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. The rise is observed across U.S. manufacturing industries and types of inventories. While the long term decline is well-understood as a consequence of improvements in transportation and information technology, the reversal of the trend has not yet been studied. This paper explores the role of increasing delivery times due to the creation of global supply chains. As foreign inputs become cheaper, firms choose to source more inputs from abroad, and in particular inputs from China, which face long delivery times and frequent delays. This increases the firms' exposure to volatility in demand leading to a greater incentive to hold inventories. I build a dynamic trade model that features stochastic delivery times for different inputs in the presence of idiosyncratic demand risk. In this framework, firms face a tradeoff when sourcing inputs from different locations between their relative price and delivery times. I find that the initial decrease in delivery times explains 61% of the decline in inventories from 1992 to 2004, and the increase in reliance on inputs from China, which face longer and more volatile delivery times, explains 34% of the increase in inventories from 2005 to 2018.

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1 Introduction

After a large decline in U.S. manufacturing inventories that started in the 1980's, the trend has reversed as shown in Figure 1. Since 2005, inventories have increased across manufacturing industries and types of inventories. While the long term decline in inventories has been studied by the literature and attributed to improvements in transportation and information technology that allowed for inputs to be more readily available,[1] the reversal of the trend has not yet been studied.

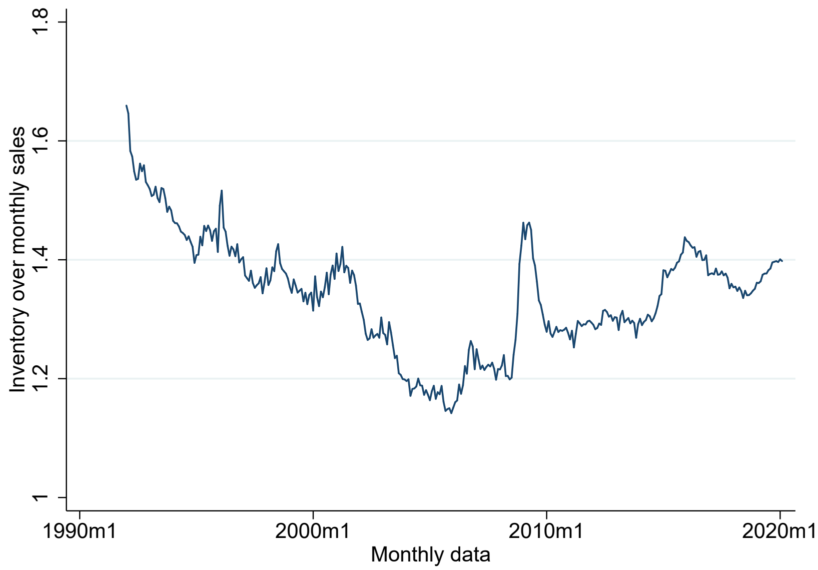
Inventories are a tool firms can use to insure against demand changes or supply chain disruptions. While firms choose to stock inventories for many reasons, this paper explores the role of longer and more volatile delivery times for inputs as U.S. firms created global supply chains. As foreign inputs become cheaper, firms choose to source more inputs from abroad, and in particular inputs from China which face long delivery times and frequent delays. This process increased their exposure to volatility in demand, as longer delivery times for inputs decrease firm's ability to meet their demand every period. Furthermore, delays increase the risk in the availability of inputs. Both channels lead to greater incentives for firms to hold inventories.

First, this paper documents a new fact: inventories have increased since 2005 across manufacturing industries and types of inventories. Second, I provide evidence that inventories are greater among industries that rely on imports for their production. Third, I show that firms across manufacturing sectors are increasingly sourcing inputs from China, which face long delivery times and delays. Based on these facts, I build a dynamic trade model that features a novel way of modeling delivery times, which includes different and stochastic delivery times for inputs. In the presence of demand volatility, firms face a tradeoff when sourcing from different locations between their relative price and delivery times. First, improvements in transportation and information technology made inputs more readily available for firms in the production process. However, as firms substituted more expensive domestic inputs with quick delivery times for cheaper inputs from China, they increased their exposure to long delivery times and delays. I find that the initial decrease in delivery times explains 61% of the decline

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

in inventories from 1992 to 2004, and the increase in reliance on inputs which face longer delivery times explains 34% of the increase in inventories from 2005 to 2018.

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. The data comes from the U.S. Census Bureau. The figure shows the decrease in inventories from 1992 to 2004 and the reversal of the long term decline from 2005 to 2018. Also note the U.S. experienced recessions on 03/2001 to 09/2001 and 12/2007 to 06/2009.

While the sharp decline in U.S. manufacturing inventories that started in the 1980's has been studied in the literature by papers such as Feinberg and Keane (2006), Plenert (2006), and Dalton (2013), this paper documents and explores the increase in the ratio of inventories over sales that started in 2005. The reversal of the trend is observed for total business inventories, and is present for the retail, wholesale, and manufacturing industries. The sharpest trend is observed in manufacturing inventories, which is the focus of this paper. The increase is an industry wide phenomenon, in the sense that all manufacturing industries display an increase in their ratios of inventories over sales. Additionally, the increase is observed across types of inventories: for finished goods, materials and supplies, and work-in-process goods (i.e., goods undergoing fabrication). Inventory for the goods undergoing fabrication have the steepest decline and rise, which suggests the risk of supply chains is important for inventory holding.

Contemporaneous with the rise in inventories, there has been an increase in the share of imported inputs over total inputs used in production by U.S. firms. They have substituted domestic inputs for foreign inputs, driven by the rise in inputs from China. Furthermore, this increase in reliance on inputs from China is observed across manufacturing industries. However, U.S. trade with China faces long delivery times and frequent delays. This is especially true when compared with delivery times for domestic inputs, or inputs coming from the other main U.S. trade partners, Mexico and Canada. For example, around 80% of the goods from China arrive via ocean transportation, which take around a month to arrive and are subject to long and frequent delivery delays.[2]

I document that industries that use more foreign inputs to produce choose to hold more inventories. Using time series data for U.S. manufacturing industries I show that an increase of 10% in the share of imported inputs is associated with an increase in total inventories of 5.9%, controlling for time and industries. The relationship is strengthened when considering inventory for goods undergoing fabrication, which grow 7.3%. While this relationship has been studied by the literature by Alessandria, Kaboski, and Midrigan (2010a) and Khan and Khederlarian (2020b) for Chilean and Indian firms, this paper shows it is also present for the U.S. manufacturing industry.

