Increasing Inventories: The Role of Delivery Times

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Abstract

U.S. manufacturing inventories have been increasing since 2005, reversing a declining trend that lasted for decades. I document the rise in inventories over sales observed across different countries' manufacturing sector, U.S. businesses, types of inventories, and across manufacturing industries and firms. While the long term decline is well-understood as a consequence of improvements in transportation technology, I explore the role of increasing delivery times in the rise of inventories. The rise in inputs from China, that face particularly long and volatile delivery times, increased firm's exposure to the demand and delivery time risk, thus increasing the incentives to hold inventories. A model with different and stochastic delivery times, calibrated to match the improvements in transportation technology and the rise in input trade, is able to explain 50% of the initial decline and 81% of the rise in inventories after 2005. Last, I find that an economy that uses more foreign inputs their prices will be lower, since firms can source cheaper inputs from abroad, but they will be more volatile since firms are more exposed to the demand and delivery time shocks.

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After a large decline in U.S. manufacturing inventories that started in the 1980's, this paper documents the rise in inventories that started in 2005. The rise in inventories over sales is observed across different countries' manufacturing sector, U.S. businesses, types of inventories, and across manufacturing industries and firms. While the long term decline in inventories has been studied in the literature and attributed to improvements in transportation and information technology that allowed for inputs to be more readily available,[1] here I study the recent rise in inventories and it's implications for firm's sourcing choices and exposure to the different sources of risk they face.

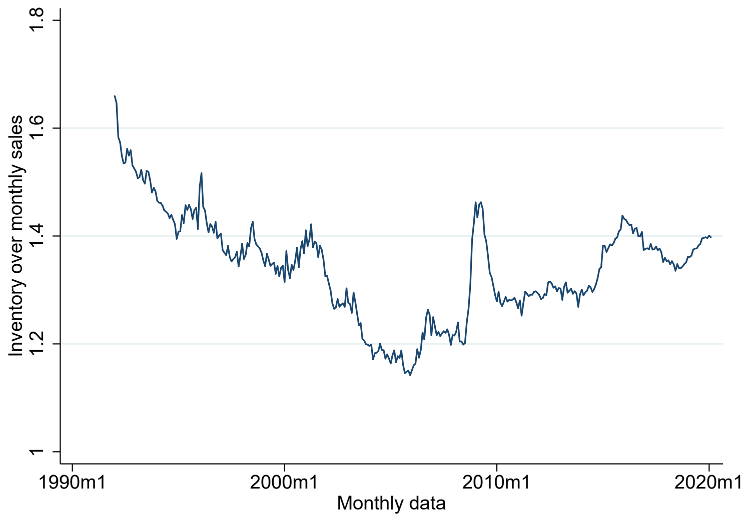
Inventories help firms insure against demand changes, productivity shocks, or supply chain disruptions. In this paper I explore the role of longer and more volatile delivery times for inputs on firm's inventory choices, as U.S. firms created global supply chains. As foreign inputs become cheaper, firms choose to source more inputs from abroad, in particular inputs from China, which face long delivery times and frequent delays. This increased their exposure to demand volatility, as longer and more volatile delivery times for inputs decrease firm's ability to meet their demand every period, thus increasing the incentives to hold additional inventories.

First, this paper documents the reversal of the long term decline in inventories. Second, I show that along the rise in inventories, there has been an increase in reliance on inputs from China, which face particularly long and volatile delivery times. Third, I show that sourcing foreign inputs is inventory-intensive across U.S. industries. Based on this evidence, I build a model that features different and stochastic delivery times for inputs in an environment with demand risk. In the presence of demand volatility, firms face a tradeoff between the relative price and the delivery times of inputs across suppliers. I calibrate the model to quantify two opposing forces of delivery times that I see in the data. First, I introduce the improvements in transportation and information technology as a decrease in delivery times over time. Then, I match the rise in the share of inputs from China, which increases the delivery times and delays firms face for their inputs. I find that the two opposing forces generate in the model similar inventory dynamics as in the data. They explain 50% of the initial decline and 81% of the rise in inventories after 2005. I show that the rise in inventories is driven by the increase in foreign inventories, which compensates for the decline in domestic inventories over time. Last, I show that as firms tradeoff the domestic inputs for the cheaper and farther inputs from abroad, they increase their exposure to volatility. I find that an economy that uses more foreign inputs their prices will be lower, since firms can source cheaper inputs from abroad, but they will be more volatile since firms are more exposed to the demand and

[1] The relationship between the decline in inventories and improvements in transportation and information technology is well documented in a series of papers, for example, Ohno (1988), O'Neal (1989), Heide and John (1990), Feinberg and Keane (2006), Dalton (2013), and Pisch (2020).

delivery time shocks.

Figure 1: Increase in U.S. manufacturing inventories



Note: Figure shows the trend of inventory-to-monthly sales for the aggregate manufacturing industry from 1992 to 2018, reported by the U.S. Census Bureau. The figure shows the decrease in inventories from 1992 to 2004 and the reversal of the long term decline that starts in 2005.

The reversal of the long term decline in inventories is present for the aggregate U.S. businesses, and across the retail, wholesale, and manufacturing sector. The sharpest trend is observed for the manufacturing sector, as shown in Figure 1, which is the main focus of this paper. Within the manufacturing sector, the decrease and subsequent rise in inventories is present across different countries, and across U.S. industries, firms, and types of inventories. Intermediate input inventories have the steepest decline and rise, which is indicative of the importance of input sourcing choices in explaining inventory dynamics.

Contemporaneous to the rise in inventories, there has been a substitution away from domestic input and towards foreign inputs across the U.S. manufacturing sectors, driven by the rise in inputs from China.[2] Inputs from China face longer and more volatile delivery times than domestic inputs, or inputs from the U.S. main trade partners, Canada and Mexico, which are transported via land. In contrast, 80% of inputs from China arrive via ocean transportation, which take around a month to arrive and are subject to more frequent and longer delays.

Alessandria, Kaboski, and Midrigan (2010a) and Khan and Khederlarian (2020a) show that sourcing foreign inputs is inventory-intensive, using data from Chilean and Indian firms. Here,

[2] The increase in the share of inputs from China is well documented by Schott (2008). Furthermore, Heise, Pierce, Schaur, and Schott (2019) show how the entrance of China to the World Trade Organization allowed for the creation of supply chains between countries.

using industry level data, I show that U.S. industries that choose to use more foreign inputs also tend to stock more inventories. The relationship is strengthened when I consider intermediate input inventory, where a 10% increase in imported inputs is associated to a rise in input inventories of 7%, controlling for time and industries. Moreover, this positive relationship is present when only considering inputs coming from China, where a 10% increase in inputs from China is related to a 5% increase in input inventories.

Motivated by the empirical evidence, I develop a model centered around the tradeoff between the price and delivery time of inputs to study the role of delivery time in firm's sourcing and inventory choices. The model builds on the work on inventories and trade by Khan and Thomas (2007) and Alessandria, Kaboski, and Midrigan (2010a), and here I introduce different and stochastic delivery times across inputs, where a stochastic share of the inputs are delivered this period, and the rest next period. Firms can chose between the cheaper foreign input, that faces longer and volatile delivery times, or the more expensive domestic input that is closer to them. I assume firms face a volatile demand, whose interaction with the stochastic delivery times of inputs creates incentives for firms to hold inventories. When firms have to wait around for the input to arrive while the demand is changing every period, they need to store some of the inputs as inventories to ensure they will be able to meet demand. But holding inventories is costly, which creates the tradeoff between the relative price and the delivery times across inputs.

I calibrate the model to match moments of the aggregate U.S. manufacturing industry in 1992. Then I model the two opposing forces of delivery times I observe in the data for the period of 1992 to 2018. First, following the literature, 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 decreases. Second, I decrease the price of foreign inputs to match the rise in inputs from China observed in the data. As firms increase their reliance on foreign inputs, the longer delivery times increase their exposure to the demand and delivery time shocks, and the incentives to hold additional inventories increases.

I find that the interaction between the stochastic delivery times and the variance of the demand can explain a large share of the inventory dynamics for the U.S. manufacturing. The opposing trends in delivery times generate in the model a similar pattern as observed in the data. The model can explain 50% of the decline in the inventories-to-output ratio, and 81% of the rise in inventories after 2005. Additionally, I need both, the technology and the trade forces, to explain the inventory dynamics observed, and show how the rise in inventories is driven by the rise in foreign input inventories, which compensates for the constant decline in domestic inventories.

Further, I use the model to analyze the tradeoff between efficiency and volatility firm's face. As firms chose to source the cheaper foreign inputs, they tradeoff efficiency for an increase in volatility, since the longer delivery times increase their exposure to the demand and delivery time shocks. I find that an economy that uses more foreign inputs their prices will be lower, and output will be higher, since firms can source cheaper inputs from abroad, but prices and output will be more volatile since firms are more exposed underlying risk they face. Last, I show that most of the incentives firms have to hold inventories come from the interaction between the mean of the delivery times and the variance of the demand, as they determine most of the level of inventories. However, as firms increase the reliance on inputs that face volatile delivery times, the variance of delivery times is important to determine the growth of inventories over time.

The focus on inventories and delivery times in this paper is related to the extensive literature on inventories and trade, in the work by Khan and Thomas (2007), Iacovello, Schiantarelli, and Schuh (2007), Kryvtsov and Midrigan (2009), Alessandria, Kaboski, and Midrigan (2010a), Alessandria, Kaboski, and Midrigan (2010b), Novy and Taylor (2014), Tamegawa (2014), Jain, Girotra, and Netessine (2014), Vieira Nadais (2017), Khan and Khederlarian (2020b), Khan and Khederlarian (2020a), and Ferrari (2020). Additionally, the frictions imposed by delivery times have been well documented by Evans and Harrigan (2005), Hummels (2007), Hummels and Schaur (2013), and Leibovici and Waugh (2019). This paper adds to the literature by documenting the recent rise in inventories, and explaining it with the rise in delivery times of inputs that occurred with the expansion of trade. The model introduces different and stochastic delivery times for inputs which allows to measure how marginal changes in delivery times affect firms sourcing and inventory choices. Last, this paper explores the tradeoff between efficiency and volatility, emphasizing the risk and costs of trade and supply chains which is related to the work by Baldwin and Freeman (2022), Jiang, Rigobon, and Rigobon (2021), Cavallo and Kryvtsov (2021), Khanna, Morales, and Pandalai-Nayar (2022), and Blaum, Esposito, and Heise (2023).

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 shows the calibration strategy, and details how I calibrate the model to quantify the two opposing forces of delivery times. Section IV presents the quantitative findings on the role of delivery times in inventories. Finally, Section V concludes.

I Increasing inventories and imported inputs

After a sharp decline in U.S. manufacturing inventories that started in the 1980's, the ratio of inventories over sales has been increasing since 2005. During this period, the share of imported inputs over total inputs used in production increased as well. This rise is driven by the increase in inputs from China, especially after China joined the World Trade Organization in 2001. Inputs from China are relevant for firms choice to hold inventories because they face particularly long delivery times and delays, as 80% of the goods arrive via ocean transportation. Last, I show evidence that industries that choose to source more foreign inputs, tend to stock more inventories.

