foreign inputs

Table 2: Moments for U.S. manufacturing industry and parameters

Quarterly model, $T = 90$

Panel A. Calibrated parameters

Parameter		Value	Moment	Model	Data
Weight domestic inputs	θ	0.867	share foreign inputs 1992	13.3%	13.3%
Variance of demand	σ_v	0.380	input inventory/output 1992	0.343	0.342

Panel B. Estimated parameters

Parameter		Value	Comment
Delivery times	λ		$\lambda = \max(0,\ 1 - days/90)$
Domestic delivery times	day^d_{1992}		$\log(days^d) \sim \mathcal{N}(35, 3.5)$
Foreign delivery times	day^f		$\log(days^f) \sim \mathcal{N}(65, 4.2)$
Input share	α	0.63	α =intermediates/output, from the BEA

Panel C. Predetermined parameters

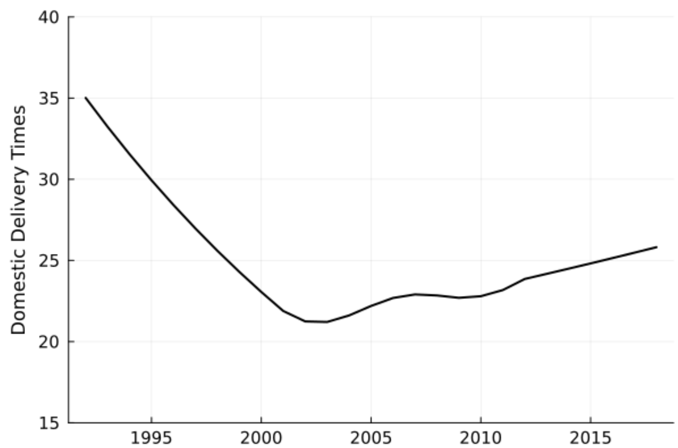
Parameter		Value	Comment
Elasticity of sub. x^f, x^d	σ	0.8	Boehm, Flaaen, and Pandalai-Nayar (2017)
Elasticity of sub. y_j	ϵ	1.5	International business cycle literature
Monthly interest rate	β	$0.96^{1/4}$	4% annual interest rate
Monthly storage rate	δ	0.075	30% annual rate

in the initial calibration, I assume the variance across time is a fixed proportion of the mean. Thus, as the mean of domestic delivery times decreases, so does the variance. The estimated mean of the distribution of domestic delivery times is shown in Figure 9. It shows an initial sharp decrease, and then a mild increase after 2003-2004.

At the same time, I model China's entrance to the WTO and the productivity increase that followed for Chinese firms during this period (Schott (2008)) as a decrease in the price of their inputs. In response, the model endogenously leads to a rise in the use of foreign inputs. I calibrate the decrease in the relative price of foreign inputs to match the rise in imported inputs from 1992 to 2018. Since the BEA began publishing the Input-Output tables in 1997, I keep the share of foreign inputs constant from 1992 to 1997. Then, I expand the series with the observed rise in inputs from China. To match the series, I vary the relative price of foreign inputs, p^f_t/p^d, which decreases at an annual average 1% rate to match the 3 percentage

and data on lead times for ocean transportation for the China-U.S. route. More details are described in Appendix D.

Figure 9: Trend for domestic delivery times

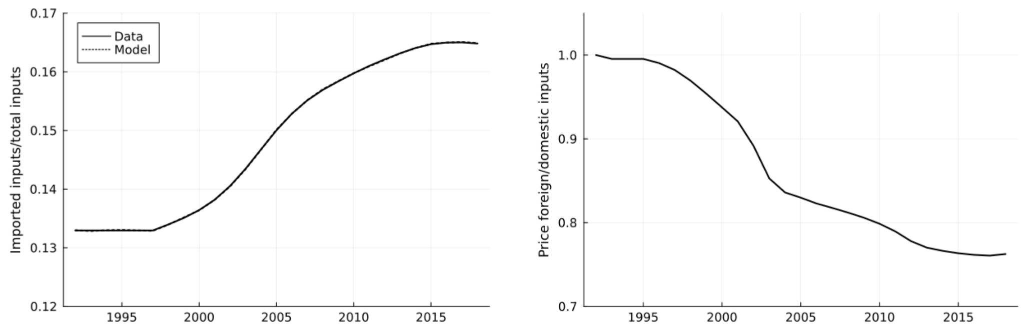


Note: The figure shows the average value of delivery times reported by the ISM for production materials and supplies for the period 1992 to 2018. The trend is adjusted for foreign inputs and smoothed using an HP filter. Further details on the series can be found in Appendix D.

point rise in the share of inputs from China. Panel b of Figure 10 shows the decline in the relative price of foreign inputs needed to match the rise in the share of inputs from China in Panel a. The slope of the decrease in the relative prices is governed by the elasticity of substitution between domestic and foreign inputs. The higher the elasticity, the easier it is to substitute between domestic and foreign inputs, and the smaller the decrease required in the relative price to match the import data. Regardless, the inventory trend is robust to different elasticity levels, as shown in Section V.

I solve the transition path from 1992 to 2018 for the final good firms, taking into account the two delivery time trends. To do so, I first calibrate the general equilibrium stationary distribution for the economy in 1992. Then, in every period firms observe an unexpected change in the mean and variance of the distribution of domestic delivery times and in the relative price of foreign inputs. To do so, I fix the aggregate variables and calculate the partial equilibrium stationary distribution of the economy for each year in the transition path. Firms are myopic in the sense that they do not take into account future changes in foreign prices and delivery times when they make their choices. Thus, orders and inventories today depend on

Figure 10: Decrease in the price of foreign inputs to match the rise in inputs from China



(a) Imported inputs over total inputs (b) Relative price of foreign inputs, p_t^f/p^d

Note: Panel a shows the matched share of imported inputs from China over total inputs from 1997 to 2018. The initial point in 1992 represents the total share of imported inputs, and then I expand the series using the share of inputs from China. Panel b shows the implied decline in the price of foreign inputs needed to match the share of imported inputs from China from Panel a.

delivery times and demand volatility in the short run and not the long run. Appendix C provides more details of the calibration and solution method.