Motivated by the evidence documented in the first section of the paper, I present a dynamic trade model to study the role delivery times for inputs play in firm's inventory decisions. I depart from the literature, which considers a deterministic one period delivery lag, and allow for variable and stochastic delivery times for inputs. In the presence of demand volatility, firms face a tradeoff when sourcing inputs from different locations between their relative price, and the delivery times each of the inputs face. Ideally, firms would be able to plan around the delivery times of their inputs and order in advance. However, when firms face a volatile demand, having to wait for the inputs to arrive diminishes firm's ability to meet their demand every period. This interaction between the inherent risk firms face and delivery times for inputs creates incentives for firms to stock inventories. The model will allow me to quantify how much of the inventory trend is driven by this specific risk channel, and how important are delivery times for firm's sourcing decisions.

I calibrate the model to match the share of imported inputs and the initial trend for the inventories

[2] Data on delivery times and delays comes from estimates reported by logistics company *Freightos*, *Sea Intelligence*, and *eeSea*.

over sales for the U.S. manufacturing inventories. To match those moments I calibrate the variance of demand and parameters in the production technology for final good firms. Additionally, I estimate the distribution of foreign delivery times to match the delivery times observed for U.S. - China trade, using estimates on ocean transportation for the imports.

Then, I model the two opposing forces of delivery times that I observe in the data for the period 1992 to 2018. First, following the literature I model the improvements in transportation and information technology as a decrease in the length and variance of domestic delivery times of inputs.[3] To inform the changes in delivery times, I use the diffusion index for future delivery times published by the Federal Reserve Bank of Philadelphia in their *Manufacturing Business Outlook Survey*. Changes in the index imply an annual decrease of 2.2% for domestic delivery times throughout the period of analysis. Second, firm's exposure to long delivery times increases as the cost of inputs from China decrease. According to the model, the cost of the foreign inputs decreases by 3.8% annually to match the rise in the share of inputs used for production that arrive from China.

The interaction between stochastic delivery times for inputs and demand volatility is an important source of risk for U.S. firms. The opposing trends in delivery times for inputs generate a similar trend in the ratio of inventories over output in the model to what is observed in the data. The interaction between the improvements in information and transportation technology, which lead to the decrease in domestic delivery times for inputs, and the increase in reliance on inputs from China which face longer and more volatile delivery times explains 61% of the decline in inventories from 1992 to 2004 and 34% of the increase from 2005 to 2018.

In the model, domestic inventories over output decrease at an average annual rate of -1.2% from 1992 to 2018, due to the decline in the mean and variance of domestic delivery times. Furthermore, foreign inventories over output increase at an average annual rate of 6.3% throughout the period, in response to the increase in reliance on riskier inputs from China which face longer and more volatile delivery times. Total inventories decrease from 1992 to 2001, driven by the decline in domestic inventories. In 2002 the trend reverses, and total inventories increase from 2002 to 2018. In this period,

[3] Empirical papers such as Li and Li (2013) and Cui and Li (2018) document the relationship between inventories and delivery times, through improvements in transportation technology.

the increase in foreign inventories is large enough to overcome the decrease in the need for domestic inventories. The tuning point in the model coincides with China's entrance to the World Trade Organization, where U.S. increased sharply the amount of inputs they sourced from China.

Last, firms choose to stock inventories for many reasons. This paper focuses on the role of delivery times, and the impact global value chains have in the level of risk firms face. This particular channel is able to generate a similar trend in inventories to what we observe in the data, and explains a third of rise in inventories. Moreover, the current framework allows for further work on the importance of delivery times in trade, and possible extensions to allow for other channels to explain the remaining trend in inventories.[4]

Related literature. This paper builds upon several strands of literature on inventories, trade and supply chains, and the importance of delivery times. First, this paper documents the recent increase in U.S. manufacturing inventories. The importance of understanding the trend is highlighted in the literature that studies the role of inventories as insurance against risk, in papers such as Humphreys, Maccini, and Schuh (2001), Auernheimer and Trupkin (2014), and Maccini, Moore, and Schaller (2015). Additionally, recent literature highlights the importance of risk in trade (Handley and Limao (2015), Handley (2014), and Baley, Veldkamp, and Waugh (2019)) and how any type of frictions become especially important in the presence of global supply chains (Hummels, Ishii, and Yi (2001) and Yi (2003)). This paper builds on these strands of literature to explore the recent inventory increase through the insurance motives for firms which increased their reliance in riskier, foreign inputs.

Second, this paper contributes to two strands on literature regarding the relationship between inventories and trade. The first strand of literature studies the role of inventories in accounting for business cycle dynamics. Alessandria, Kaboski, and Midrigan (2010a), Novy and Taylor (2014), and Ferrari (2020) study how inventories can explain for fluctuations of trade and international business cycles. Similarly, Khan and Thomas (2007), Iacovello, Schiantarelli, and Schuh (2007), Kryvtsov and Midrigan (2009), and Tamegawa (2014) incorporate inventory decisions in a framework to study how inventories help explain business cycle dynamics. The second strand of literature documents the pos-

[4]The model already contains other motives for inventory holding through variations in the firm-level risk, changes in interest rates, trade policy uncertainty, among others.

itive relationship between inventories and imported inputs, in papers such as Alessandria, Kaboski, and Midrigan (2010b), Jain, Girotra, and Netessine (2014), Vieira Nadais (2017), Khan and Khederlarian (2020b), and Khan and Khederlarian (2020a). Alessandria, Kaboski, and Midrigan (2010b) estimates that Chilean manufacturers hold more than twice as many months' worth of foreign inputs on hand than of domestic inputs, and Khan and Khederlarian (2020b) document a similar relationship for Indian's manufacturing firms. This paper builds on this fact, and documents the relationship for U.S. manufacturing industries. This paper contributes to both literatures by emphasizing the role of delivery times for inputs in explaining the inventory investment for firms. This paper follows the theoretical framework introduced in Alessandria, Kaboski, and Midrigan (2010a) and Khan and Thomas (2007), and incorporates a novel flexible and stochastic delivery time specification. Doing so allows me to measure how changes in delivery times for different inputs affect sourcing and inventory decisions.

Third, the frictions of delivery times in trade has been well documented by Evans and Harrigan (2005), Hummels (2007), Hummels and Schaur (2013), and Leibovici and Waugh (2019). Additionally, empirical papers such as 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. Li and Li (2013) find that investment in transportation infrastructure leads to a decline in inventories for Chinese firms, and Cui and Li (2018) provide evidence that being connected to the high-speed rail system in China leads to 9.5% reduction in local firms' input inventory spending. This paper studies these relationships in a quantitative framework, and documents its relationship with inventories held by U.S. industries.

Fourth, this paper calibrates the dynamic trade model to match the two opposing trends in delivery times. I follow the literature on the adoption of *just-in-time* management and *Japanese-style* procurement practices and its effect on inventory management, by Ohno (1988), O'Neal (1989), Heide and John (1990), Han, Wilson, and Dant (1993), Feinberg and Keane (2006), Dalton (2013), and Pisch (2020). They show the adoption of these practices allowed for the large drop in U.S. manufacturing inventories that started in the 1980's. Firms were able to adopt these practices due to important improvements in transportation and information technology, which decreased the delivery times for inputs.