Data. Aggregate inventory and sales data comes from the *Manufacturer's Shipments, Inventories, and Orders* survey from the U.S. Census Bureau. Sectors reported are matched to the North American Industry Classification System (NAICS) three-digit industries. Inventories reported by the U.S. Census Bureau include the value of all inventories that the firm owns, if they are located within the U.S., in a customs warehouses, or being transported to or from the U.S., as long as they are owned by a U.S. firm. I leave sector *Petroleum and Coal Products*, 324, out of the analysis presented. The petroleum sector is volatile by nature, and only accounts for 5% of total manufacturing inventories (average 1992-2018).[3] Firm-level data on inventories for public U.S. firms is reported by WRDS Compustat. Import data by country of origin and method of transportation used is reported by the U.S. Census Bureau obtained from Schott (2008) website. Data on domestic and foreign inputs, and output are reported by the Bureau of Economic Analysis Input-Output Tables.[4] Imported input data is available from 1997-2019 for three digit NAICS industries.

1.1 Increasing Inventories

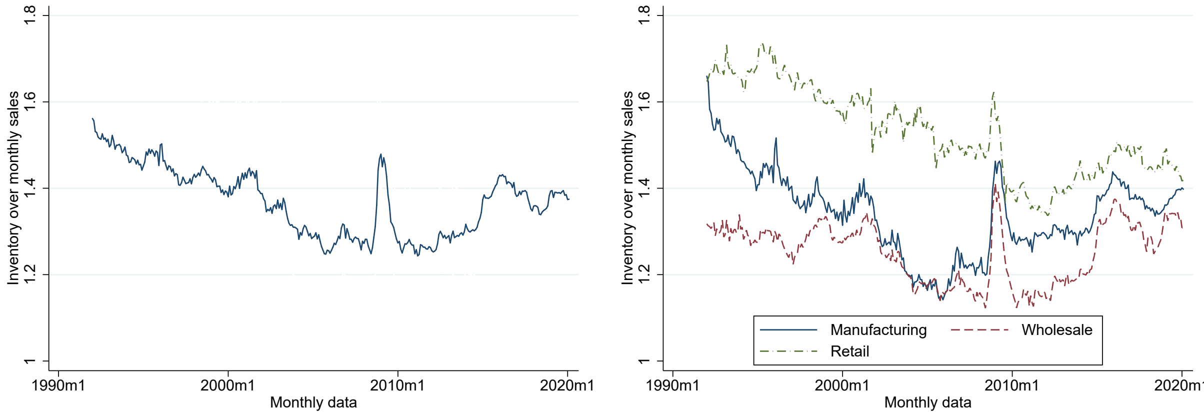
The reversal of the long term decline in inventories is observed for the aggregate U.S. businesses, as shown in Figure 2a. The manufacturing sector observes the largest rise starting in 2005,[5] as depicted in Figure 2b, and the wholesale and retail sector observe an increase in inventories starting around 2010. Within the manufacturing sector, the decrease and subsequent increase in inventories is present across the types of inventories, industries, and firms. Additionally, I find this pattern is present in different countries' manufacturing sector.

[3] In Appendix A I show the inventory to sales trend holds when we include the petroleum sector. Additionally I show results hold if I exclude the transportation sector as well.

[4] In appendix B I shows a similar analysis and findings using imported input data from (i) World Input-Output Database, (ii) OECD Input-Output Tables, and (iii) end-use classification by the U.S. Census Bureau.

[5] A longer time series for the manufacturing inventories to sales ratio, from 1958-2018, 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 business

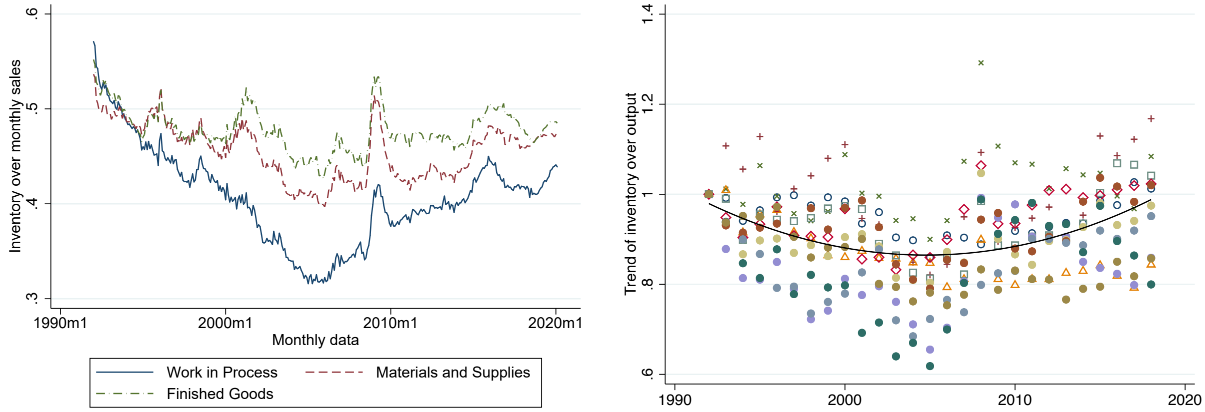
Note: The Figures show the trend of inventories over sales. Panel a shows the rise in inventories after 2005 for the total businesses in the U.S. and panel b shows the trend for the three types of businesses as defined by the U.S. Census Bureau; manufacturing, wholesale, and retail. Sharpest trend is observed in the manufacturing sector.

The rise of manufacturing inventories is present across types of inventories and industries, 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, which I will refer to as input inventory. Input inventory has the steepest decrease and increase, which shows the importance of input sourcing choices for firms inventory holdings. Panel b shows the rise in inventories across the NAICS three digit manufacturing sectors. I show a scatterplot of the industries from 1992 to 2018, and thir quadratic fit.

The reversal of the long term decline in inventories is observed across U.S. manufacturing firms. Figure 4a shows the quadratic fit of the publicly available manufacturing firms reported in Compustat North America database, that have complete inventory data from 1992 to 2018. Additionally, the rise in inventories is observed across different countries' aggregate manufacturing sector. Figure 4b shows the scatterplot and the quadratic fit of the index of inventories to sales for Australia, Canada, Japan, and South Korea. Data is retrieved from each of the countries statistical website.[6]

[6]Further evidence of the rise at the firm level and across countries is shown in appendix A.

Figure 3: Increasing manufacturing inventories across types of inventories and industries

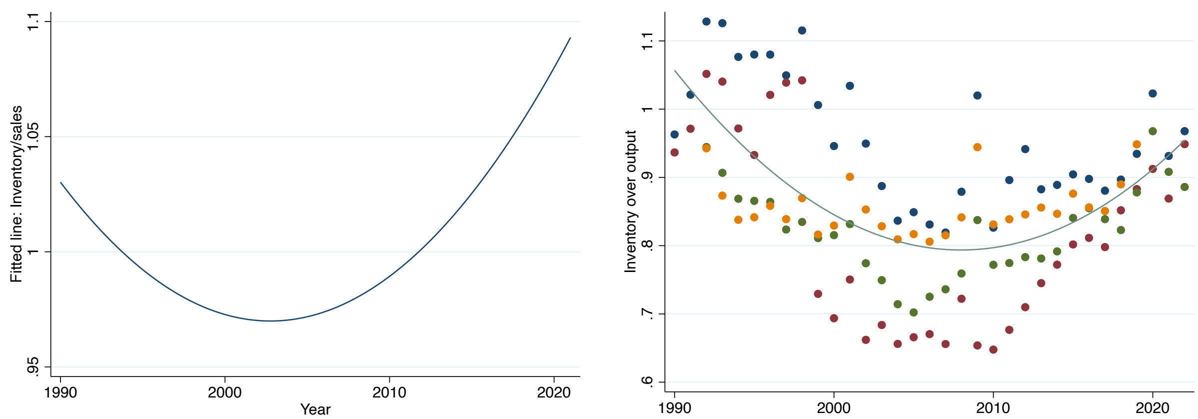


(a) Types of inventories

(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, which are raw goods used in production, and work-in-process inventory, which are goods undergoing fabrication. Panel b shows a scatterplot and a quadratic fitted line of the index of inventories to sales ratio for the NAICS three digit manufacturing industries.

Figure 4: Increasing manufacturing inventories across countries and U.S. firms



(a) Quadratic fit of the trend across firms

(b) Quadratic fit of the trend across countries

Note: Panel a shows the quadratic fit for the trend of inventories over sales for all the publicly available firms from Compustat that have complete inventory data from 1992 to 2018. Panel b shows the scatterplot and quadratic fit for the index of the manufacturing inventories over output for Australia, Canada, Japan, and Korea, collected from each of the countries statistical website.

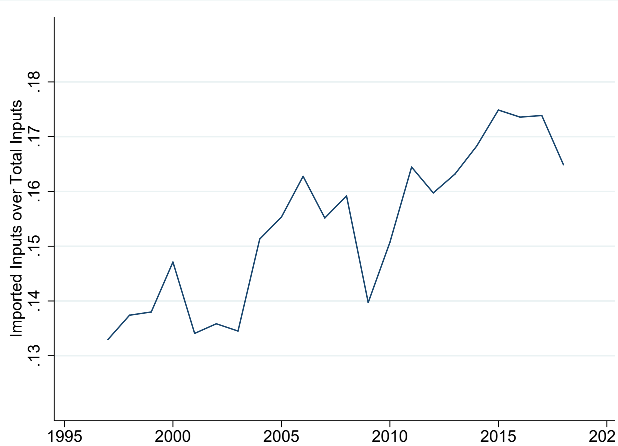
1.2 Increase in reliance on inputs from China

Along the rise in inventories, there has been a substitution away from domestic input and towards foreign inputs used in production across the U.S. manufacturing sectors, as shown in Figure 5a.

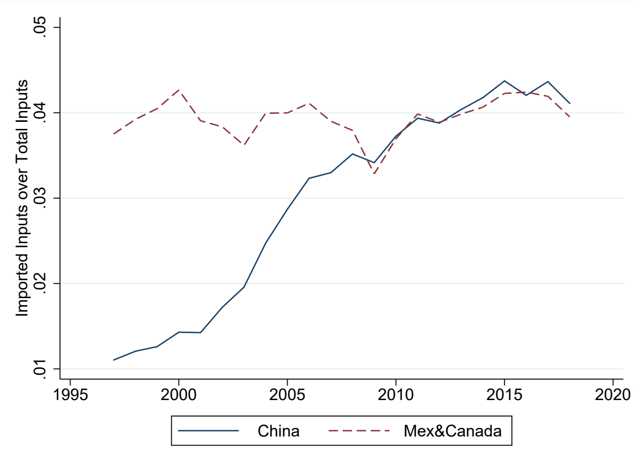
The increase in the share of imported inputs, which increased from 13.3% in 1997 to 16.5% in 2018, is driven by the rise in inputs from China. Figure 5b show the share of imported inputs for the U.S. main trade partners: Canada, Mexico, and China. The share of inputs from Mexico and Canada remain relatively constant, whereas inputs from China grow around 3 percentage points during this period. This trend is robust to data from the World Input-Output Database (WIOD), Organization for Economic Cooperation and Development (OECD), and the U.S. Census Bureau end-use classification, as shown in Appendix B. Furthermore, the rise in inputs from China is observed across manufacturing sectors.[7].

Import data by country of origin comes from the U.S. Census Bureau, retrieved from Schott (2008). Data on domestic and foreign inputs are published by the BEA Input-Output tables. I compute the share of imported inputs by country of origin following a similar methodology used by the BEA for the *Import Matrices*. 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. More details on Appendix B.

Figure 5: Substitution towards 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 the trend of 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 trade partners with the U.S.: Mexico, Canada, and China. Data comes from the U.S. Census Bureau and the 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 share of imported inputs. More on this in appendix B, which includes the analysis using data from (i) WIOD, (ii) OECD , and (iii) US Census end-use classification, and shows similar trends across sources.