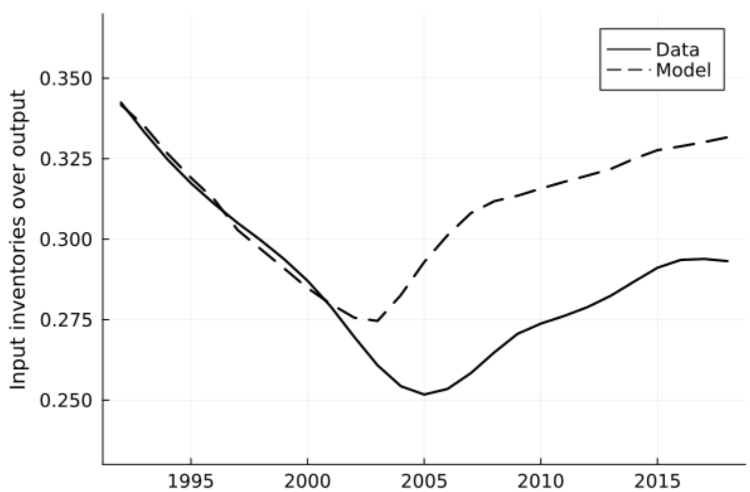
IV Results: Inventory Dynamics

An important share of inventory dynamics is accounted for by changes in the delivery times of inputs. First, I detail how the advances in transportation and information technology, together with the rise in global sourcing, generate in the model an untargeted pattern similar to that for inventories as observed in the data. The model accounts for 50% of the initial decline in the inventories-to-output ratio and 81% of the rise in inventories after 2005. Next, I examine the efficiency and volatility trade-off firms face. I find that in an economy that uses more foreign inputs, prices will be lower and output will be higher, since firms can source cheaper inputs from abroad. However, both prices and output will be more volatile because firms are more exposed to demand risk via longer delivery times. Last, I show that the inventory trend and results are robust to different model specifications.

4.1 Role of delivery times in inventories

The opposing forces in delivery times generate in the model an untargeted pattern similar to the inventories observed in the data, as shown in Figure 11. The solid line denotes the sum of the work-in-process and material inventories to quarterly output, smoothed using the Hodrick-Prescott filter. The dashed line denotes the model results. Here the mean and variance of domestic delivery times is decreasing over time while, at the same time, the relative price of foreign inputs decreases. The inventory trend is untargeted in the model's calibration, with the exception of the initial level of inventories used to calibrate the variance of demand.

Figure 11: Trend of inventories over output: model vs data



Note: The figure shows the comparison between the inventories to quarterly output in the data and the model. Data include the sum of work-in-process and material inventories and is smoothed using the Hodrick-Prescott filter. The two opposing forces, technology and trade, generate a trend in inventories over output in the model similar to that observed in the data.

The model generates the reversal of the long term decline in inventories and matches the initial decline in inventories remarkably well until 2003. In the model the inventory trend pivots in 2003, following the entrance of China to the WTO in 2001, whereas inventories in the data increase until 2005. In the model, the pressure on inventories from the rise in inputs from China overtakes the improvements in technology earlier than in the data. While this two-year gap could be explained by other channels discussed below, the model does a good job of showing a growth in inventories after 2005 similar to that in the data. The initial decline in inventories follows the decrease in domestic delivery times, where the increase is driven by the rise in the use of foreign inputs, which face longer and more volatile delivery times. Additionally, part of the increase is due to the small rise in domestic delivery times observed in the data (see Figure 9).

The model accounts for 50% of the initial decline in inventories and 81% of the rise in inventories after 2005. Table 3 shows average annual growth rates of inventories over output in the model and the data. The model's growth rates are computed taking the average of the simulated stationary distributions for each year in the analysis. From 1992 to 2004, inventories over output in the data decrease at an average annual growth rate of 2.3%, and in the model at a rate of 1.2%. From 2005 to 2018, inventories rise at a rate of 1.2%, and in the model at a rate of 1.0%.

Although delivery times are not the only force affecting inventories, they are an important factor in a firm's choice to hold inventories and can explain the majority of the long-term trend. Other factors that can explain part of the inventory trend are changes in the demand risk firms face over time, which is held constant in the benchmark economy. A more volatile demand, either driven by Amazon's penetration in the market or the recent rise in trade policy uncertainty, could help explain part of the inventory trend. Other forces that would increase the incentives for firms to hold inventories could be the potential improvements in the inventory storage technology or the low interest rates, which lower the cost of holding inventories. While these factors are not the focus of this paper and delivery times can explain the majority of the inventory dynamics, the model presented here is flexible enough to incorporate and quantify those forces.

The rise in inventories is driven by the increase in foreign inventories, which is large enough to compensate for the decline in domestic inventories. Using the model, I can decompose inventories held into domestic and foreign inputs, which are not reported in the data. Figure 12 shows the total inventory over output trend on the left axis, along with domestic input inventories over output. For the period

Table 3: Average annual growth rates: Inventory/output

	Total		Foreign	Domestic
	1992 – 2004	2005 – 2018	1992 – 2018	1992 – 2018
Data	−2.3%	1.2%		
Benchmark model	−1.2%	1.0%	1.5%	−0.5%
Delivery time channel	**50**%	**81**%		
Technology: decline in delivery times	−1.4%	0.4%	0.0%	−0.6%
Trade: decline in foreign prices	0.2%	0.5%	1.5%	0.1%

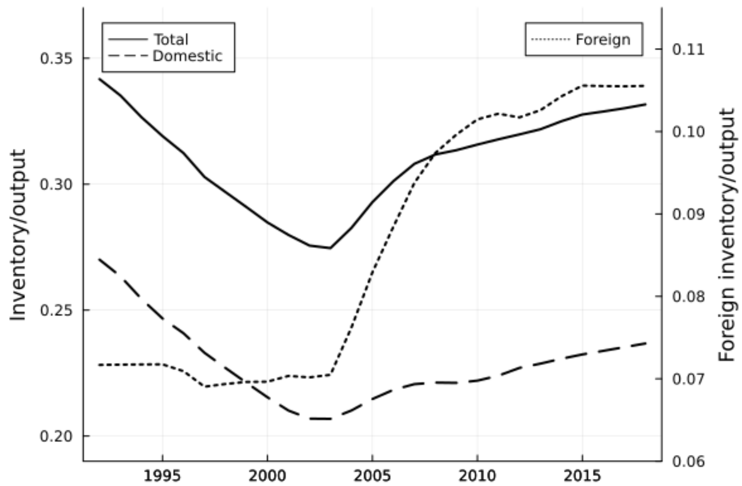
Average annual growth rates reported in the table are computed from the average level of inventories over output of simulated stationary distributions for each year in the period of analysis and compared with the the data. Data refer to the sum of work-in-process and material inventories over quarterly output. The data series is smoothed using the Hodrick-Prescott filter.

of analysis, domestic input inventories decrease at an annual average rate of 0.5%, following a trend similar to that of the mean of domestic delivery times, as shown in Figure 9.

Domestic inventories decline because, first, firms are substituting away from these inputs and sourcing more foreign inputs; and second due to the decline in domestic delivery times. As a result, firms need to hold less of these inventories. Foreign input inventories are increasing throughout the period at an annual 1.5% rate, as denoted by the dotted line on the right axis and in the third column of Table 3. Foreign inventories rise because firms are substituting toward these inputs, and also because foreign inputs are inventory-intensive. As firms source more foreign inputs, they need to hold more inventories to insure the production process from the increase in exposure to demand risk via longer delivery times. Further, they face additional delivery time risk, since foreign inputs are subject to longer and more frequent delays. The decrease in inventories is driven by the change in domestic inventories, while the rise follows the increase in foreign inventories, which compensates for the total decrease in domestic inventories.