Firm's increase in exposure to long delivery times and delays is due to the increase in reliance in imports from China. 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 via the adoption of *Japanese-style* procurement practices. Additionally, goods coming from China face long delivery times and frequent delays since most of them arrive via ocean transportation. Ganapati, Wong, and Zic (2020) document how ocean transportation is time intensive, since the majority of trade arrives via U.S. ports indirectly, where a large number of shipments is channelled through a small number of *entrepôts* before arriving to their final destination.

Last, this paper helps understand how the risk associated to delivery times impact global supply chains, along with the growing literature on the importance of risks in global supply chains. Papers such as Baldwin and Freeman (2022) and Jiang, Rigobon, and Rigobon (2021) study how just-in-time process and the fragmentation of the production process left supply chains vulnerable to different type or risks. In particular, Cavallo and Kryvtsov (2021) studies the price effects of aggregate socks, such as the 2020-2021 pandemic in the event of inventory stockouts.

Layout. The paper is organized as follows. Section 2 documents the increase in U.S. inventories, across types of business, manufacturing industries, and type of inventories. Section 3 provides evidence on the increase in U.S. firms exposure to long delivery times and delays for inputs. The first subsection provides evidence of the substitution towards inputs from China, which face long delivery times and frequent delays. The second subsection shows that sectors that use more foreign inputs to produce tend to stock more inventories. Motivated by the reduced form evidence, section 4 presents the model and main mechanism. Section 5 details the calibration for the model and the two opposing trends in inventories. Section 6 presents the quantitative findings on the role of delivery times in inventories. Finally, 7 concludes.

2 Increasing Inventories

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. The increase is observed across manufacturing industries and types of inventories. Manufacturing inventories are an important part of the economy; they represent 12% of manufacturing gross output on average for the period 1992 to 2018. Understanding the changes and overall trend of inventories is important because inventories are an important tool for firms to use to insure against risks. This section documents and provides more detail on the trend in U.S. inventories.

Data. Inventory and sales data comes from the *Manufacturer's Shipments, Inventories, and Orders* survey from the U.S. Census Bureau. They report monthly data on sales, total inventories, and types of inventories from 1992 to 2018. The data is available for aggregate classified industries that can be matched to 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., or in customs warehouses, or being transported to or from the U.S., or any inventories in transit.[5] Throughout the paper, I leave sector 324 *Petroleum and Coal Products* out of the analysis. The petroleum sector is volatile by nature, and only accounts for 5.1% of total manufacturing inventories (average 1992-2018).

2.1 Increase in U.S. inventories

This paper focuses on studying and documenting a new fact:[6] the reversal of the long term decline of U.S. manufacturing inventories observed in Figure 1. However, the trend is also present in total business inventories, which includes the inventories for the retail, wholesale, and manufacturing industries.[7] Furthermore, the inventory trend is present across each of these sectors.[8] The trend is

[5] More information on the goods included in the reported value of inventory can be found in appendix A.

[6] To the extent of my knowledge, this is the first paper to document the increasing trend in U.S. inventories.

[7] The business sector and their sub-sectors are defined by the U.S. Census Bureau.

[8] Figures of inventory over sales trends for different types of business can be found in the appendix D, Figure 21.

sharpest for manufacturing inventories, which observe the steepest decrease and increase.[9]

The decrease in the ratio of manufacturing inventories over sales that started in the 1980's has been studied by the literature and attributed to improvements in transportation and information technology. These technological improvements allowed delivery times for inputs to decrease. Papers such as Han, Wilson, and Dant (1993), Feinberg and Keane (2006), Dalton (2013) and Heise, Pierce, Schaur, and Schott (2019), study the decrease in inventories through the adoption of *just-in-time* inventory management practices, and *Japanese-style* procurement systems. These inventory management systems consist on inputs being ordered and delivered just before they are needed in the production process, which result in a reduction of the inventory held on-site. The decrease in delivery times for inputs allowed for these systems to be implemented. There was an important increase in the use of air transportation, and firms were able to track and organize their supply, inventories, and production with new information technology.

The reversal in the long term decline in inventories occurred despite the continuous decrease in delivery times. This paper's hypothesis is that the compositional shift to foreign inputs from China is the driver for the reversal of the long term inventory decrease. The next section details the relationship between imports, delivery times for inputs, and inventories.

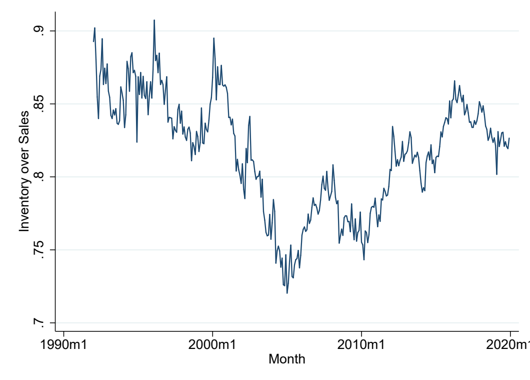
2.2 Increase across manufacturing industries and types of inventories

The increase in the ratio of manufacturing inventories to sales is observed across manufacturing industries and types of inventories. Figure 2 shows the inventory-sales ratio for the four largest manufacturing industries,[10] and the remaining can be found in appendix L. These industries account for 47% of manufacturing gross output, and 48% of total manufacturing inventories (average of 1992-2018). Although the level of inventories held varies across industries, the increasing trend is present across industries.

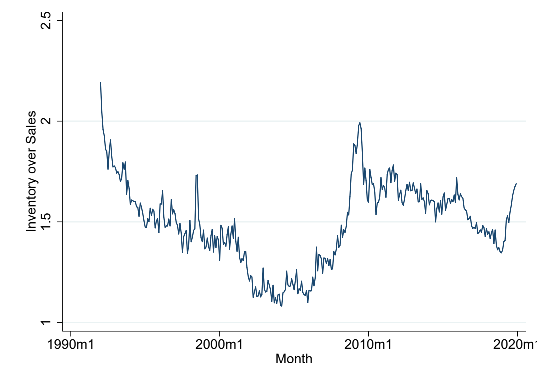
[9]Some cross country analysis for Japan and Canada can be found in the appendix. Manufacturing inventories have a similar trend to the observed in the U.S.

[10]Industries defined by the NAICS three digit industries. Figures of the all three digit NAICS industries can be found in the appendix L.