Imports from China face longer and more volatile delivery times than domestic inputs or

[7]Data and graphs on the rise in inputs from China across sectors is reported in appendix D

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, which takes longer and is subject to more frequent and longer delays. The remainder 20% of imports arrive via air, and these proportions are common across manufacturing industries.[8] Ganapati, Wong, and Zic (2020) document the time-intensity of ocean transportation, where the majority of trade arrives via U.S. ports indirectly, and ships go through specific hubs before reaching their final destinations. Imports from China via ocean take around 25 days to arrive to the West Coast, and 35 days to the East Coast, according to Freightos. Delivery delays occur more frequently in ocean transportation due to port congestions, customs delays, and weather conditions according to Sea Intelligence and eeSea.[9]

1.3 Inventories increase with imported input intensity

Alessandria, Kaboski, and Midrigan (2010a) and Khan and Khederlarian (2020a) document that sourcing foreign inputs is inventory-intensive. Here, using industry level data for the U.S. manufacturing I similarly show that industries that choose to use more imported inputs tend to stock more inventories.[10] Figure 6a shows the positive relationship between imported inputs and total inventories across the NAICS three digit manufacturing sectors, where the fitted line has a slope of 0.3.[11] The relationship is strengthened when considering input inventory (work-in-process inventory), as shown in Figure 6b, where the slope of the fitted line equals 0.9. Furthermore, Table 1 shows the time series results where a 10% increase in imported inputs is associated with a raise in inventories of 6% and a raise 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 3.5%, and input inventories 4.2%.

Moreover, there is a positive relationship between inputs from China and inventories stocked across industries. Table 1 shows that a 10% increase in the use of inputs form China is associated

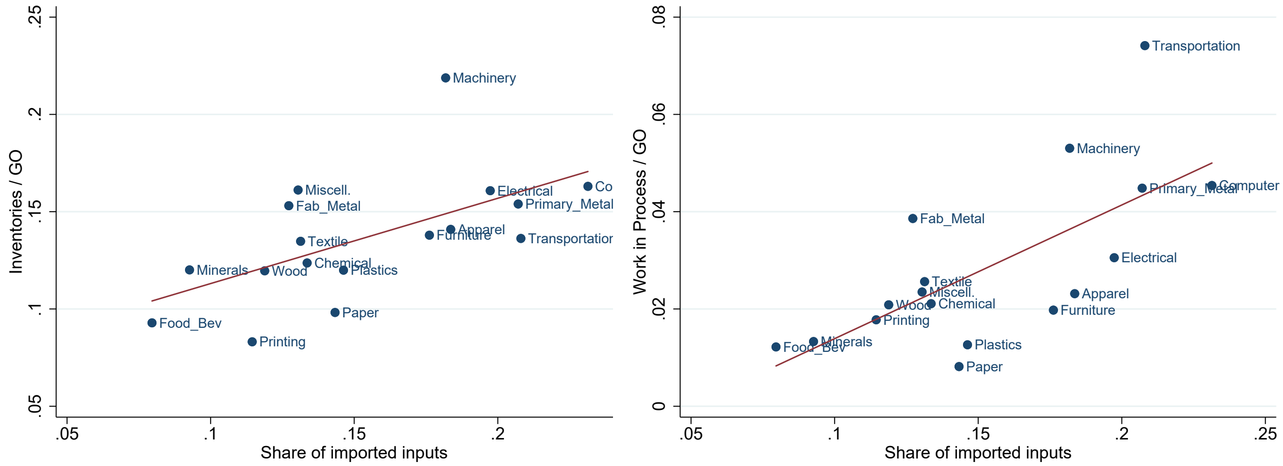
[8] More data on the transportation of imports across industries can be found in the appendix D.

[9] Sea Intelligence and eeSea specialize in the study and report of carrier reliability, transit times, and vessel delays for ocean container shipment 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. Additionally, around 10% of all arrivals were more than 3 days delayed, according to *Schedule Reliability* 2020 report from eeSea.

[10] Alessandria, Kaboski, and Midrigan (2010a), use firm level data for Chilean firms and find that importing firms have inventory to output ratios that are roughly twice those of firms that purchase materials only domestically. Khan and Khederlarian (2020a) find a similar result using firm level data for Indian firms. Additionally, the empirical work by Shirley and Winston (2004), Li and Li (2013), and Cui and Li (2018) document the relationship between inventories and delivery times, through improvements in transportation technology.

[11] Similar results are shown in Appendix B using imported input data reported by the WIOD.

Figure 6: Inventories increase with imported input intensity



(a) Total inventory

(b) Intermediate input inventory

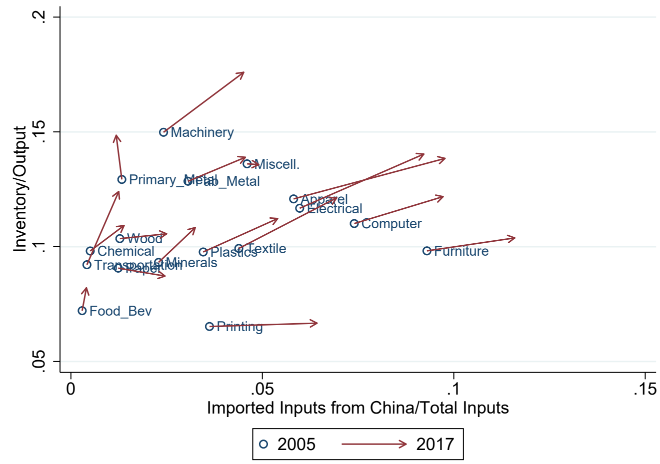
Note: The Figure shows the average of imported inputs over total inputs and the inventory-to-output share for each NAICS 3 manufacturing industry from 1997 to 2018. The line represents the fitted line for each scatter plot. Correlation between total inventories and imported inputs is 0.59, and 0.68 for intermediate inputs.

with a raise of 4% in total inventories and 5% in input inventories (column 7). The relationship remains when controlling for value added, where the increase of 10% in inputs from China increases total inventory by 2% and input inventory by 3%, as shown in column 8. Additionally, Figure 7 shows how inputs from China and total inventory change from 2005 to 2017 across industries. The bullet points mark the initial level in 2005, and the arrows pointing towards the northeast indicate a contemporaneous growth in both variables over time.

II A model of delivery times and inventories

I present a model centered around the tradeoff between the price and the 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 in Khan and Thomas (2007) and Alessandria, Kaboski, and Midrigan (2010a), I develop a model where firms choose to stock inventory to insure against demand and delivery time shocks. In the model, a stochastic share of the inputs are delivered this period, and firms have access to the rest order until next period. The introduction of delivery times allows me to quantify how marginal changes in the distribution of delivery times

Figure 7: Industries use more inputs from China and hold more inventories: 2005 to 2017



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 3 manufacturing industries for 2005. The arrow shows the change in the values for the year 2017, showing a contemporaneous increase in inventories and inputs from China across industries.

affect firm's choices.[12]

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, competitive firms that produce the domestic and foreign inputs, and a domestic representative consumer. Uncertainty in the model is given by firm-specific, independent and identically distributed (iid), demand shocks 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. Each firm faces the demand from the representative consumer, which is a function of the per-period, *iid*, firm-specific demand shock, v_j, total production, Y, and price index, P.

$$y_j(p_j) = v_j\, Y\, (P/p_j)^{\epsilon} \qquad \text{where } v_j \sim_{iid} G\,(\mu_v,\ \sigma_v) \ \ \forall\, j \tag{1}$$

Firm's technology combines the domestic input, x_j^d, foreign input, x_j^f, and labor, l_j, to produce

[12]Models in the literature consider a deterministic one period delivery lag for all inputs, which length is fixed to the assumed length of the period in the model calibration (e.g. monthly, quarterly).

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

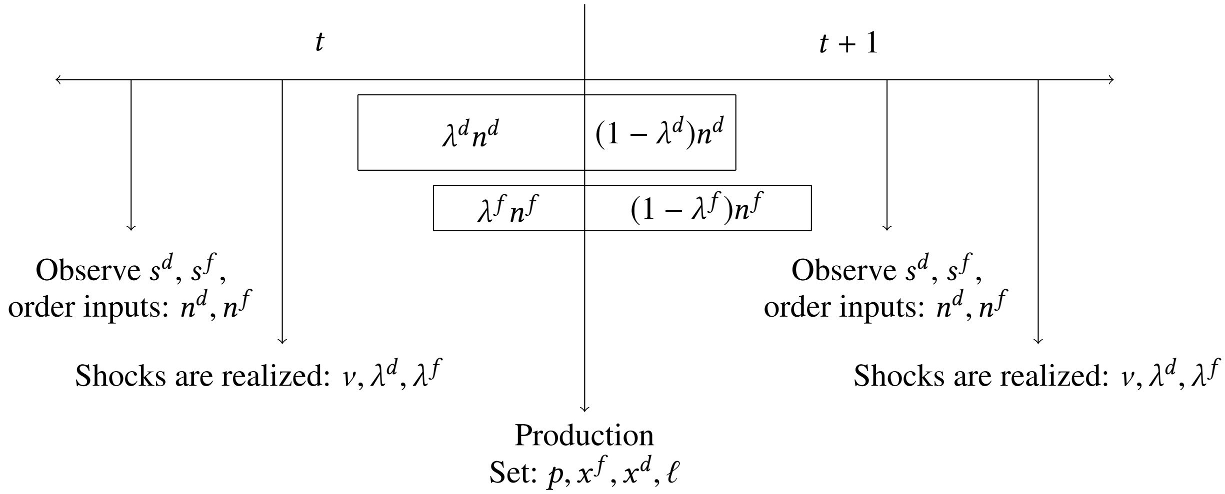
The table reports results for the regression $\log(y_{it}) = \beta_0 + \beta_1 \log(a_{it}) + \beta_2 \log(x_{it}) + \delta_i + \delta_t + \epsilon_{it}$, where i denotes industry, t year, y_{it} inventories, a_{it} value added, x_{it} intermediate inputs, and δ fixed effects. Columns 1, 2, 5, and 6 report the regression results for the 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 for the time series results across industries.

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 for U.S. manufacturing sector. Domestic inputs have a weight, θ, to match the initial level of domestic to foreign inputs used. Last, I assume a Cobb-Douglas function between the intermediate input and labor.

$$y_j = \left(\theta^{\frac{1}{\sigma}} \, {x_j^d}^{\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\sigma}} \, {x_j^f}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}\,\alpha} {\ell_j}^{1-\alpha} \tag{2}$$

Domestic and foreign inputs, $i = \{d, f\}$, face stochastic delivery times, where 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, as shown in equation (3). Firms are able to store inventories of domestic and foreign inputs, which depreciate at rate δ.

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



Equation 4 shows that inventories available next period, $s_j^{\prime i}$, are equal to 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, $(1-\lambda_j^i)\, n_j^i$.

$$x_j^i \leq s_j^i + \lambda_j^i n_j^i \qquad \text{where} \quad \lambda_j^i \sim_{iid} G^i(\mu_\lambda^i, \sigma_\lambda^i) \tag{3}$$

$$s_j^{\prime i} = (s_j^i + \lambda_j^i n_j^i - x_j^i)(1-\delta) + (1-\lambda_j^i)\, n_j^i \qquad \text{for} \quad i = \{d,\ f\} \tag{4}$$

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 what their demand and delivery times shock is for the period. Firms order 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 of order, $\{\lambda^d, \lambda^f\}$, arrives and can be used for production. Firms decide on the amount of inputs, x^d, x^f, the amount of labor, ℓ, and set price, p. These choices and the law of motion of inventories define the inventories for tomorrow. The reminder of the order arrives early next period and is added to the next period's inventory. Firms behave monopolistically by setting prices. If a firm is constrained in the amount of inputs and has an inventory stock-out, due to a high demand or 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 around for their inputs to arrive, while their demand is changing every period, they need to store some of this inputs as inventories to ensure they will be able to meet their demand. Additionally, firms hold inventories since delivery times are stochastic and firms don't have certainty on 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 tradeoff between the relative price and delivery times across inputs.