Both the technology and trade forces are necessary for the model to generate a trend in inventories similar to that in the data, as shown in Figure 13. The solid line denotes the model's benchmark trend for inventories, which includes both changes in the mean and variance of the distribution of domestic delivery times (*technology*) and the decline in the relative price of foreign inputs (*trade*). The dotted line denotes the trend for inventories over output, where I only consider the technology channel,

Figure 12: Rise in foreign inventories



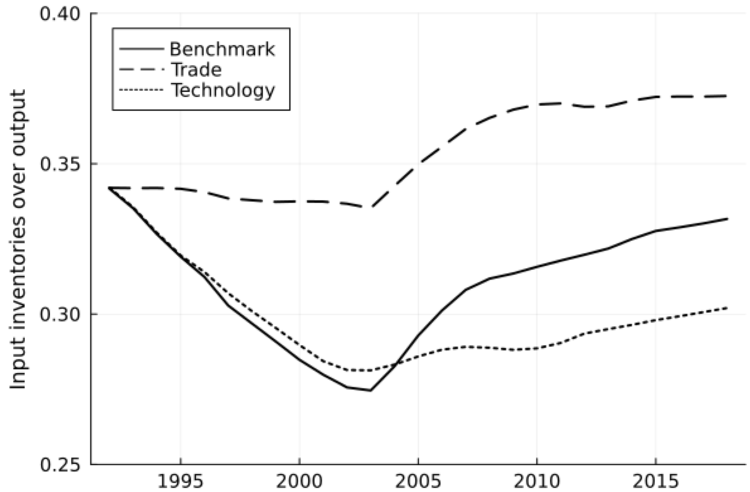
Note: The figure shows the model's total inventories and domestic inventories over output on the left axis and foreign inventories over output on the right axis. It shows that the rise in total inventories is driven by the rise in foreign inventories, which compensates for the decline in domestic inventories.

and fix the share of foreign inputs used in production to the initial level in 1992. In this case, inventories over output initially decrease at a rate similar to that in the benchmark, but then inventories stagnate, increasing slightly following the trend for domestic delivery times. In contrast, inventories increase throughout the period of analysis when I only consider the rise in foreign inputs depicted by the dotted line. Here, I calibrate the price of foreign inputs to match the rise in foreign inputs observed in the data, holding the distribution of domestic delivery times constant to the level of 1992. The decrease in domestic delivery times generates the decline in inventories, but is not able to fully capture the observed rise in inventories. I need to include both trends in delivery times, the technology and trade channels, to fully capture the observed decrease and increase in inventories.

4.2 Decomposing volatility: Efficiency and volatility trade-off

The model is centered on the trade-off between the price and delivery times across inputs. As the price of foreign inputs decreases, firms increase their reliance on

Figure 13: Technology and trade forces are needed to match inventory dynamics



Note: The figure shows the trend for the inventory-to-output ratio for three model scenarios. The solid line represents the benchmark model and the dotted line inventories taking into consideration only improvements in transportation and information technology (technology), represented by the decrease in domestic delivery times. Last, the dotted line represents the trend of inventories when I consider only the rise in foreign inputs (trade).

these inputs. Firms trade off efficiency by sourcing low cost inputs from abroad for an increase in volatility, since the longer delivery times of foreign inputs increase their exposure to demand risk. I examine this trade-off by comparing the stationary distributions of economies with different shares of foreign inputs. The benchmark economy in 2018 represents the economy with a large share of foreign inputs, of 16%, and the technology economy in 2018 has a lower share share of foreign inputs, of 13% (initial share in 1992). Both economies have the same distribution of domestic delivery times. Table 4 shows that in an economy with a higher share of foreign inputs, prices are lower since firms source cheaper inputs from abroad, output is higher, and firms hold more inventories. However, these variables are more volatile because firms are more exposed to demand and delivery time risk.

While inventories help the firm deal with delivery times and a volatile demand, it is never optimal to fully insure production. To do so, firms would need to stock sufficient inventories to satisfy the highest demand shock possible. Since

Table 4: Higher share of foreign inputs:
Higher and more volatile output

	Change mean	Change st. deviation
Price of final good	-2.6%	9.7%
Production	13.9%	12.3%
Composite input	4.2%	7.9%
Inventories	5.8%	11.3%

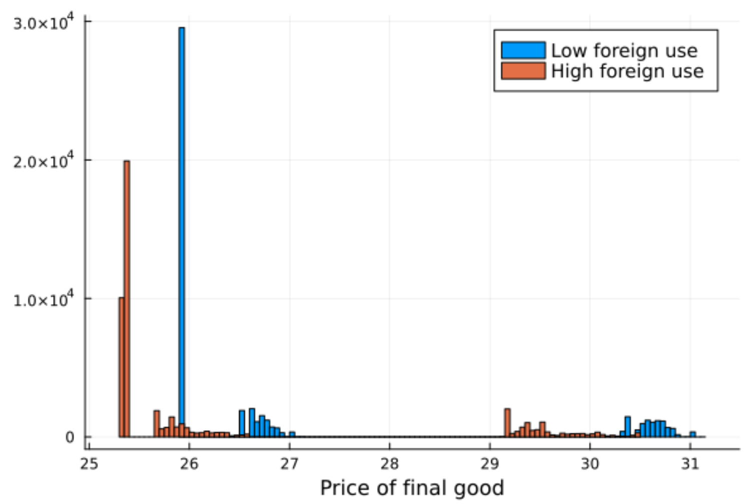
The percentage change shown is calculated by comparing an economy that uses more foreign inputs, represented by the benchmark economy in 2018, and an economy that uses the 1992 share of foreign inputs, represented by the technology economy in 2018. The percentage change is computed from the average level of prices, output, inputs, and inventories of the simulated stationary distribution. An economy that uses a higher share of foreign inputs, their output will be higher and prices will be lower, but both will be more volatile.

inventories are costly, there is a fraction of high demand shocks where the firm is constrained and will stock-out. When a firm is constrained, they raise the price of the final good up to the point where the consumer demands its entire stock. As firms use more of the foreign inputs and the volatility they face increases, holding inventory costs constant, the share of constrained firms increases from 8% to 12%. Even though firms set lower prices on average, firms raise prices more frequently since they are more often constrained. This raises the standard deviation of the stationary distribution of prices, as shown in Figure 14. This effect permeates the output, composite input, and inventory holdings, where volatility increases as well.