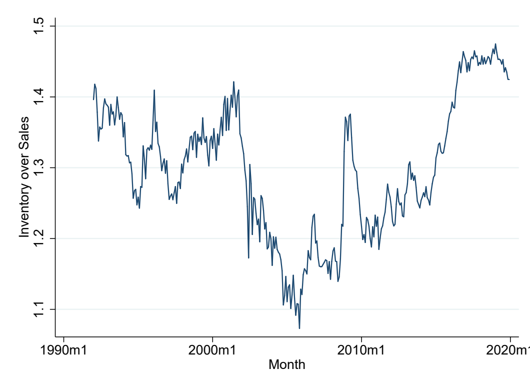
Figure 2: Increasing inventories across manufacturing industries



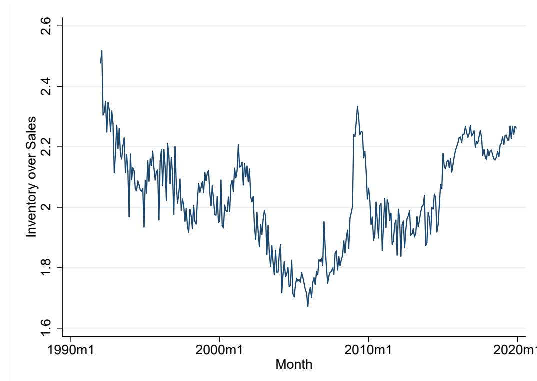
(a) Food and Beverage



(b) Transportation



(c) Chemicals



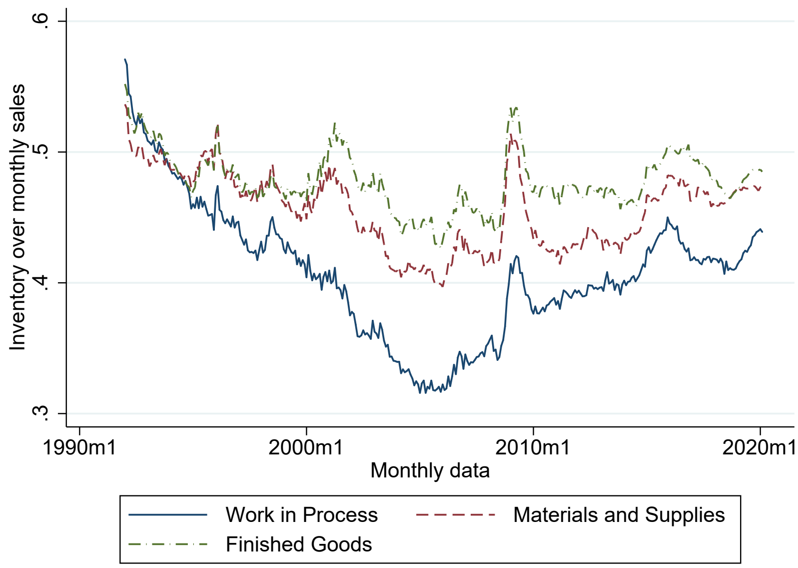
(d) Machinery

Note: The figures show the inventory-to-monthly sales for the four largest manufacturing industries from 1992 to 2018. These industries account for 47% of manufacturing gross output, and 48% of total manufacturing inventories (average of 1992-2018). Figures of the remaining 3 digit NAICS industries can be found in the appendix L. Although the level of inventories held varies across industries, the increasing trend is present across industries. The data comes from the U.S. Census Bureau.

The increasing trend is also present across types of inventories, as defined by the U.S. Census Bureau. Figure 3 shows the inventory trend for the three types of inventories: work-in-process, materials and supplies, and finished goods. Work-in-process inventory represents commodities undergoing fabrication within firms and long-term contracts for undelivered items, materials and supplies inventory is composed of all unprocessed, raw, and semi-fabricated commodities and supplies, and finished goods inventory is the value of all completed products ready for shipment and goods bought for resale requiring no further processing or assembly. Throughout the paper, I refer to intermediate input inventory as the work-in-process inventories.

Intermediate input inventory represents 30% of inventories (average 1992-2018), and exhibits the sharpest decrease and following increase. This provides evidence of the importance of supply chains in the trend of inventories. This paper focuses on studying this type of inventories, which is key to understand insurance motives within a global supply chain.

Figure 3: Increase is sharpest for intermediate input inventories



Note: The Figure shows the inventory-to-monthly sales for the three types of inventories from 1992 to 2018. The types of inventories are defined by the U.S. Census Bureau: work-in-process (intermediate input), materials and supplies, and finished goods. While inventories increase across types of industries, the trend is sharpest for intermediate input inventory.

3 Increase in reliance on inputs from China

This section details evidence of the increase in the share of foreign inputs for production which increased firms exposure to long and volatile delivery times. In particular, there was a substitution of domestic inputs for inputs that were coming from China. Most of the goods that are coming from China arrive via ocean transportation, which takes around a month to arrive and face long and frequent delays. Additionally, I provide reduced form evidence of the relationship between inventories and delivery times for inputs. Manufacturing industries that use more imported inputs to produce tend to stock more inventories.

Data. Import data comes from Schott (2008), purchased from the U.S. Census Bureau. It includes import data by country of origin and transportation method, for each 10 digit Harmonized Tariff Schedule Code from 1989 to 2018. Data on domestic and foreign intermediate inputs used in production, output, and value added, come from the Input-Output tables published from the Bureau of Economic Analysis. Intermediate input data is available from 1997 to 2018, for three digit NAICS industries.[11]

3.1 Substitution towards foreign inputs, driven by the increase in inputs from China

Figure 4a shows the increase in the share of imported inputs over total inputs, suggesting the emergence of global supply chains.[12] The increase in imported inputs is present across all manufacturing industries.[13] U.S. firms substituted away from domestic towards foreign inputs, whose share increased from 13.3% in 1997 to 16.5% in 2018. Figure 4b shows evidence that the increase is driven by the rise in imported inputs from China, which increased from 1.1% of total inputs used in production in 1997 to 4.1% in 2018.

I compute data on imported intermediates by country of origin following a methodology used by the Bureau of Economic Analysis for the *Import Matrices*. I extend their assumption that imports are used in the same proportion across all industries and final uses to obtain the country of origin share of imported inputs. Thus, 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.[14] The share of imported inputs over total inputs for a given country of origin i and industry j is given by share of imports over total imports from country i in industry j times the share of imported inputs over total inputs in industry j.

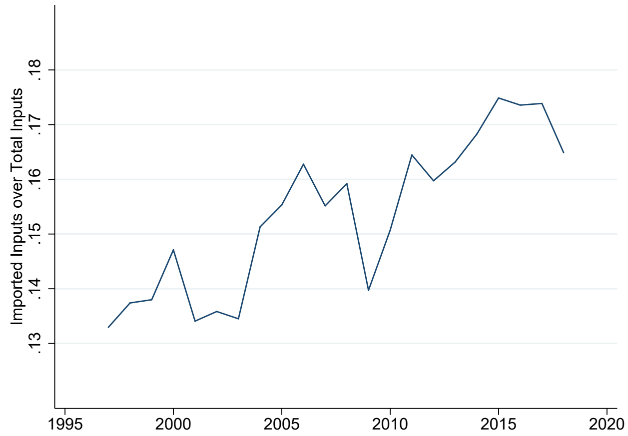
[11] Other methodologies and sources of data to obtain the country of origin specific intermediate inputs are included in the appendix A.