The recursive problem for the final good producer is given by the following two Bellman equations, corresponding to the choices made within the timing constraint. For clarity, I drop the subscript denoting the specific firm in the unit continuum, $j \in [0,1]$. The value function, $V(s^d,\ s^f)$, defines the optimal order of inputs, given the initial inventories of each input and the expectation over the demand and delivery time shocks. Then, given the order of inputs and shocks for the period, firms decide on the amount of inputs used in production, labor, and prices described by the value function $\tilde{V}(s^d,\ s^f,n^d,\ n^f,\ \eta)$, where firms maximize present and future profits. The problem is subject to 6 constraints: the demand from the consumer (equation 1), the production function (equation 2), the two constraints for the domestic and foreign inputs used in production (equation 3), and the two law of motions for domestic and foreign inventories (equation 4).

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

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

Domestic and foreign input firms. There is a unit continuum of competitive domestic inputs firms, $j \in [0,1]$, whose variety is demanded by the final good firm that produces that same variety within the continuum. To produce the domestic input, x^d_j, equation (5) shows the firm uses a Cobb-Douglas production function using labor, ℓ^d_j, and the composite input, N^d_j. Additionally, there is a unit continuum of foreign input producers, that produce the variety, x^f_j. All firms along the continuum have access to the same technology, so there is a unique price for domestic inputs, p^d, and one for foreign inputs, p^f. I abstract from modeling the problem of the foreign inputs firms, and take as given the input price, p^f.

$$x^d_j \ = \ N_j^{d\,\alpha}\ \ell_j^{d\,1-\alpha} \tag{5}$$

Representative consumer. The representative domestic consumer demands the unit continuum of final good varieties, $y_j \in [0,1]$, and uses a CES aggregator with elasticity of substitution ϵ, to obtain the final consumption good, C, and the composite good, N, as shown in equation (6). The price of consumption and the composite input is denoted by P. The consumer sells the composite input to the domestic inputs firms that use it as input in its production, PN, where $N = \int_0^1 N^d_j\, dj$. Additionally, to buy the continuum of final good varieties, the representative consumer receives labor income, wL, and the profits from the continuum of final good firms, $\int_0^1 \Pi_j \, dj$, as described in equation (7).

$$C + N = \left[\int_0^1 v_j^{\frac{1}{\epsilon}} \, y_j^{\frac{\epsilon-1}{\epsilon}} \, dj \right]^{\frac{\epsilon}{\epsilon-1}} \tag{6}$$

$$\int_0^1 p_j \, y_j \, dj = P \, N + w \, L + \int_0^1 \Pi_j \, dj \tag{7}$$

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 $\eta = (v, \lambda^d, \lambda^f)$; 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:[13]

- Policy functions solve the final good firm problem, domestic input firm problem, and the representative consumer;
- Final good market clears, where the demand of domestic consumer is equal to the supply of the final good firm for each of the varieties, $j \in [0,1]$;
- Domestic input market clears, where the demand of the final good firms is equal to the supply of the domestic input firm for each of the varieties, $j \in [0,1]$;
- Composite good market clears, where the supply of the consumer is equal to the total demand by domestic input firms, $N = \int_0^1 N_j^d \, dj$;
- Labor market clears, where the fixed labor supply of the consumer is equal to the labor demand of domestic input firms and final good firms, $L = \int_0^1 \ell_j^d \, dj + \int_0^1 \ell_j \, dj$.

2.2 Mechanism of the model

The model is centered around the tradeoff between the price and the delivery times for inputs. If a firm chooses to source the cheaper foreign input, that faces longer and more volatile delivery times, then it can chose to stock more inventories to be able to meet the demand every period. The firm's choice of input relies not only of their relative price, but also on the difference in their delivery times, which expose the firm to demand risk and additional delays, and the firm may need to incur in the cost of storing additional inventories. 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. Appendix C shows the proposition and proof for the full model

[13] The foreign input firms are not modeled in this economy, and I take their prices as given.

presented in this section. The first order condition for the final good firm is given by equation (8). 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, plus the price over markup, p/μ, weighted by the proportion of the order that arrives today. The first order condition shows how the value of inventories increases when delivery times rise.

$$\underbrace{p_{input}}_{\text{input price}} = \underbrace{(1-\lambda)}_{\substack{\text{order} \\ \text{arrives t+1}}} \underbrace{(1-\delta)\,\beta\, E_{\eta'}\, V_{s'}(s',\eta')}_{\substack{\text{discounted value of an} \\ \text{additional unit of inventory}}} + \underbrace{\lambda}_{\substack{\text{order} \\ \text{arrives t}}} \underbrace{p/\mu}_{\substack{\text{price} \\ \text{over markup}}} \tag{8}$$

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 (8), 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, $p = \mu\, p_{input}$, and when firms are constrained they raise their price to meet demand, $p > \mu\, p_{input}$. Thus, there is a negative relationship between the value of inventories and λ.

As delivery times for inputs decrease, due to improvements in transportation and information technology, then firms will choose to stock less inventories, as the value of an additional unit of inventories decreases. On the other hand, as the price of inputs from China decrease, due to China's entrance to the World Trade Organization and an increase in the productivity of their firms, U.S. firms will substitute away from domestic input and towards foreign inputs, given the CES assumption in equation (2). Inputs from China face longer delivery times than domestic inputs, and thus the average delivery times for inputs increases. Longer delivery times increase firm's exposure to the demand risk they face. Firms trade off the cheaper input for an increase in their exposure to volatility and, in response, firms increase their inventories.

Additionally, 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 for the increase in risk. Similarly for the variance of demand shocks. If there is more volatility in demand, firms will need to increase their inventories to insure against the additional risk they face.

III Quantifying frictions

I calibrate parameters of 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 of 1992 to 2018. I use the model to study the frictions imposed by delivery times, and the macroeconomic implications of sourcing inputs from abroad. Further details regarding the solution method can be found in appendix C, and robustness checks on the benchmark calibration are in the next section.

3.1 Benchmark calibration

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 is a 30% annual rate. The elasticity of substitution between domestic and foreign inputs, σ, equals 0.6, 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 parameters of the model is listed in Table 2.

I assume a log normal distribution for demand shock, with mean zero. The variance of the demand, σ_ν, and the weight of the domestic inputs, θ, and are jointly calibrated to match the sum of intermediate input and material inventories over output, and the amount of foreign inputs used in production in 1992. As a result, the variance of the demand equals 0.38, and $\theta = 0.13$. In the model, the variance of the demand includes all the uncertainty that firms may face (demand and productivity), with the exception the 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 me 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 with the literature which includes fixed one period delays. Here I describe how to interpret the parameter λ and how I estimate it using data on delivery days.

Interpreting delivery times: λ. Given the number of days in a given period, T, the parameter λ represents the proportion of days of the period the firm is able to use the order to produce. Equation (9) shows the relationship between the delivery days observed in the data and the parameter λ. If the delivery time is longer than the length of the period, then λ is capped at a one period delay, which which is commonly used in the literature. If not, then it is equal to the proportion of days of the period the firm has the input in its warehouse and can use it to produce, $1 -$ delivery days$/T$. There is an implicit assumption that the order is made on the first day of the period. This could be thought 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.

$$\lambda_j^i = \max(\, 0,\ 1\ -\ \text{delivery days}_j^i/T) \qquad \text{for } i = \{d, f\} \ \text{ and firm } j \tag{9}$$

The number of delivery days is drawn from a log normal distribution estimated using the the mean and variance of the delivery days in the data. For the domestic delivery days, I use data from the Institute of Supply Management, 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 equal 35 days. To estimate the variance of the distribution, I calculate the standard deviation for the average days from 1992-2018 which equals 5 days. I then estimate the variance such that 95% of the distribution lies within the $+/-5$ days.

To estimate the delivery times for foreign inputs, I use data on the average delivery days and delays for ocean shipping in the U.S.-China trade route. On average from 1992 to 2018, 80% of the goods coming from China are transported via ocean, and the remaining 20% arrive via air. These transportation proportions are common across manufacturing industries.[14] I assume, for simplicity, that all goods are transported via ocean and use ocean transit times and delays, reported by the shipping platform *Freightos*, to estimate the distribution of foreign delivery times.

Ocean transportation from China takes around 25 days to arrive to the West Coast, and 35 days to the East Coast. Delivery days on this route vary around +/- 10 days. To estimate the foreign delivery times, I assume the distribution of foreign delivery days is log-normal where the geometric mean equals the 30 days of the US-China route (assuming half of the goods arrive on the East Coast and the other half from the West Coast) plus the 35 days of domestic transit. Similarly, the standard deviation is assumed to be such that around 95% of the distribution lies within the sum of the reported average delays of the foreign and domestic transit.

[14] See appendix D for more data on transportation methods across manufacturing sectors.

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

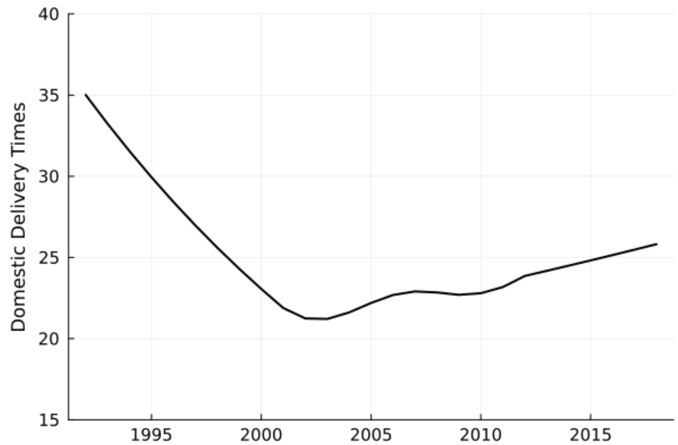
Parameter		Value	Comment
Elasticity of sub. x^f, x^d	σ	0.8	Boehm, Flaaen, and Pandalai-Nayar (2017)
Elasticity of sub. y_j	ϵ	1.5	International business cycle literature
Monthly interest rate	β	$0.96^{1/4}$	4% annual interest rate
Monthly storage rate	δ	0.075	30% annual rate

3.2 Opposing delivery time trends

To examine to what extent can delivery times explain the reversal in the U.S. manufacturing inventory trend, I calibrate the model for the two opposing forces of delivery times: direct decrease in delivery times representing the technology channel, and indirectly, delivery times increase when firms increase their reliance in foreign inputs that face longer delivery times, the trade channel. I model improvements in transportation and information 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, adjusted for the foreign transit times and smoothed using an Hodrick-Prescott filter. I assume the variance is a fixed proportion of the mean, so over time the delays for domestic inputs also decrease. Figure 27 shows the mean of the distribution for every period, and further details on the trend are shown in Appendix D.