Last, I use the model to decompose the firm's incentives to hold inventories. Firms stock inventories due to (i) the interaction between the mean of delivery times and the variance of demand (*demand risk*), and (ii) the variance of delivery times (*delivery time risk*). First, to isolate the role of demand risk, the dashed line in Figure 15 shows an economy with only demand shocks, in which delivery times are positive but deterministic. Second, the solid line, which represents the benchmark trend in inventories, includes both demand and delivery time risk. The difference between the dashed and solid trends denotes the effect of delivery time risk.

Most of the incentives firms have to hold inventories come from demand risk. The level of inventories is similar across scenarios in 1992, meaning that delivery

Figure 14: Lower mean and higher variance in prices when sourcing foreign inputs



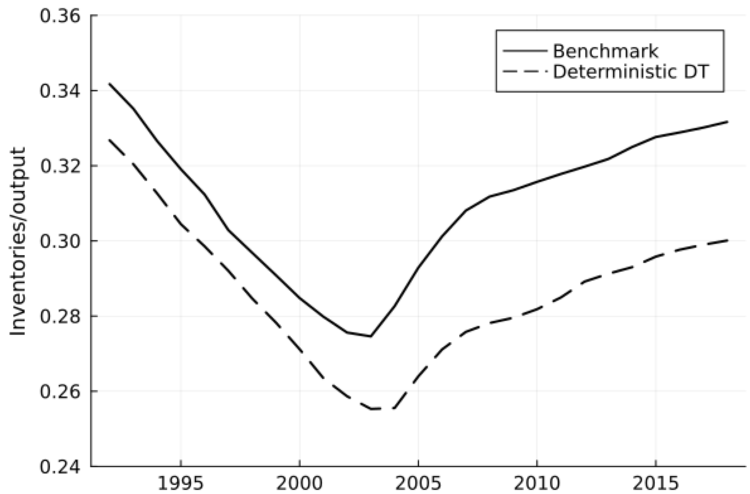
Note: The figure shows the stationary distribution for final good prices. *Low foreign use* represents the price distribution of the technology economy in 2018, in which the share of foreign inputs is the one in 1992. *High foreign use* shows the price distribution of the benchmark economy in 2018, which includes the rise in foreign inputs.

time risk do not play a large role in the volatility firms face. However, by 2018 the difference in inventory levels between scenarios increases. With the increase in reliance on inputs that face volatile delivery times, delivery time risk becomes more important in determining the level of inventories. Further, the scenario with delivery time risk has a higher average growth rate in inventories and is key to match the growth observed in the data. While both sources of volatility are relevant, demand risk determines most of the level of inventories and delivery time risk shapes the growth of inventories over time.

4.3 Sensitivity analysis

The trend for inventories to output is robust to different model specifications. Figure 16a shows the series of inventories over output for different values of the elasticity of substitution of the final good firms, ϵ, and the elasticity between foreign and domestic inputs, σ. The benchmark model is calibrated for $\epsilon = 1.5$ and $\sigma = 0.8$,

Figure 15: Demand vs delivery time shocks

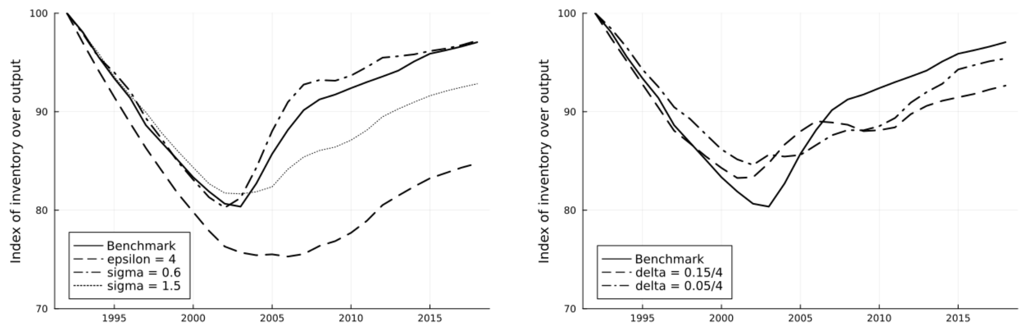


Note: The figure shows the inventory-to-output ratio for two model scenarios. The solid line denotes the series for the benchmark economy, which includes demand and delivery time shocks. The dashed line denotes the series for an economy with only demand volatility, in which delivery times are positive but deterministic, and hence isolate the effect of demand shocks. The figure shows that both sources of volatility are relevant, and while the variance of demand determines the level of inventories, the variance of delivery times shapes growth over time.

and here I show that the inventory trend is robust for $\epsilon = 4$ and $\sigma = \{0.6, 1.5\}$. The lower the substitutability of inputs, σ, the larger the change in inventories, because firms are unable to switch between inputs within a period to smooth production. A similar effect occurs for the elasticity for final goods, ϵ. Here, a higher ϵ lets the consumer adjusts its demand for each final good and final good firms adjust their inventories to a lesser degree. Regardless, the reversal of the long-term decline in inventories is present across the different values of elasticity.

Figure16b shows that the inventory trend is robust for different values of storage costs. The benchmark economy sets storage costs, δ, to a quarterly rate of 7.5% (30/4%) which implies a 30% annual rate. Here I show the inventory trend for storage costs of 5% and 15%. Lower storage costs increase firms' incentives to hold inventories, which makes the inventory more sensitive to change in the price and delivery times. While different values of storage cost affect the *level* of inventories, the trend for inventories is robust to different storage costs.

Figure 16: The inventory trend is robust to different levels of ϵ, σ, and δ



(a) Imported inputs over total inputs

(b) Relative price of foreign inputs, p_t^f/p^d

Note: The figure shows model results for inventory over output for different values of elasticity of substitution between domestic and foreign inputs, σ, between final goods, ϵ, and for storage costs, δ. The trend for inventories to output is robust to different parameter values.

V Conclusion

Although the benefits of global sourcing from having access to lower price inputs are well-documented, a new strand of the literature emphasizes the risks and vulnerabilities of international trade. The recent increase in supply chain disruptions has sparked interest in creating robust and resilient networks. However, the role of inventories in mitigating the additional risks firms face when engaging in trade has received little attention. Here, I highlight the value of inventories as a tool firms have to absorb shocks and smooth production. I find new evidence of the reversal of the long-term decline in U.S. manufacturing inventories, which after a 25-year decline have been increasing since 2005. The rise in inventories is present across U.S. businesses and within manufacturing across industries, public firms, and types of inventories. The pattern is also observed in the manufacturing sectors of Australia, Canada, Japan, and South Korea.