[12] Additional measures of global supply chains over time are shown in the appendix G, such as vertical specialization (as defined by Yi (2003)) and export use across time for the U.S. manufacturing industries.

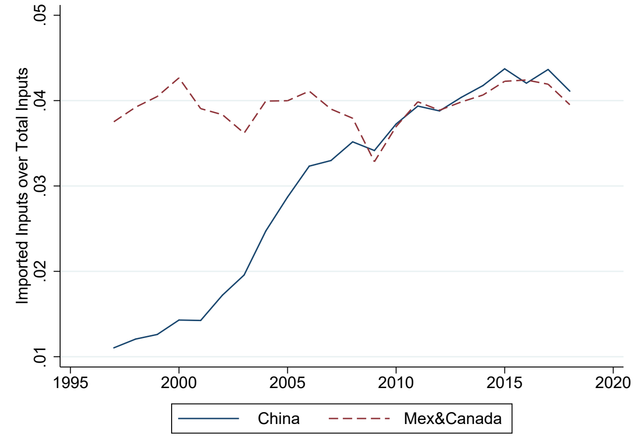
[13] While the level of the share of imported inputs varies across, the increase in the share of foreign inputs is observed across all sectors.

[14] More detail on the methodology used can be found on appendix A.

Figure 4: Substitution towards imported inputs driven by the increase 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.

Figure 4b shows the trend for the share of intermediate inputs used in production for the U.S. main trade partners. The share of inputs from Mexico and Canada remained relatively constant throughout the period. In contrast, the share of imported inputs over total inputs from China increased, especially after the entrance of China to the World Trade Organization in 2001, and the increase is observed across manufacturing sectors.[15]. The increase in the share of imported intermediates from China can account for most of the increase in the total share of imported intermediates shown in 4b.

3.2 Inputs from China face long delivery times and delays

Inputs that arrive from China face longer and more volatile delivery times than delivery times of domestic inputs or foreign inputs sourced from Mexico and Canada, which are the countries that U.S. trades the most with. Domestic inputs and inputs from Mexico and Canada are transported mainly by land, truck and rail. In contrast, most of the imports from China arrive via ocean transportation, which takes longer and is subject to more delays than land transportation.

[15]With the exception of industries that do not import at all from China, such as *Transportation* and *Primary Metals* This fact has been documented in the literature in paper such as Schott (2008).

On average, 80% of imports from China arrive via ocean transportation and the remaining 20% via air. These proportions are common across manufacturing industries.[16] Ocean transportation takes longer and is subject to more frequent and longer delays than land or air transportation. Ganapati, Wong, and Zic (2020) document how ocean transportation is time intensive, since the majority of trade arrives via U.S. ports indirectly, where ships go through specific hubs before reaching their final destinations. Goods coming from China via ocean take around 25 days to arrive to the West Coast, and 35 days to the East Coast, according to data from logistics shipping company *Freightos*, which is digital freight network that specializes in the U.S.-China trade route. Delivery delays occur more frequently in ocean transportation due to port congestions, customs delays, and weather conditions according to *Sea Intelligence* and *eeSea*, which are companies that 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*.

3.3 Inventories increase with imported input intensity

This section provides reduced form evidence of the positive relationship between inventories (and intermediate input inventories) and imported inputs (and inputs from China). I provide evidence using the average value across industries and the changes from 2005 and 2017. Figure 5 shows the positive relationship between inventories over output and imported inputs over total inputs across manufacturing industries. The scatter plot shows the average of each variable for 1997 to 2018 for the NAICS three industries, except petroleum.[17] It includes the regression line, which has a slope of 0.29. The relationship is strengthened when considering intermediate input inventories shown in Figure 5b,[18], where the coefficient of the regression equals 0.85. This provides further evidence of the

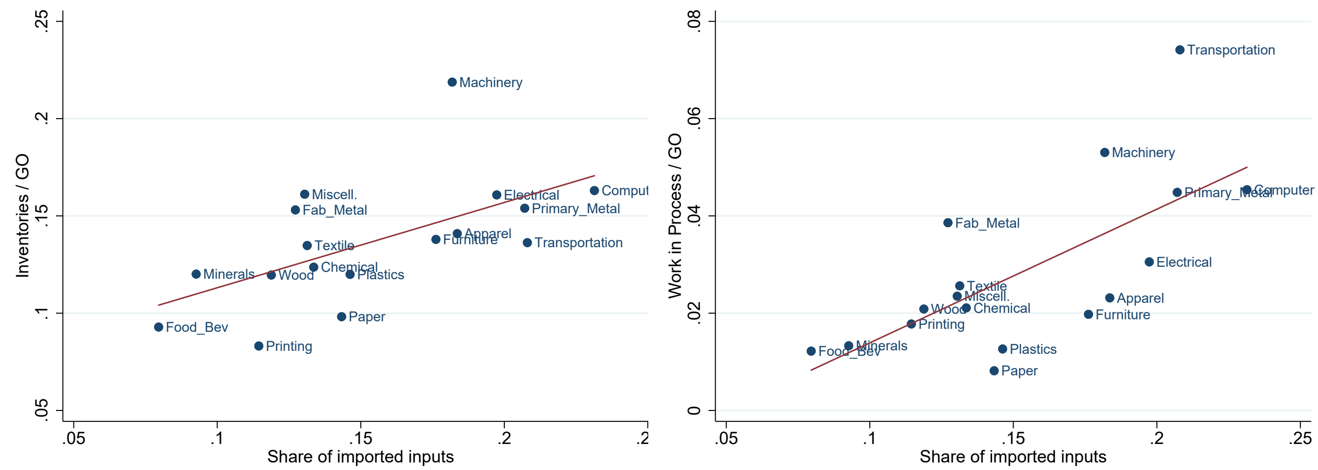
[16]More data on the transportation of imports across industries can be found in the appendix I.

[17]Total of 17 manufacturing industries in the analysis.

[18]Intermediate input inventory is defined as the work in process inventory, which are goods undergoing fabrication within firms.

importance of supply chains in the inventory levels firms choose to stock.

Figure 5: 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.