On the other hand, there is the trade channel, which refers to the decrease in the cost of inputs form China which increased the reliance on these inputs which have longer delivery times and delays. To match this trend in the model, I calibrate the relative price of inputs, p^f_t/p^d, to match the share of imported inputs in the period from 1992 to 2018. The initial point in 1992 is the total

Figure 9: Mean of 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 a HP filter. Further details on the series can be found in appendix D.

share of foreign inputs, which I then grow with the rise in inputs from China.[15] The relative price of foreign inputs decreases at an annual average 1% rate to match the increase in share of inputs from China of 3 percentage points. 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. Note that the slope of the trend in the relative prices is governed by the elasticity of substitution between the domestic and foreign inputs. Although, results are robust to different levels of the elasticity, as I show in the next section.

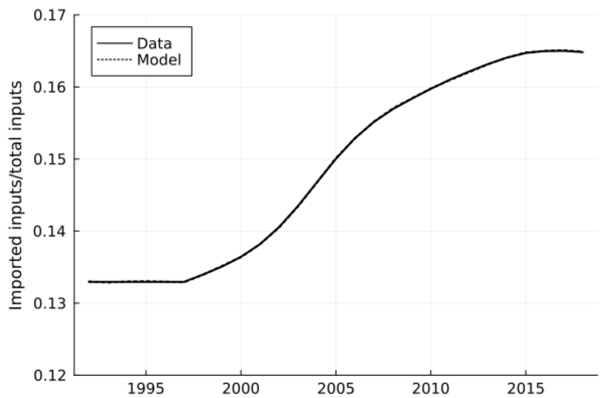
I solve for the transition paths from 1992 to 2018 for the final good firms, taking into account the two delivery time trends. I first obtain the calibrated general equilibrium stationary distribution for the economy in 1992. Then every period firms observe a change in the mean of the distribution of domestic delivery times, and a change in the relative price of foreign inputs. I fix the aggregate variables and calculate the partial equilibrium stationary distribution of the economy for each year in the transition path. More details are described in the Appendix C.

IV Results: Inventory Dynamics

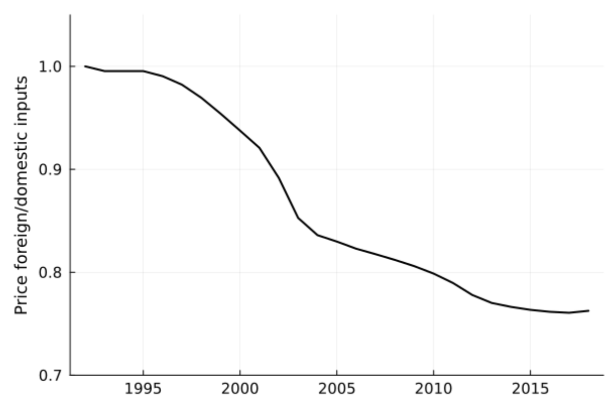
I find that the calibrated model is able to generate a similar inventory dynamics as in the data. Both the technology and the trade forces are needed to match the data, and the model is able to explain

[15] The Bureau of Economic Analysis starts reporting the data from 1997, so I assume the share of imported inputs is constant from 1992 to 1997.

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 grow 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.

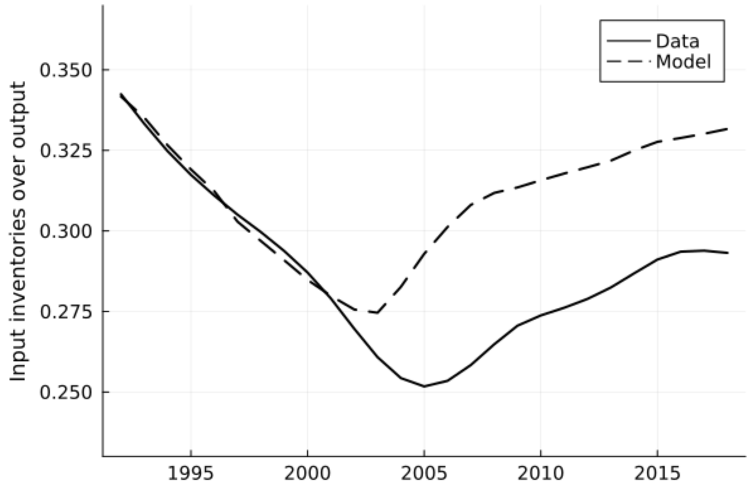
50% of the initial decline in the inventory trend, and 81% of the rise in inventories after 2005. Further, the rise in inventories is driven by the rise in foreign inventories, which compensates for the constant decline in domestic input inventories. I then use the model to explore the efficiency and volatility tradeoff firms face. I find that an economy that uses more foreign inputs their prices will be lower and output will be higher, since firms can source cheaper inputs from abroad, but both prices and output will be more volatile since firms are more exposed to the demand and delivery time shocks.

4.1 Role of delivery times in inventories

The opposing forces in delivery times generate in the model a similar pattern as observed in the data, as shown in Figure 11. The solid line shows the sum of the work in process and material and supplies inventories to quarterly output, smoothed using the Hodrick-Prescott filter. The dashed line shows the model results, where on one hand the mean of domestic delivery times is decreasing, and on the other, the relative price of foreign inputs declines over the period. Note the inventory trend is a untargetted moment in the model, with exception of the initial level of inventories used to calibrate the variance of demand.

Inventories to sale ratio in the model decline at a similar rate as in the data until 2003. In the model, the inventory trend pivots as China enters the World Trade Organization in 2001, when

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 includes the sum of work-in.process and materials and supplies inventories and is smoothed using the Hodrick-Prescott filter. The two opposing forces, technology and trade, generate a similar trend in the ratio of inventories over output in the model as is observed in the data.

imported inputs experience a large increase. In the data inventories start increasing until 2005, and although the pivot point has a two year difference, both the model and the data grow at a similar rate. 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% as shown in Table 3. From 2005 to 2018, inventories rise at a rate of 1.2%, and in the model at a rate of 1.0%. Thus, the model is able to account for 50% of the initial decline in the inventory trend, and 81% of the rise in inventories after 2005.

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 could help explain the remainder of the inventory trend are possible changes in the demand risk firms face over time, which is held constant in the benchmark economy. Additionally, the more recent rise in trade policy uncertainty could be contributing to the rise in inventories. Similarly, the low interest rates that lower the cost of holding inventories could be providing further incentives to hold inventories. However, the documented recent rise in markups, which increases the value of output relative to inputs, could create downward pressures on the inventory to output ratios.

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 is not reported in the data. Figure 12 shows the total

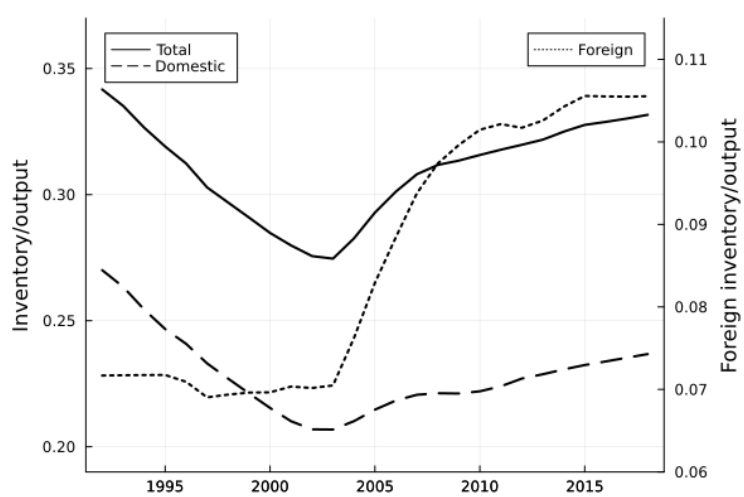
Table 3: Average annual growth rates: inventory/output

	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 the simulated stationary distributions for each year in the period of analysis, and compared to the data. The data refers to the sum of work in process and materials and supplies inventories over quarterly output. The time series is smoothed using the Hodrick-Prescott filter.

inventory over output trend in the left axis, along with the domestic input inventories over output. Domestic input inventories decrease at an annual average rate of 0.5%, following a similar trend as the mean of domestic delivery times, shown in Figure 9. Domestic inventories decline because firms are substituting away from these inputs and due to the decline in the domestic delivery times, so firms need to hold less of these inventories. Foreign input inventories are increasing throughout the period at an annual 1.5% rate, as shown in the dotted line in the right axis, and in the third column of Table 3. Foreign inventories rise because firms are substituting toward these inputs, and because foreign inputs are inventory-intensive. As firms source more foreign inputs then firms need to hold more inventories to insure their production process from the increase in exposure to demand risk, via the longer delivery times, and the rise in delivery time risk, since foreign inputs have longer and more frequent delays.

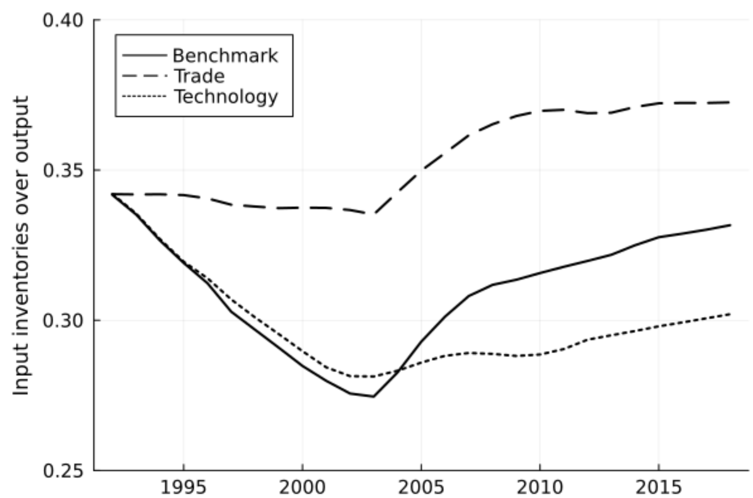
Figure 12: Rise in foreign inventories compensates for the decline in domestic



Note: The Figure shows the series for 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 the rise in total inventories is driven by the rise in foreign inventories, which compensates for the decline in domestic inventories.

Both, technology and trade forces, are necessary for the model to generate a similar trend in inventories to the data, as shown in Figure 13. The solid line shows the model's benchmark trend of inventories, that includes both the changes in the mean of the distribution of domestic delivery times, and the decline in the relative price of foreign inputs. The dotted line shows the trend of inventories over output where I only consider the improvements in transportation and information technology, 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 similar rate as in the benchmark, but then inventories stagnate and grow slightly following the trend of domestic delivery times. In contrast, when only considering the rise in foreign inputs, shown in the dotted line, inventories increase throughout the period of analysis. In 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 fixed to the level of 1992. Improvements in information and transportation technology generate an important decrease in the incentives for firms to hold domestic inventories throughout the period of analysis. The reduction in the cost of foreign inputs increases the need for foreign inventories, and drives the rise in the total inventories over output after 2003.

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



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

4.2 Decomposing volatility: efficiency and volatility tradeoff

The model is centered around the tradeoff between the price and delivery times across inputs. As the price of foreign inputs decrease, firms increase their reliance on these inputs and increase their holding of costly inventories in response to the longer delivery times they face. Firms are trading off efficiency, by sourcing the low cost inputs from abroad, for an increase in volatility, since the longer delivery times increase their exposure to demand risk and foreign inputs face more volatile delivery times.