I study inventory dynamics in a model of global sourcing, centered on the trade-off between the relative price and delivery times of inputs across suppliers. I depart from the literature and introduce a tractable method for modeling stochastic delivery times for inputs in an environment with idiosyncratic demand shocks. As lower price inputs from abroad become more accessible, firms substitute away from domestic inputs and toward foreign inputs. Foreign inputs face longer and more volatile delivery times, which increase firms' exposure to demand shocks. Longer delivery times hinder firms' ability to respond to shocks within a period and meet their demand. To mitigate the additional risk, firms raise their inventories.

The rise in global sourcing is an important component of inventory dynamics. I calibrate the model to match two trends in delivery times. First, following the literature, I model improvements in transportation and information technology as a decrease in the mean and variance of the distribution of domestic delivery times. Second, I model the rise in global sourcing as a decrease in the price of foreign inputs, who face longer delivery times. Based on the interaction of these two forces, I find that the model accounts for 50% of the initial decline in inventories and 81% of the rise in U.S. manufacturing inventories after 2005. Further, I show that as firms increase global sourcing, they trade-off access to lower price inputs for an increase in volatility. Thus, prices are lower and output is higher, but both are more volatile.

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FOR ONLINE PUBLICATION

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.

1.1 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 further 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

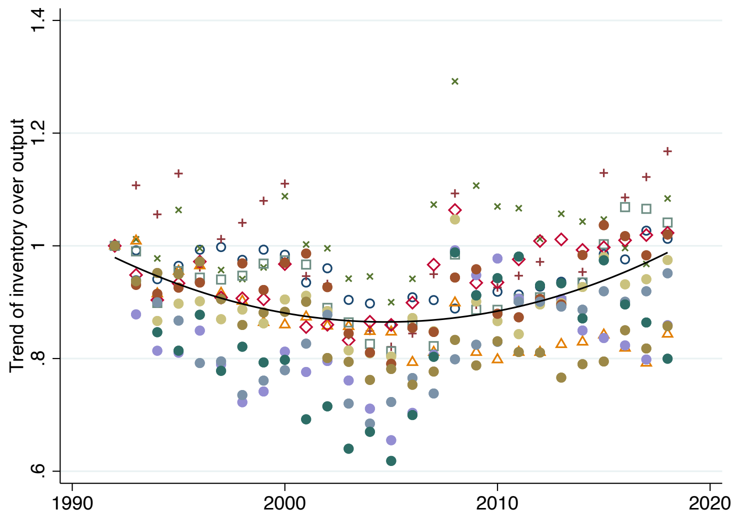
1.2 Increasing inventories across manufacturing industries

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 17. 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 17 shows the trend of inventory to sales across industries, and the quadratic fitted line. Last, Figure 19a shows the overall trend in inventories to sales holds when we include the Petroleum and Coal sector (NAICS 324). Figure 19a 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.

1.3 Increase in inventories across sectors using NBER-CES database

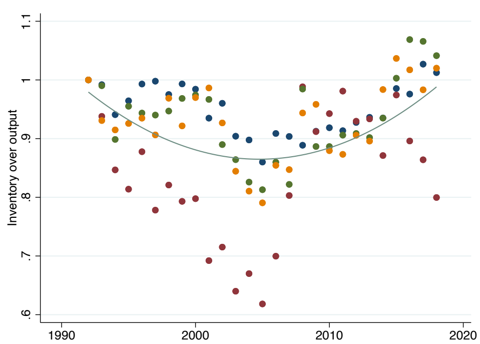
An additional source that includes data on inventories is the NBER-CES Manufacturing Industry Database. They include yearly data from 1958-2018 for NAICS 6-digit industries. The key disadvantage of the dataset is that they do not include information on the different types of inventories, so I can only see the trend for the total inventories across industries. Figure 20a 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 20b 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. Addi-

Figure 17: Increasing inventories across industries

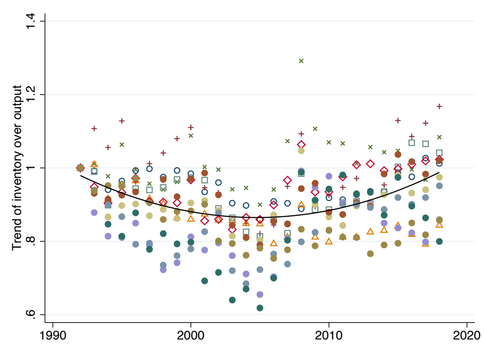


Note: The Figure shows the trend of inventory-to-sales ratio for the NAICS 3-digit industries (excluding Petroleum and Coal Products). It includes the quadratic fitted line of the trend, showing the initial decrease and following increase after 2005.

Figure 18: Increasing inventories across manufacturing sectors



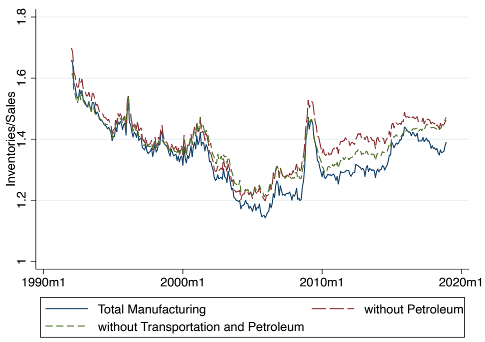
(a) Four largest sectors



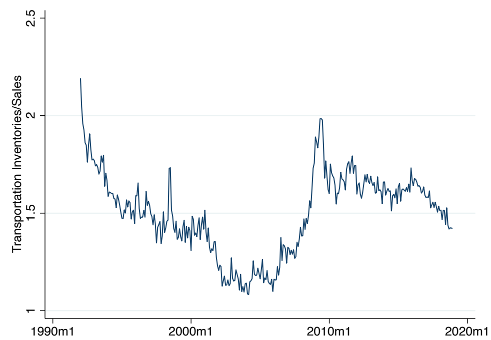
(b) All sectors

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 19: 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.

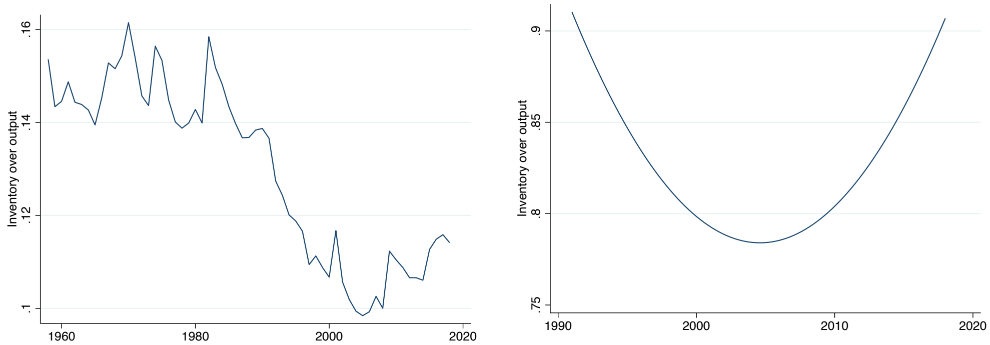
tionally, Table 5 shows the results using a time series regression with fixed effects for the period 1990 to 2005 (column 1), and for 2006 to 2018 (column 2). Results show an initial annual decrease in the ratio of inventories-to-sales of 1%, and an increase of 1% after 2005.