I explore the relationship between imported inputs and inventories by estimating the regression in equation (1), whose results are shown in Table 1. It shows the results for the average from 1997 to 2018. For each industry i, y_i denotes average inventories, x_t average imported inputs (total or inputs from China), and a_{it} average value added. Column [1] of panel A that an increase of 10% in the imported inputs is associated with an increase in total inventories of 9.3%. When I weight the regression using sales, total inventories increase 8.6% (column [2]), and 5.4% when controlling for value added (column [3]). The relationship is strengthened with input inventory (defined as work-in-process by the U.S. Census Bureau) in panel B. Column [2] shows that an increase of 10% in the imported inputs increases input inventories by 1.2. Furthermore, Table 1 also reports the coefficients for the estimated regression using the average of the imported inputs from China. In this case, column [5] shows that an increase of 10% of inputs from China is associated with an increase of 5.9% in total inventories, and 8.4% for intermediate inputs inventories.

$$\log(y_i) = \beta_0 + \beta_1 \log(a_i) + \beta_2 \log(x_i) + \epsilon_i \tag{1}$$

Table 1: Positive relation between average of inventories and imported inputs across industries

Average of variables

Panel A

	log(inventory avg)							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
log(imported inputs avg)	0.93***	0.86***	0.54***	0.49***				
	[0.07]	[0.07]	[0.12]	[0.10]				
log(inputs China avg)					0.59*	0.17	-0.10	-0.10
					[0.34]	[0.33]	[0.14]	[0.12]
log(value added avg)			0.46***	0.48***			1.01***	0.98***
			[0.13]	[0.11]			[0.10]	[0.09]
Weighted using sales		✓		✓		✓		✓
R^2	0.92	0.90	0.95	0.96	0.16	0.02	0.89	0.89
N	17	17	17	17	17	17	17	17

Panel B

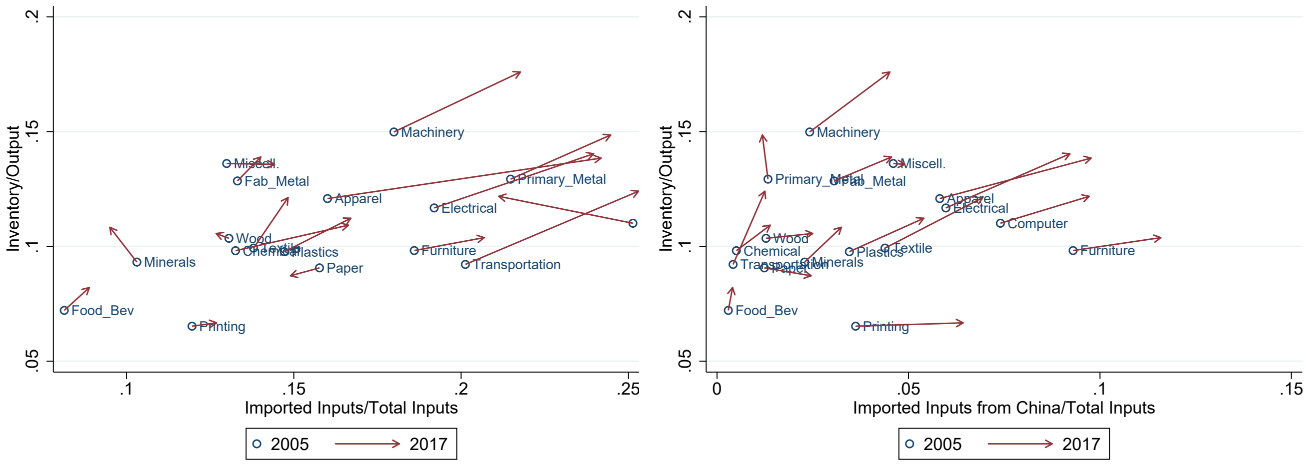
	log(input inventory avg)							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
log(imported inputs avg)	1.19***	1.25***	0.94***	1.17***				
	[0.12]	[0.13]	[0.27]	[0.26]				
log(inputs China avg)					0.84*	0.46	0.04	0.12
					[0.45]	[0.47]	[0.28]	[0.30]
log(value added avg)			0.3	0.10			1.19***	1.23***
			[0.3]	[0.30]			[0.20]	[0.24]
Weighted using sales		✓		✓		✓		✓
R^2	0.86	0.87	0.86	0.87	0.19	0.06	0.78	0.68
N	17	17	17	17	17	17	17	17

Data for NAICS 3 digit industries. The tables report the regression results of the average from 1997 to 2018 of the log of inventories on the log of imported inputs. Includes a total of 17 observations (one observation per industry).
Note $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Further evidence of the contemporaneous increase in the share of inputs from China and the increase in inventories is shown in Figure 6. Figure 6a shows the levels for inventory-to-output and the share of imported inputs over total inputs used in production for the 17 manufacturing industries in the analysis. I plot the levels for 2005 - the turning point year in the inventory trend -, and the arrows show the change in the levels observed for 2017. Similarly, Figure 6b shows the change for the inputs sourced from China. The figures show how manufacturing industries both increased their level of imported inputs (inputs from China) and inventory levels from 2005 to 2017 (most arrows point towards the north-east).

Additionally, Table 2 shows the positive relationship between the changes in inventories and total imported inputs and inputs from China from 2005 to 2017. It shows the estimated coefficients of equation (2), where z_{it} represents the inventory to output ratio, and b_{it} the imported input over total

Figure 6: Industries source more foreign inputs and hold more inventories: 2005 to 2017



(a) Total imported inputs (b) Imported inputs from China

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 2017. The figures provide evidence of the contemporaneous increase in both, the inventories and imported inputs across manufacturing industries.

inputs ratio. By weighting the regression using industry sales, column [3] shows a coefficient of 0.35 for the total share of imported inputs, and column [4] reports a coefficient of 0.12 for imported inputs from China. Both of these coefficients increase when I consider intermediate input inventory, where the coefficients for the share of imported inputs equal 1.2 and 0.3 for the share of inputs form China (column 7, 8 respectively).

$$\frac{\log(z_{i,2017})}{\log(z_{i,2005})} = \beta_0 + \beta_1 \frac{\log(b_{i,2017})}{\log(b_{i,2005})} + \epsilon_i \tag{2}$$

Last, I explore the relationship between inventories and imported inputs across time and industries. The results are in appendix K and continue to show that sectors that choose to source more foreign inputs also choose to stock more inventories, when including fixed time and industry effects and when controlling with value added. Evidence that inventories increase with imported input intensity has been established by the literature for other countries. 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 Khed-

Table 2: Strong relation between changes in inventories and imported inputs: 2005 to 2017

	Δ_{05-17} log(inv/output)				Δ_{05-17} log(input inv/output)			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Δ_{05-17} log(imported inputs/total inputs)	0.25^{*}		0.35^{**}		0.62^{*}		1.19^{***}	
	(0.14)		(0.15)		(0.34)		(0.38)	
Δ_{05-17} log(inputs China/total inputs)		0.07		0.12^{**}		0.18		0.27^{*}
		(0.07)		(0.05)		(0.17)		(0.16)
weight using sales			✓	✓			✓	✓
R^2	0.18	0.06	0.27	0.24	0.18	0.07	0.40	0.16
N	17	17	17	17	17	17	17	17

Data for NAICS 3 digit industries. The table reports the regression results of the change between 2005 to 2017 of the log of inventory over output on the log of imported inputs over total inputs and includes a total of 17 observations (one observation per industry).
Note $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.10$.

erlarian (2020a) find a similar result using firm level data for Indian firms. This paper focuses on the U.S. manufacturing industry, and provides evidence of the relationship for industry level data.