Through the lens of the model, I explore this tradeoff by comparing the stationary distribution of an economy that uses a larger share of foreign inputs to produce, represented by the benchmark economy in 2018, vs the technology economy in 2018 which uses a lower share of foreign inputs to produce. Table 4 shows that an economy that uses more foreign inputs, prices are going to be lower since firms source the cheaper inputs from abroad, output will be higher, and firms will hold more inventories. However, these variables are more volatile since firms are more exposed to the demand and delivery time risk. The increase in inventory holdings is not sufficient to completely smooth out production, and the share of firms constrained in the amount of inputs used in production (see equation 3) increases from 8% to 12%.

Table 4: Efficiency vs volatility

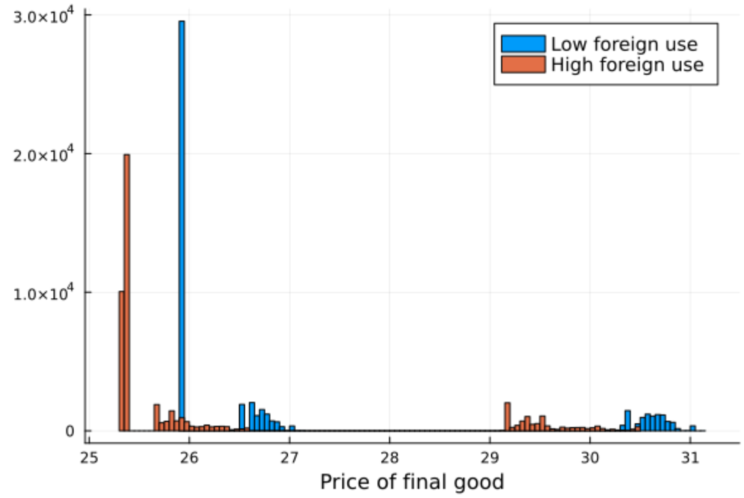
Rise in inputs from China: higher and more volatile output

	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 use 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 more of the foreign inputs output will be higher, and prices will be lower, but output will be more volatile.

As firms use more of the foreign inputs the probability they are constrained in a given period increases due to the longer delivery times and delays. When a firm is constrained, they rise the price of the final good up to the point where the consumer demands its entire stock. Even though firms set lower prices on average, firms raise prices more frequently as they are more frequently constrained, which raises the standard deviation of the stationary distribution of prices, shown in Figure 14. This effect permeates to the output, composite input, and inventory holdings, where volatility increases as well.

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



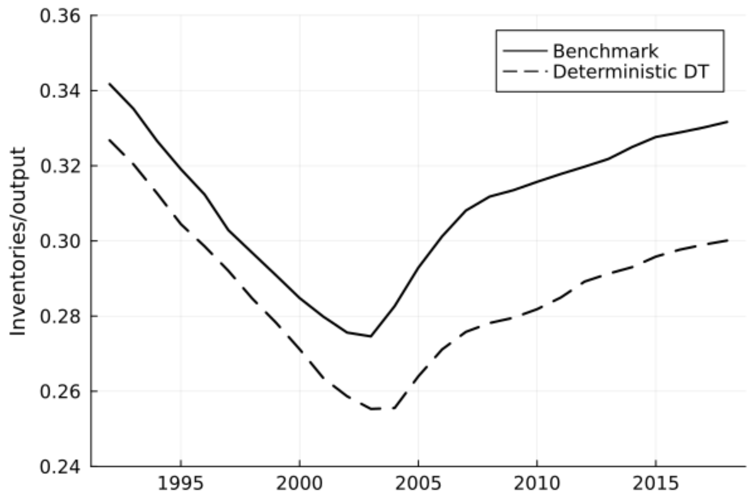
Note: The Figure shows the stationary distribution for the final good prices. *Low foreign use* represents the price distribution of the technology economy in 2018, where the share of foreign inputs is the one in 1992. *High foreign use* shows the price distribution of the benchmark economy in 2018,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

Both types of shocks, demand and delivery times are relevant in firms choice to hold inventories. Using the model, I can analyze the rise in volatility firms face from (i) the interaction between the mean of the delivery times and the variance of the demand, and (ii) the variance of delivery times. Figure 15 shows the inventory ratio series for two scenarios. The solid line shows the benchmark trend in inventories, including both the demand and delivery time shock. The dashed line shows an economy with only demand volatility, where delivery times are positive but deterministic. Most of the incentives firms have to hold inventories come from the interaction between the mean of the delivery times and the variance of the demand. The level of inventories is similar across scenarios in 1992, meaning that delivery delays do not play a big role in the volatility firms face. However, as firms increase the reliance on inputs that face volatile delivery times, the second moment becomes more important in determining not only the level, but also the changes in the stock of inventories over time. Both sources of volatility are relevant, and while the variance of the demand determines the level of inventories, the variance of delivery times helps shaping the growth over time.

4.3 Sensitivity analysis

The trend of inventories to output is robust to different parameter values. 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 the foreign and domestic inputs, σ. The benchmark

Figure 15: Demand vs delivery time shocks



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

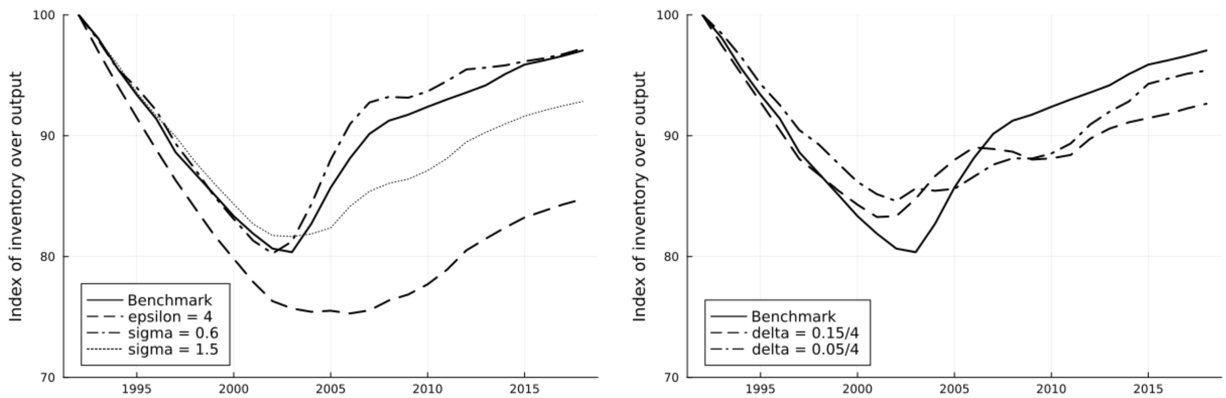
model is calibrated for $\epsilon = 1.5$ and $\sigma = 0.8$, and here I show the inventory trend is robust for $\epsilon = 4$, and $\sigma = \{0.6, 1.5\}$. The lower the substitutability of inputs, the larger the change in inventories, as firms are unable to switch between inputs to smooth out production. A similar effect occurs with a higher elasticity for the final goods, where the consumer adjusts its demand for each final good and final good firms adjust less their inventories. Regardless, the reversal of the long term decline in inventories is presents across the different values of elasticity.

Figure16b shows the inventory trend for different values of the storage costs, which in the benchmark economy is set to a quarterly rate of $30/4\%$. Different values of storage cost affect the level of inventories, where the lower the storage costs the higher the level of inventories firms are willing to hold. But the trend of the inventories is robust to different values of the storage costs, as shown in Figure 16b.

V Conclusion

This paper documents the reversal in the long term decline of U.S. manufacturing inventories over output, which has been increasing since 2005. The increase is observed across U.S. business, manufacturing industries, firms, and types of inventories. Additionally the pattern is observed in the

Figure 16: 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 the model results for the inventory over output for different values of the elasticity fo substitution between domestic and foreign inputs, σ, between final goods, ϵ, and for the storage costs, δ. The trend of inventories to output is robust to the different parameter values.

manufacturing sector of Australia, Canada, Japan, and South Korea. The decline of inventories is well understood as a consequence of the improvements in transportation and information technology that made inputs more readily available for firms. In this paper I explore the role of the rise in intermediate input trade, which increased the delivery times for inputs, has on the rise in inventories. In particular, I focus on the rise in inputs from China, which face long delivery times and delays, which increase the exposure to the demand risk U.S. firms face.

I introduce a novel dynamic trade model centered around the tradeoff between the relative price and delivery times of inputs. It features different and stochastic delivery times for inputs, and firms choose to stock inventories to insure against the demand and delivery time shocks. I calibrate the model to quantify the two opposing forces of delivery times: the technology force which decreases the delivery times for domestic inputs, and the trade force which increases the reliance on inputs from China that face long and volatile delivery times. I find that the model generates a similar trend of inventories as observed in the data. the model accounts for 50% of the initial decline, and 81% of the rise in inventories after 2005. Further, I use the model to analyze the tradeoff between efficiency and volatility. As firms chose the cheaper foreign input, they tradeoff efficiency for and increase in volatility, since the longer delivery times increase their exposure to demand and delivery time shocks. I find that an economy that uses more foreign input, their prices will be lower, and output higher, but both will be more volatile.

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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

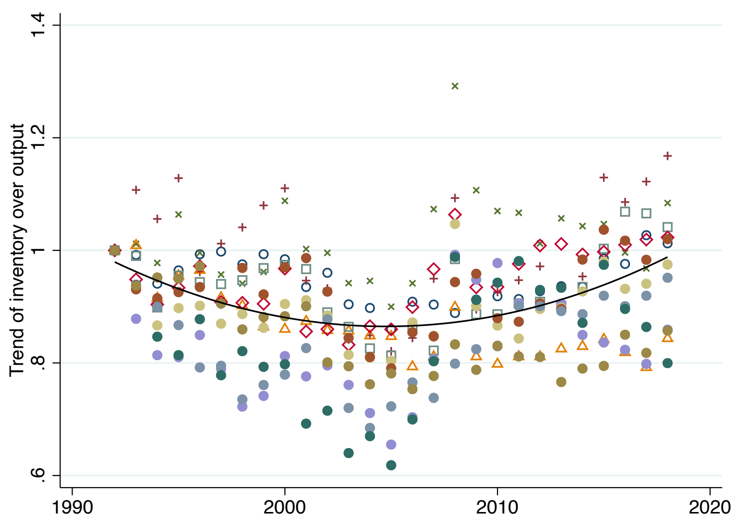
Inventories reported exclude the following goods:

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 the 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 **??**. 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.

Figure 17: Increasing inventories across industries

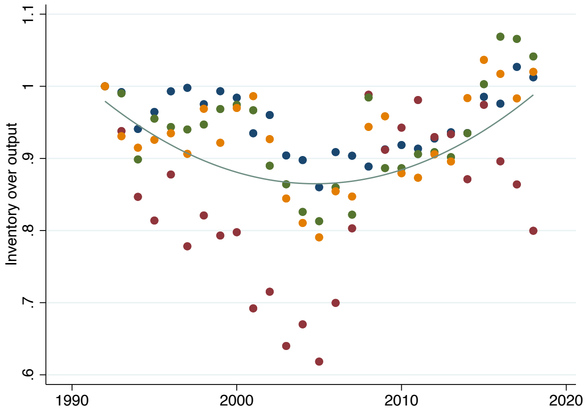


Note: The Figure shows the trend of inventory-to-sales ratio for the NAICS 3-digit industries (excluding Petroleum and Coal Products). It includes the quadratic fitted line of the trend, showing the initial decrease and following increase after 2005.