1.4 Increase in inventories across firms using Compustat

The rise in inventories is also observed across firms, using the Compustat North America database. [8] 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 21a 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 21b shows the trend for the seven largest firms in the dataset.

[8] 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.

Figure 20: Increasing inventories: NBER-CES database



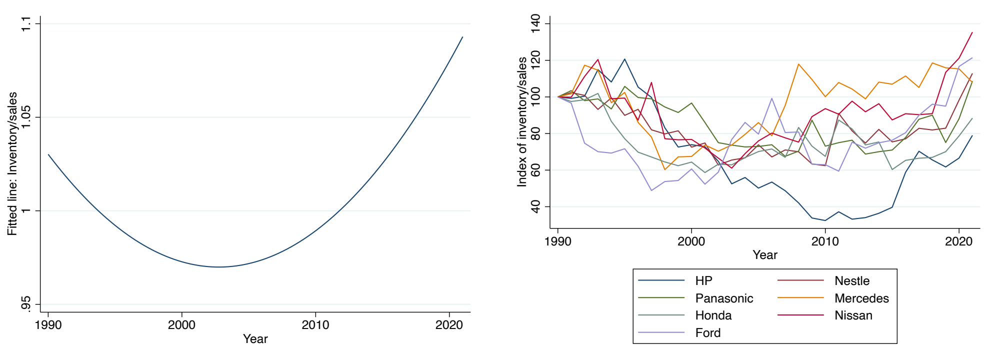
(a) Long term trend for total manufacturing sector

(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.

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 21: 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.

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.

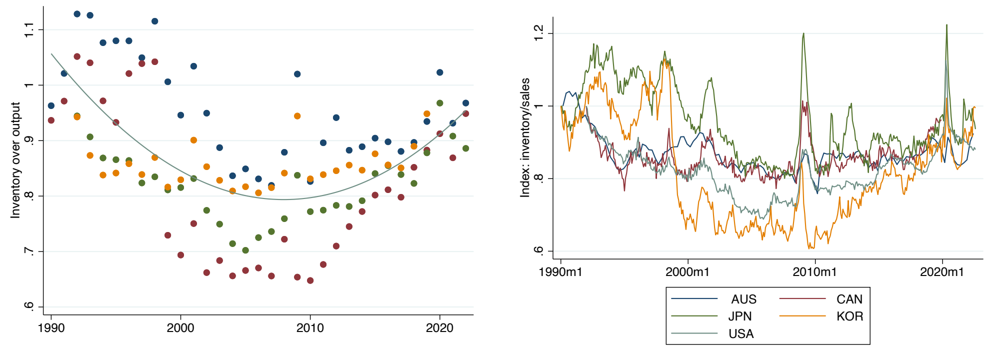
1.5 Increase in manufacturing inventories across countries

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 statistical website for the manufacturing sector. Figure 22a 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.

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

Figure 22: 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.

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.

2.1 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.

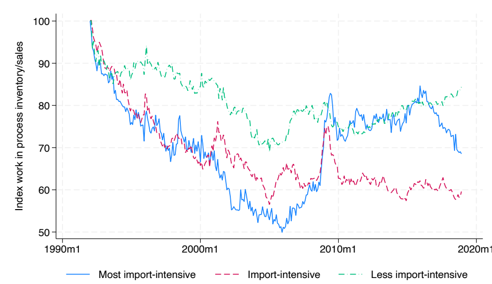
They aggregate industries 311 and 312, 313 and 314, and 315 and 316 to form three industries. I adopt this aggregation in my analysis as well, and obtain 18 total manufacturing industries. Then I drop the sector 324, *Petroleum and Coal Products* from the analysis in this paper due to its volatile nature.

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 23: 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 23a 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 23b. 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.

2.2 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 24a 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 24c 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 24b shows that inputs from Mexico and Canada remain relatively stable for the period of analysis across data sources.

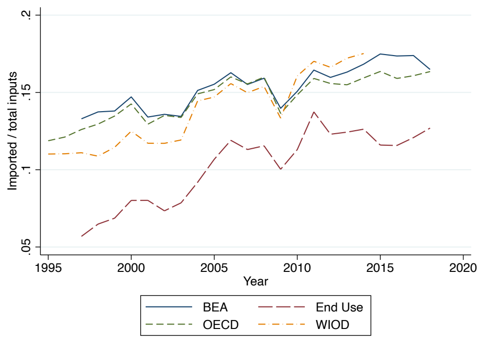
2.3 Rise in inputs form China across manufacturing sectors

Figure 25 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 literature.

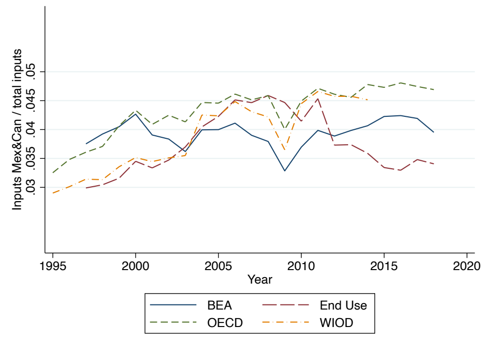
2.4 Inventories increase with imported input intensity: WIOD data

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 26a 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 26b. Furthermore, 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

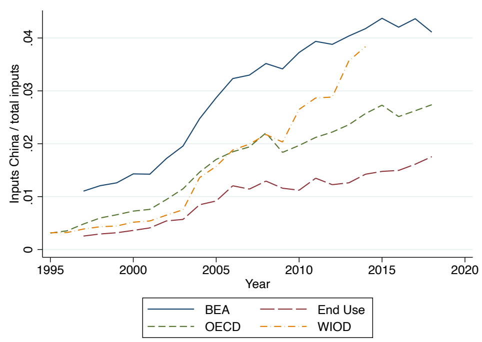
Figure 24: Rise in foreign inputs driven by inputs from China: across data sources



(a) Rise in the share of imported inputs



(b) Inputs from Mex and Canada relatively constant



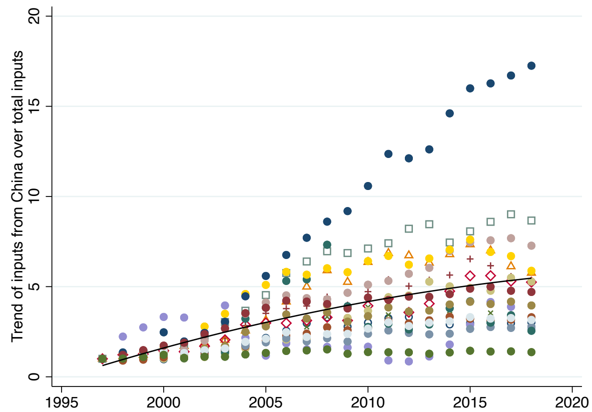
(c) Rise in inputs from China

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.