4 A model of delivery times and inventories

Motivated by the descriptive evidence, this section details a model to study the role delivery times for inputs play in firm sourcing and inventory decisions. The model will allow me to quantify how much of the inventory trend is driven by this specific risk channel, and how important are delivery times for inputs for firm's sourcing decisions. Following the theoretical framework for inventories and trade, introduced in Alessandria, Kaboski, and Midrigan (2010a), and Khan and Thomas (2007), I develop an international dynamic stochastic general equilibrium model. In the model, firms choose to stock inventory to insure against demand volatility and positive and stochastic delivery times. The first subsection details the economy's environment and technologies. The second subsection defines the competitive equilibrium, and last subsection explains the main mechanism of the model.

I depart from the literature, and introduce a model with stochastic delivery times for inputs. In the model, inputs can arrive either in this period or the next, and the share of inputs that is available within these periods is stochastic.[19] The additional flexibility allows me to quantify how marginal

[19]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).

changes in the distribution of delivery times affect firm's sourcing and inventory decisions.

4.1 Environment

Time is discrete and indexed by $t \in \{0, 1, 2, ..., \infty\}$. The economy is composed of (i) a unit continuum of monopolistically competitive final good producer, (ii) a unit continuum of competitive firms that produce the domestic intermediate inputs, (iii) a unit continuum of competitive firms that produce the foreign intermediate inputs, and (iv) a domestic representative consumer. Uncertainty in the model is given by firm-specific, independent and identically distributed, demand shocks and delivery time shocks for each of the inputs every period.[20]

4.1.1 Final good firms

Constraints of the final good firm. Each of the unit continuum of final good firms $j \in [0, 1]$ faces the demand from the representative domestic consumer. The demand has a per-period, *iid*, firm-specific demand shock v_j, and is a function of total production, $C + N$, and the price index, P. In this context, firms behave monopolistically, in the sense that they produce a unique variety and set prices, p_j.

$$y_j(p_j) = \left(\frac{P}{p_j}\right)^{\epsilon} (C + N)\, v_j \tag{3}$$

$$v_j \sim_{iid} G\,(0,\ \sigma_v) \quad \forall\, j$$

Firms have access to a production technology, which combines the domestic input, foreign input, and labor to produce the final good variety, y_j. The domestic and foreign input are combined using a constant elasticity of substitution (CES) aggregator, with elasticity σ. This particular assumption is needed for the model to be able to match the increase in reliance on imported inputs observed for U.S. manufacturing data. Additionally, domestic inputs have a weight, θ, which allows me to match the level of domestic to foreign inputs used by firms. Lastly, there is a Cobb-Douglas function between

[20] There is no aggregate uncertainty in the model.

the intermediate input and labor.

$$y_j = \left(\theta^{\frac{1}{\sigma}} \, {x_j^d}^{\frac{\sigma-1}{\sigma}} \; + \; (1-\theta)^{\frac{1}{\sigma}} \, {x_j^f}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1} \, \alpha} \, {\ell_j}^{1-\alpha} \tag{4}$$

Domestic and foreign inputs face stochastic delivery times, where only a fraction λ_j^d and λ_j^f of the order of each of the inputs, n_j^d and n_j^f, is available for them to produce that period. The inputs used to produce, x^d, x^f, are constrained to be less than or equal to the total level of inventories for the input, and the fraction λ of the order that arrives before production takes place. Section 4.3 details how to relate the parameter of delivery times λ back to the data, and its interpretation within the structure of the model. The constraints are then:

$$\begin{aligned} x_j^d \quad & \leq \; s_j^d + \lambda_j^d \, n_j^d \\ \underbrace{x_j^f}_{\text{choice of input}} \quad & \leq \; \underbrace{s_j^f + \lambda_j^f \, n_j^f}_{\text{amount available}} \end{aligned} \tag{5}$$

$$\lambda_j^d \sim_{iid} G^d \quad \text{and} \quad \lambda_j^f \sim_{iid} G^f$$

Firms can store inventories of the domestic and foreign inputs, s_j^d and s_j^f respectively. Inventories pay a per period storage cost at rate $(1-\delta)$. The law of motion for each of the input inventory is given by the remainder of the input left after production, discounted at the storage rate, and the remainder of the order, $(1-\lambda)$, that arrives at the end of the period. Note that inventories are stored as intermediate inputs, before they are produced as finished goods.[21]

$$\begin{aligned} s_j^{\prime d} \quad & = (s_j^d + \lambda_j^d \, n_j^d - x_j^d) \; (1-\delta) \; + \; (1-\lambda_j^d) \, n_j^d \\ \underbrace{s_j^{\prime f}}_{\text{inventories t+1}} \quad & = \underbrace{(s_j^f + \lambda_j^f \, n_j^f - x_j^f)}_{\text{inputs after production}} \; \underbrace{(1-\delta)}_{\text{storage cost}} \; + \; \underbrace{(1-\lambda_j^f) \, n_j^f}_{\text{order arrives end of period}} \end{aligned} \tag{6}$$

Inventories in the model follow the definition of the inventories in the data. Inventories reported

[21] I could write the model where all inputs are transformed to final goods and stored as final goods, but the inventories I want to match in the data are intermediate input inventory.

in the U.S. Census Bureau include the value of the goods that the firms have in their U.S. warehouses plus the value of the goods owned by the firms which are in transit, whether they are being transported within the U.S, or to and from the U.S. In the model, total inventories are the amount of foreign and domestic inventories. The law of motion for inventories includes the inventories stored in warehouses, $(s+\lambda n-x)(1-\delta)$ and inventories in transit, $(1-\lambda)n$, for each of the domestic and foreign inputs.

The interaction between positive delivery times for the domestic and foreign inputs and the demand shock creates incentives for firms to hold inventories. If firms were only facing positive delivery times, then they could plan around the delivery time and order the inputs in advance. But when firms are additionally facing uncertain demand, then not having immediate access to their inputs diminishes their ability to meet their demand every period. Firms choose to hold inventories of their inputs to be able to meet their fluctuating demand every period, when facing possibly long delivery times for inputs. Additionally, firms choose to hold inventories because of the volatility of delivery times.