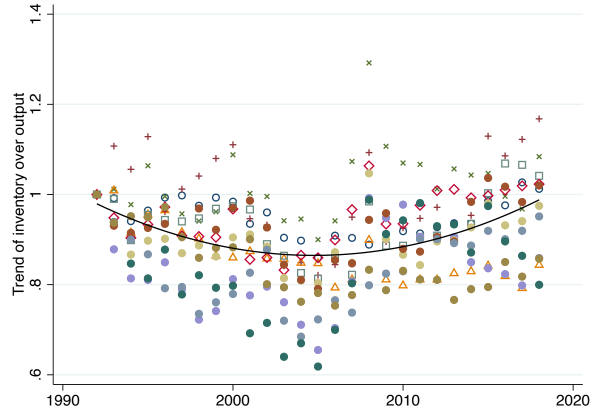
1.3 Increase in inventories across sectors using NBER-CES database

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,

Figure 18: Increasing inventories across manufacturing sectors



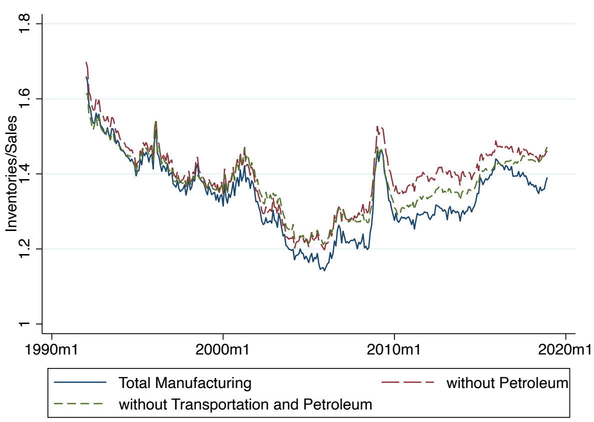
(a) Four largest sectors



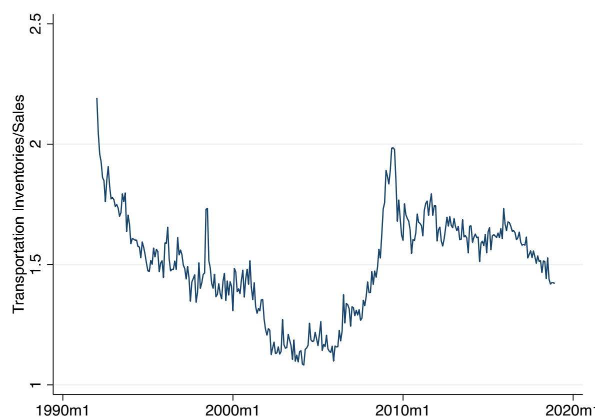
(b) All sectors

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

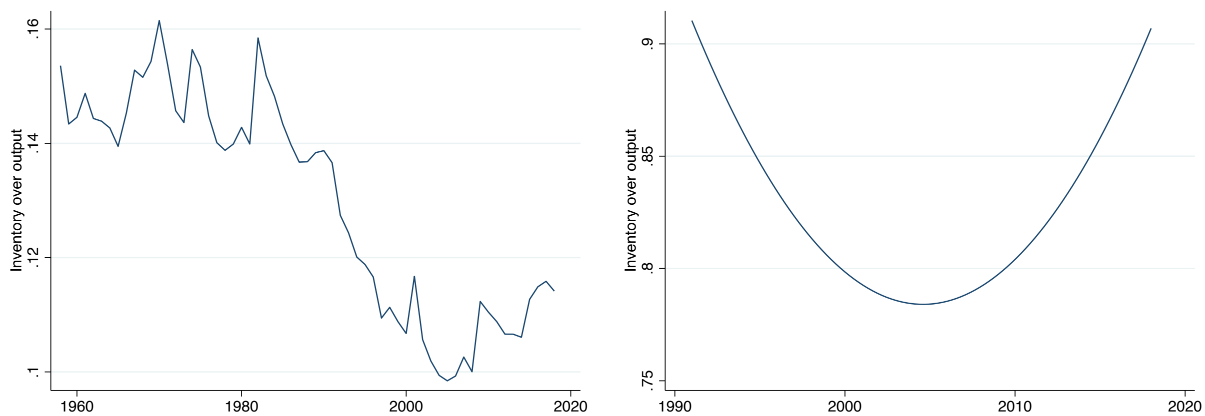


(b) Transportation (336) sector

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.

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

Figure 20: Increasing inventories: NBER-CES database



(a) Long term trend for total manufacturing sector (b) Rise in inventories across six-digit NAICS industries

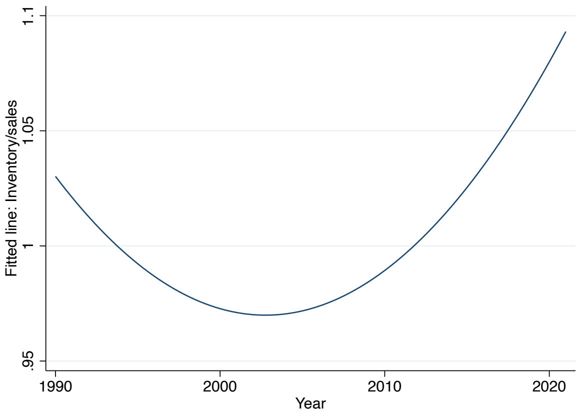
Note: The Figures show the trend of inventories over sales. Panel a shows the long term trend for the total manufacturing industry. Panel b shows the quadratic fit of the scatter plot of the trend (index) of the inventories-to-sales for all the six-digit manufacturing industries.

1.4 Increase in inventories across firms using Compustat

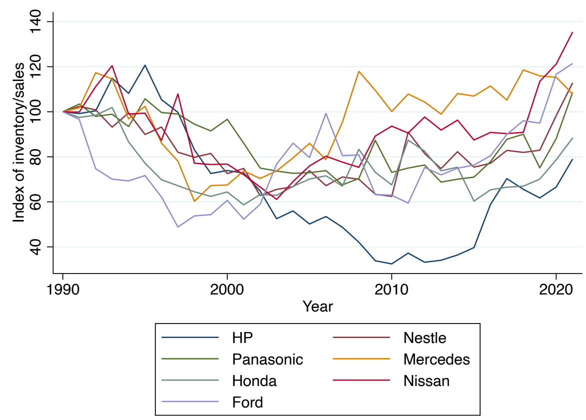
The rise in inventories is also observed across firms, using the Compustat North America database. [16] For the analysis, I constraint the dataset to manufacturing firms that have available inventory and sales data for the period 1990-2021, which gives me a total of 478 U.S. public firms. Figure 21a 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. 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.

[16] 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 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

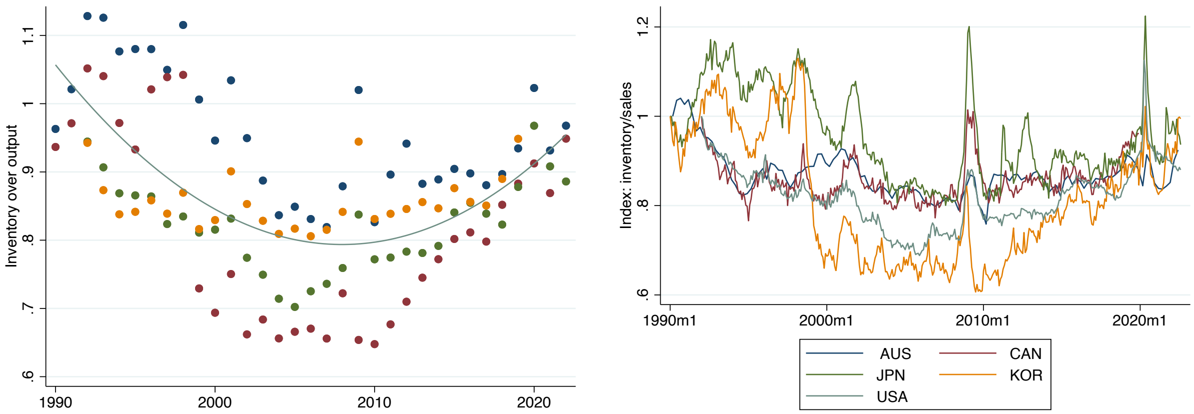
	Inventory/sales			
	Sectors		Firms	
	1990 – 2005	2006 – 2018	1990 – 2005	2006 – 2021
	(1)	(2)	(3)	(4)
Year	−0.0101	0.0093	−0.0010	0.0018
	(0.0011)	(0.0012)	(0.0002)	(0.0001)
Constant	20.900	−17.8109	2.1857	−3.422
	(2.1880)	(2.5080)	(0.3769)	(0.2490)
Fixed effects	sector-level	sector-level	firm-level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

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.

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. 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. Last, it shows evidence of the growth in inputs from China across manufacturing sectors.

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:

$$\frac{\text{Country } i \text{ imported inputs in } j}{\text{Total inputs used in } j} = \frac{\text{Imports from } i \text{ in } j}{\text{Total imports of } j} \frac{\text{Imported inputs from } j}{\text{Total inputs used in } j} \tag{10}$$

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.

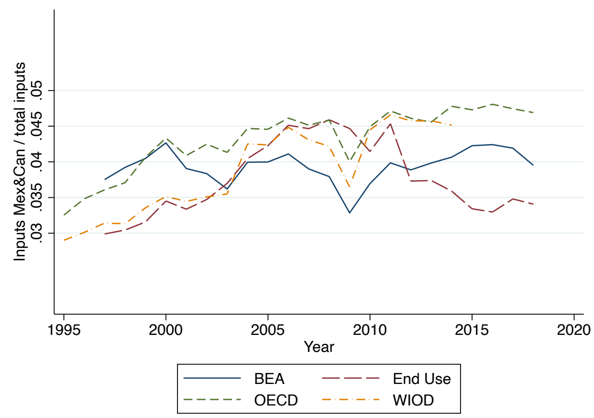
The **World Input Output Database** reports the share of imported inputs for each manufacturing sector across countries of origin. It additionally shows the amount of domestic and foreign inputs used in production, and reports annual data for the period 1995-2014. A similar data source are the **OECD 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 23a shows the substitution away from domestic inputs and towards 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.

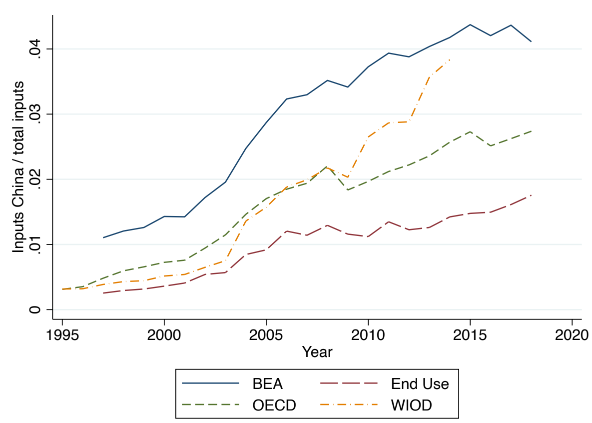
Figure 23c similarly shows the rise in inputs from China across data sources. The largest rise is observed in the WIOD data, which grows 3.5 percentage points from 1995 to 2014. Following is the data from the BEA, which grows 3 percentage points from 1997-208, and the OECD data which grows 2.4 percentage points. Last are the industrial supplies from China, which not only show the lowest level, but also grow only 1.5 percentage points. Figure 23b shows that inputs from Mexico and Canada remain relatively stable for the period of analysis across data sources.