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.

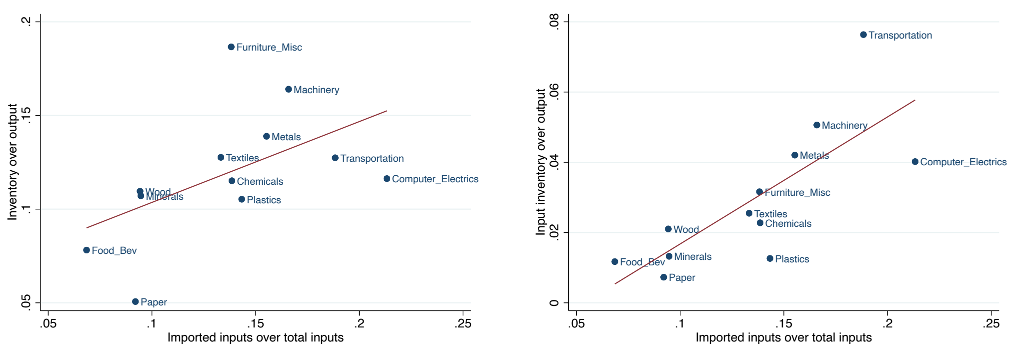
Moreover, the positive relationship between inputs from China and inventories stocked across industries is also present using the WIOD. Table 6 shows that a 10% increase in the use of inputs form China is associated with a raise of 6% in total inventories and 7% in input inventories (column 7). The relationship remains when controlling for value added, where the increase of 10% in inputs from China

Figure 25: 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.

Figure 26: Inventories increase with imported input intensity: WIOD inputs

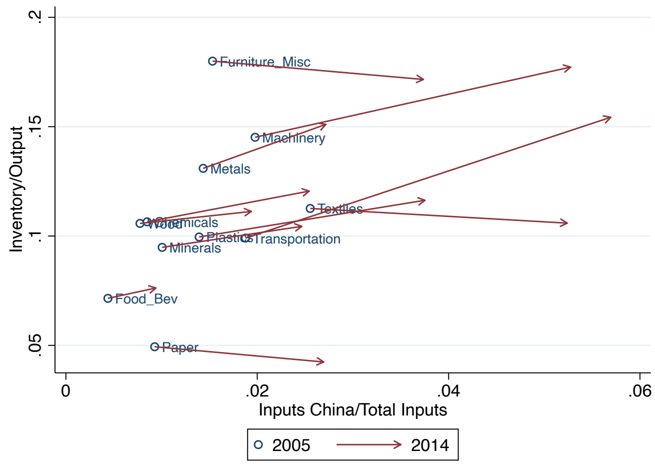


(a) Total inventory (b) Intermediate input inventory

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.

increases total inventory by 5% and input inventory by 6%. Additionally, Figure 27 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 27: 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.

2.5 Rise in the use of foreign inputs across countries

Figure 28 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 2018. Note Japan's index grew at a higher rate, so I plot their index on the right axis.

2.6 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 Wong and

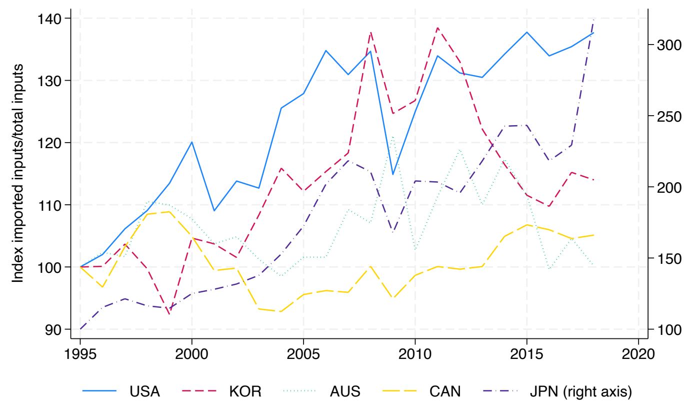
Table 6: Positive relation between inventories and imported inputs: WIOD inputs

	[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.

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

Figure 28: 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.

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.

3.1 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, $(s^d, s^f, \nu, \lambda^f, \lambda^d)$.

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, $\eta = (\nu, \lambda^d, \lambda^f)$.

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

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).[9]

3.1.1 **Step one:** given $(n^d, n^f, s^d, s^f, \eta)$ I solve for the four cases: both

[9] 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.

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).

$$
\begin{aligned}
\frac{1}{p} &= \frac{\epsilon-1}{\epsilon} \; \frac{\alpha^\alpha \, (1-\alpha)^{1-\alpha}}{w^{1-\alpha}} \; \left(\theta \left(\frac{1-\delta\lambda^d}{1-\delta} \; \frac{1}{p^d}\right)^{\sigma-1}\right) + (1-\theta)\left(\frac{1-\delta\lambda^f}{1-\delta} \; \frac{1}{p^f}\right)^{\sigma-1}\Bigg)^{\frac{\alpha}{\sigma-1}} \\
y &= P^\epsilon \; p^{-\epsilon} \; Y \; \nu \\
x &= \frac{\epsilon-1}{\epsilon} \, \alpha \, p \, y \left(\theta \left(\frac{1-\delta\lambda^d}{1-\delta} \; \frac{1}{p^d}\right)^{\sigma-1}\right) + (1-\theta)\left(\frac{1-\delta\lambda^f}{1-\delta} \; \frac{1}{p^f}\right)^{\sigma-1}\Bigg)^{\frac{1}{\sigma-1}} \\
x^f &= \left(\frac{\epsilon-1}{\epsilon} \, \alpha \, p \, y\right)^\sigma \; \left(\frac{1-\delta\lambda^f}{1-\delta}\right)^\sigma \; \frac{1-\theta}{x^{\sigma-1} \, (\tau \, p^f)^\sigma} \\
x^d &= \left(\frac{\epsilon-1}{\epsilon} \, \alpha \, p \, y\right)^\sigma \; \left(\frac{1-\delta\lambda^d}{1-\delta}\right)^\sigma \; \frac{\theta_a}{x^{\sigma-1} \, p^{d\,\sigma}} \\
\ell &= \frac{\epsilon-1}{\epsilon} \, (1-\alpha) \, \frac{p \, y}{w}
\end{aligned}
$$

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.