Figure 23: 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



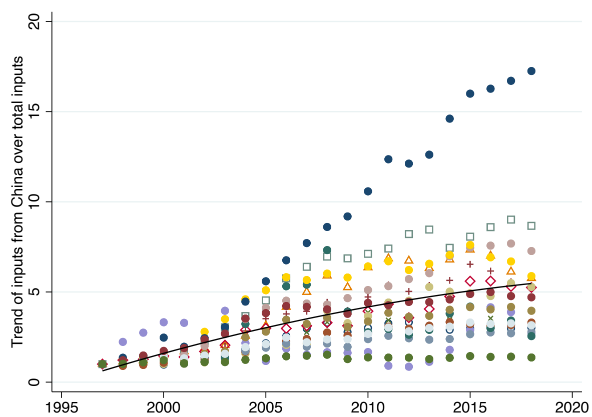
(c) Rise in inputs from China

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.

2.3 Rise in inputs form China across manufacturing sectors

Figure 24 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.

Figure 24: Rise in inputs from China across industries



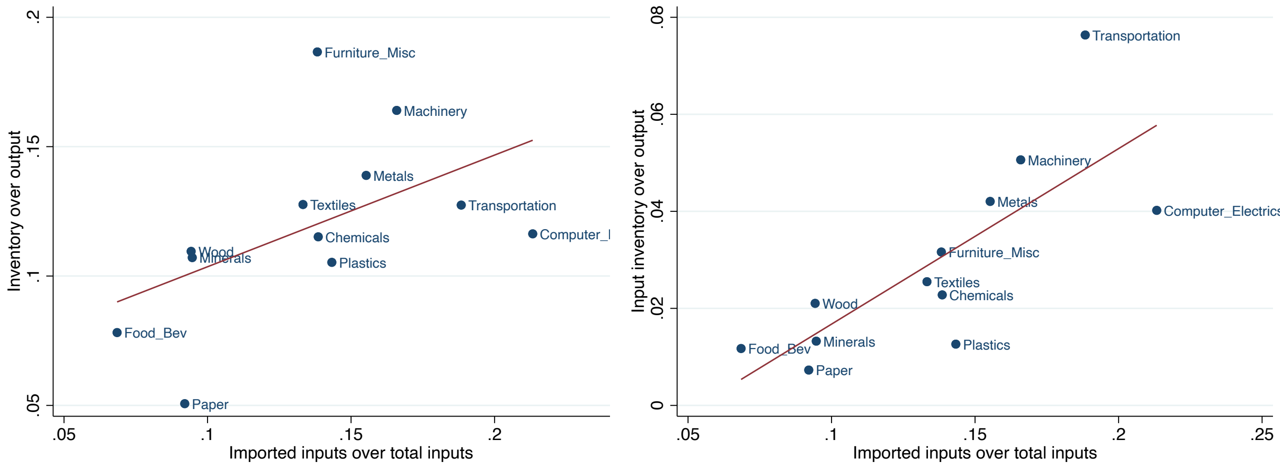
Note: The Figures show the trend (index) of the growth in the share of inputs from China over total inputs used in production, for the three digit NAICS manufacturing sectors, and the associated fitted line.

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 25a 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 25b. 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 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

Figure 25: 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.

7). The relationship remains when controlling for value added, where the increase of 10% in inputs from China increases total inventory by 5% and input inventory by 6%. Additionally, Figure 26 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 towards the growth experiences until 2017.

C Solving and calibrating the model

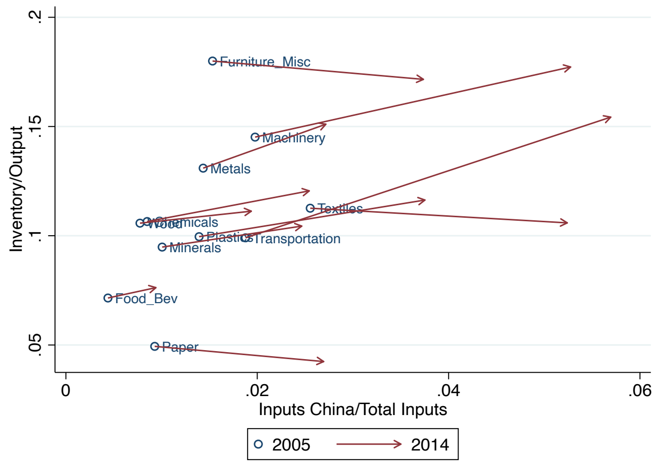
In this section I provide details on the algorithm used to solve the model, and the calibration strategy. I abstract from denoting specific firms j to simplify the notation.

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

Figure 26: 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.

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

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

$$Y = C^g + N^g$$

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

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

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

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

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.

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).[17]

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

3.1.1.1 **Both inputs are unconstrained, x^f_{unc}, x^d_{unc}.** Note these equation do not depend

[17] 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.

on the actual orders or stock of inventories, (n^d, n^f, s^d, s^f).

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

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

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

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.

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

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

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

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

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

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

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

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

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

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

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

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

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

4. Given the policy functions for the final good firm (p_j, x^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.

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

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

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

$$P = \left(\int_0^1 v_j\, {p_j}^{1-\epsilon}\, dj \right)^{\frac{1}{1-\epsilon}}$$
$$N = \int_0^1 N_j^d\, dj$$
$$C = \frac{w\, L + \int_0^1 \Pi_j dj}{P}$$

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.

$$\tilde{V} = \max p^{1-\epsilon}\, P^{\epsilon} \nu Y \; - p^d \Big(\frac{s^{d'} - (1-\delta)(s^d - x^d)}{1-\lambda^d\delta}\Big) \; - p^f \Big(\frac{s^{f'} - (1-\delta)(s^f - x^f)}{1-\lambda^f\delta}\Big) \; + \beta\, V(s'^d,\; s'^f)$$
$$\text{s.t. } x^d \le s^d + \lambda^d \Big(\frac{s^{d'} - (1-\delta)(s^d - x^d)}{1-\lambda^d\delta}\Big) \qquad (\mu^d)$$
$$x^f \le s^f + \lambda^f \Big(\frac{s^{f'} - (1-\delta)(s^f - x^f)}{1-\lambda^f\delta}\Big) \qquad (\mu^f)$$

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

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

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.

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

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:

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

and from the first order condition with respect to s'^i, $\mu^i=\frac{1}{\lambda^i}\left(\,p^i-\;(1-\lambda^i)\,\beta\,E_{\eta'}V_{s'^i}\,\right)$, 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

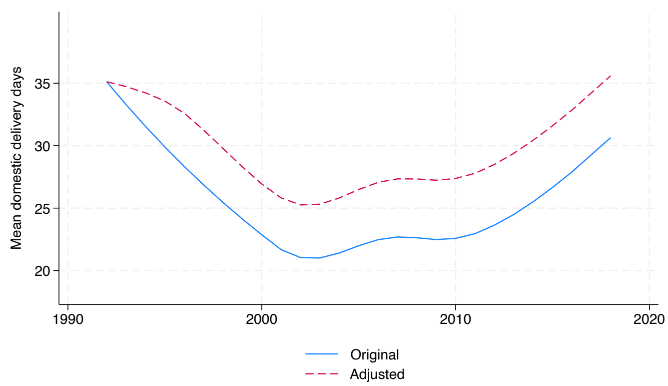
This section provides details on the domestic delivery times, using data from the Institute of Supply Management. Additionally, it details the method of transportation for U.S. imports from China, and the lead times for this route using data from the logistics company Freightos.

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, foreign and domestic. Then to estimate the trend of domestic delivery times, I adjust the ISM data for the delivery times of foreign inputs. I first take the value for 1992, and grow the series using the growth rate for the smoothed capital expenditures series. 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 from 1992 to 2001 to obtain the final series reported in Figure 27.

Figure 27: Mean of domestic delivery times



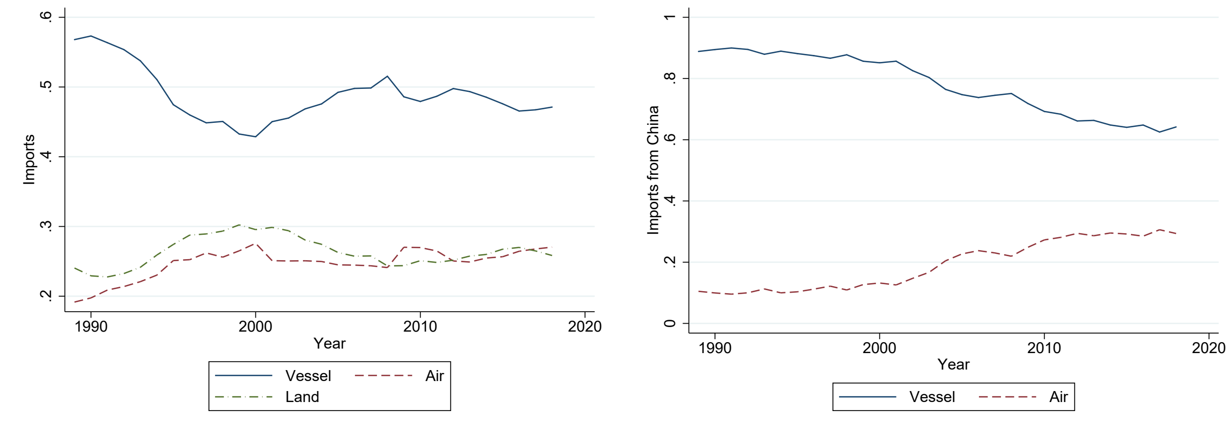
Note: The Figure shows the value of the average reported by the ISM of the delivery times for production materials and maintenance and operation supplies, adjusted by the lead times of foreign inputs.

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 28a 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 28b shows that on average, 80% of imports from China arrive via ocean vessel. Additionally, the share of vessel is decreasing, and more goods are shipped via air. Compared to the U.S. average for imports, more imports from China via ocean transportation, and the remaining via air.

The proportions of air vs ocean transportation for the goods coming from China remain relatively constant across manufacturing sectors, with the exception of the computer and electronic manufacturing sector, 334. Figure 29 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 towards more air transportation.

Figure 28: Method of transportation for U.S. imports

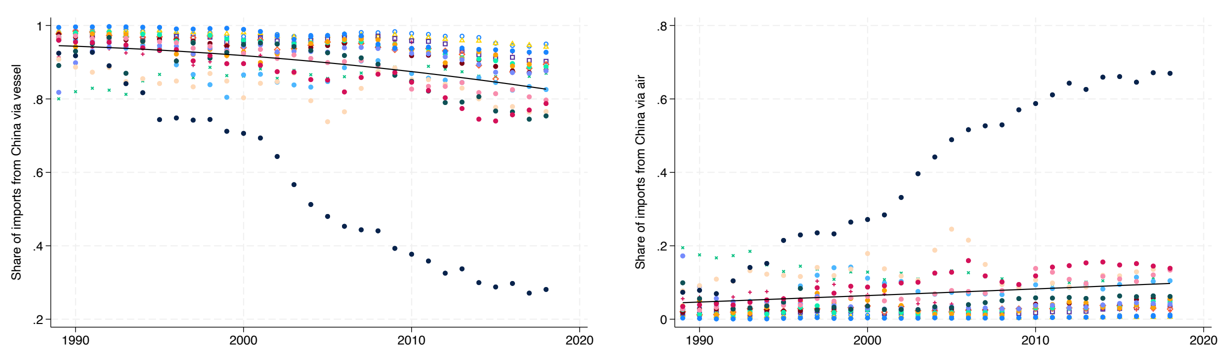


(a) Transport method for US imports

(b) Transport method for imports from China

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

Figure 29: 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.