$$
\begin{aligned}
x^d &= s^d \; + \; \lambda^d \, n^d \\
x &= \left(\theta^{\,\frac{1}{\theta}} \; x^{d\,\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\theta}} \; x_g^{f\,\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}
\end{aligned}
$$

$$
\begin{aligned}
py &= p^f \frac{\epsilon}{(\epsilon-1)\,\alpha}\;\frac{1-\delta}{1-\delta\lambda^f}\left(\frac{x_g^f\;x^{\sigma-1}}{\theta}\right)^{1/\sigma} && \text{(Back out py from equation for } x^f\text{)}\\
\ell &= \frac{\epsilon-1}{\epsilon}\,(1-\alpha)\,\frac{p\,y}{w}\\
y &= x^{\alpha}\;\ell^{1-\alpha}\\
p &= P\left(\frac{y}{v\;y}\right)^{\frac{1}{\epsilon}}\\
x^f_{update} &= \left(\frac{\epsilon-1}{\epsilon}\;\alpha\;p\;y\right)^{\sigma}\;\left(\frac{1-\delta\lambda^f}{1-\delta}\right)^{\sigma}\;\frac{1-\theta}{x^{\sigma-1}\;(p^f)^{\sigma}}
\end{aligned}
$$

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_g^d and then solve for the values of x^f, x, py, ℓ, p, y. Then I update the value of the guess for x_g^d 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.

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

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, η).

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^d_j), I can obtain the analytical solution for the decision variables of the input firm, labor demand and composite input demand, ℓ^d, N^d.

$$\begin{aligned} \ell^d_j &= (1-\alpha)\, p_j\ x^d_j / w \\ N^d_j &= \alpha\ p_j\ x^d_j / P \end{aligned}$$

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 equa-

tions. 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.

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

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

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

3.2 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.

3.3 Proposition proof

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

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.

$$\tilde{V} = \max p^{1-\epsilon} P^{\epsilon} \nu Y \; - p^d \left(\frac{s^{d'} - (1-\delta)(s^d - x^d)}{1 - \lambda^d \delta} \right) \; - p^f \left(\frac{s^{f'} - (1-\delta)(s^f - x^f)}{1 - \lambda^f \delta} \right) \; + \beta \, V(s'^d, \, s'^f)$$

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

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

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 $A^f = (x^f/\theta)^{\frac{1}{\sigma}}$.

$$(wrt\; p) \qquad \frac{\epsilon - 1}{\epsilon}\, p\, A = \frac{A^d}{1 - \lambda^d \delta}\big((1-\delta)p^d + (1-\lambda^d)\mu^d\big) \; + \; \frac{A^f}{1 - \lambda^f \delta}\big((1-\delta)p^f + (1-\lambda^f)\mu^f\big)$$

$$(wrt\; s'^d) \quad (1 - \lambda^d \delta)\beta V_{s'^d} = p^d - \mu^d \lambda^d$$

$$(wrt\; s'^f) \quad (1 - \lambda^f \delta)\beta V_{s'^f} = p^f - \mu^f \lambda^f$$

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

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

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

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

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.

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

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:

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

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.

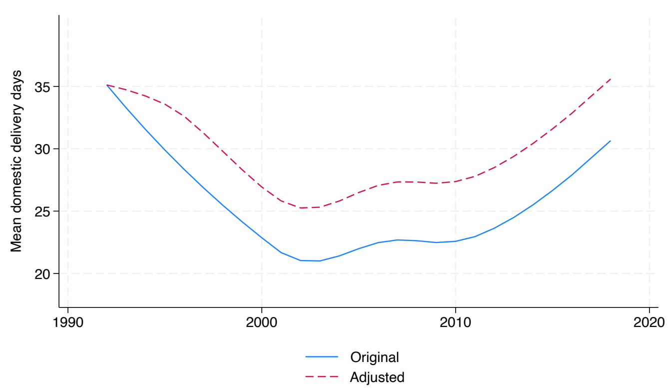
4.1 Domestic delivery times

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 29.

Figure 29: Mean of domestic delivery times

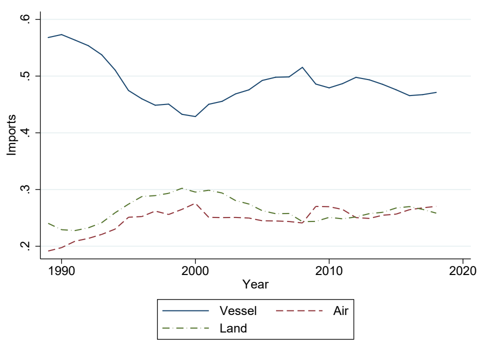


Note: The Figure shows the value of the average reported by the ISM of the delivery times for production materials and maintenance and operation supplies, adjusted by the lead times of foreign inputs.

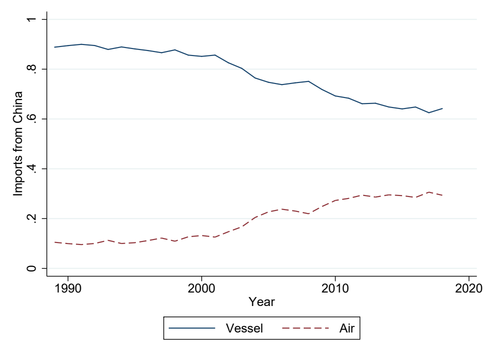
4.2 Transportation of U.S. imports

This section provides detail on the method of transportation for total U.S. imports and imports that come from China. Figure 30a 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 30b 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.

Figure 30: Method of transportation for U.S. imports



(a) Transport method for US imports

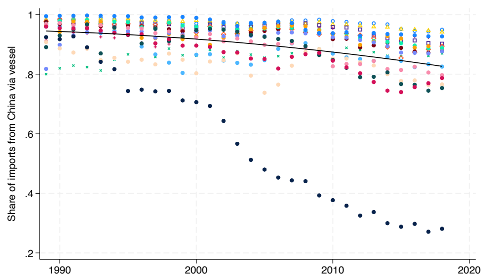


(b) Transport method for imports from China

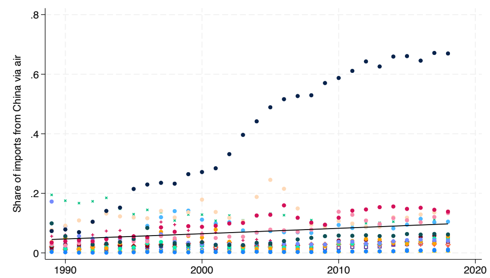
Note: The Figure show the share of imports that arrive via land, ocean, and air to the U.S., from 1989 to 2018, using data from the U.S. Census Bureau and retrieved from Schott (2008) website. Panel a shows the share of imports for each method of transportation for all U.S. imports. On average, 50% of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

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 31 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: 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.