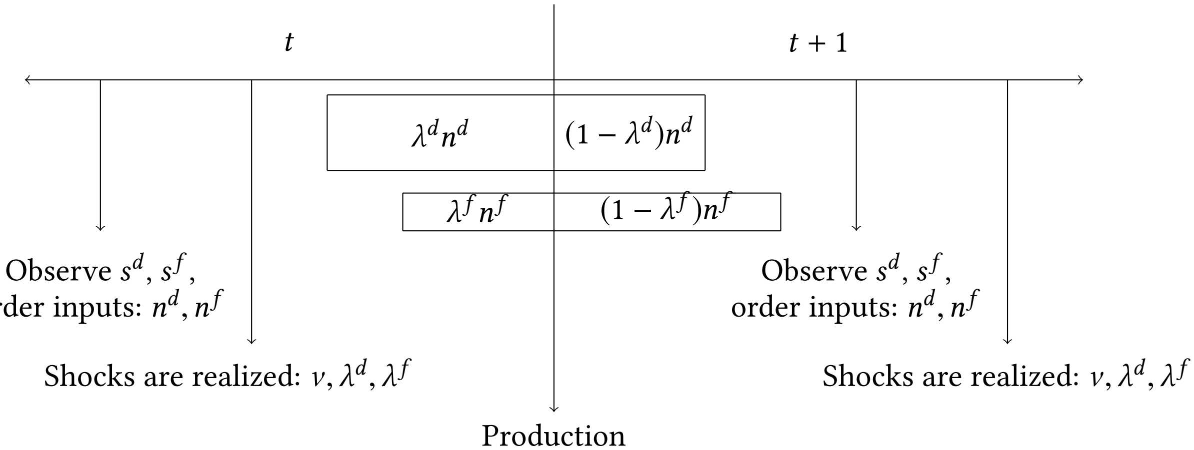
Last, firms face a timing constraint, where they must decide how much of the domestic and foreign inputs to order before they know what their demand and delivery times shock is for the period. This assumption introduces a precautionary motive for holding inventories, where firms will order according to the expected shocks.

Figure 7 details the timing for a final good firm, j. At the beginning of the period t, the final good firm observes their level of inventories, s^d, s^f, and decides on the amount to order of the domestic and foreign input, n^d, n^f. Then the firm-specific demand and delivery time shocks are realized, $\nu, \lambda^d, \lambda^f$. Right before production takes place, a fraction of the orders $\lambda^d\, n^d$ and $\lambda^f\, n^f$ arrives and can be used for production in this period. The reminder of the orders, $(1-\lambda^d)\, n^d$ and $(1-\lambda^f)\, n^f$ arrives early next period and is added to the inventories of the firms.

Final good firms have two different disincentives to holding inventories. Firms pay storage costs for their inventories, at rate δ. Additionally, firms face positive interest rates, denoted by β.

Recursive final good firm's problem. The recursive problem for the final good producer is

Figure 7: Timing – firms order inputs before shocks are realized



given by the two following Bellman equations, corresponding to the choices made within the timing constraint. I drop the subscript denoting the specific firm in the unit continuum, $j \in [0, 1]$, for clarity. The beginning of the period value function $V(s^d,\ s^f)$, which defines the optimal order of inputs, given the level of inventories the firms starts the period with. This choice is made taking the expectation over the possible demand and delivery shocks for the period.

$$V(s^d,\ s^f) = \max_{\{n^d, n^f\}} E_\eta\left[\tilde{V}(s^d,\ s^f,\ n^d,\ n^f,\ \eta)\right] \qquad \text{where } \eta = (\nu,\ \lambda^d,\ \lambda^f) \tag{7}$$

Then given the choice of inputs and shocks for the period, firms decide on the amount of inputs used in production, labor, and prices for variety y. This problem is defined by value function $\tilde{V}(s^d,\ s^f\ , n^d,\ n^f,\ \eta)$, where firms maximize present and future profits. Firms profits are given by the sales of the final good firm, $p\ y(p)$, minus labor costs, $w\ \ell$, and the cost of the domestic and foreign orders, $p^d n^d$ and $\tau p^f n^f$. The maximization is subject to the six constraints described above, constraint for each of the inputs, law of motion of inventories for domestic and foreign inputs, production technology, and demand function from the representative consumer.

$$\tilde{V}(s^d,\ s^f\ , n^d,\ n^f,\ \eta) = \max_{\{p, x^d, x^f, \ell\}} p\ y\ (p) - w\ \ell - p^d\ n^d - \ \tau\ p^f\ n^f + \beta\ V(s'^d,\ s'^f) \tag{8}$$

4.1.2 Representative domestic consumer

The representative domestic consumer demands the unit continuum of final good varieties, $y_j \in [0, 1]$. The consumer aggregates the final good varieties using a CES aggregator with elasticity of substitution ϵ to obtain the final consumption good, C, and the composite good, N. Each variety has a specific per period demand shock, v_j. The consumer aggregates the final good varieties to produce the composite good, N, which is sold to the domestic inputs firms that uses it as input in its production. The constant elasticity of substitution aggregator of the final good varieties in equation (9) defines the demand each of the final good firms face, described in the section above.

$$C + N = \left[\int_0^1 v_j^{\frac{1}{\epsilon}} \, y_j^{\frac{\epsilon-1}{\epsilon}} \, dj \right]^{\frac{\epsilon}{\epsilon-1}} \tag{9}$$

To buy the continuum of final good varieties, the representative consumer receives labor income and the profits from the continuum of final good firms. The consumer supplies labor to the domestic input and final good firms, and owns the continuum of final good firms.

$$\int_0^1 p_j \, y_j \, dj = w \, L + \int_0^1 \Pi_j \, dj \tag{10}$$

4.1.3 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. Each domestic input firm produces the domestic input, x_j^d, using labor, ℓ_j^d, and the composite input, N_j^d. They have access to a Cobb-Douglas production function using labor and the composite input, similar to the technology of the final good firms.

$$x_j^d = (N_j^d)^{\alpha} \, (\ell_j^d)^{1-\alpha} \tag{11}$$

There is a unit continuum of foreign input producers, that produce the variety, x_j^f, demanded by the final good firm j. I abstract from modeling the problem of the foreign inputs firms, and take as given the price of the final good firms, p^f. These inputs face iceberg transportation costs, τ, which the final good firm pays for.

4.2 Competitive Equilibrium

A general equilibrium steady state in this model is given by state contingent policy functions for the (i) final good firms $j \in [0, 1]$, $\{n^d_{jt}(s),\ n^f_{jt}(s),\ s'_{jt}(s, n, \eta),\ x^d_{jt}(s{\cdot}n, \eta),\ x^f_{jt}(s, n, \eta),\ \ell_{jt}(s, n, \eta),\ p_{jt}(s, n, \eta)\}^{\infty}_{t=0}$, where $s = (s^d, s^f)$, $n = (n^d, n^f)$, and $\eta = (\nu, \lambda^d, \lambda^f)$ for the (ii) domestic input firms $j \in [0, 1]$ $\{N^d_{jt},\ \ell^d_{jt}\}^{\infty}_{t=0}$, and for the (iii) domestic consumer $\{y_{jt},\ N_t,\ C_t\}^{\infty}_{t=0}$ and prices $\{w_t,\ P_t,\ p^d_t,\ p^f_t\}^{\infty}_{t=0}$ such that the following conditions hold:[22]

1. Policy functions solve the final good firm problem;
2. Policy functions solve the domestic input firm problem;
3. Policy functions solve the representative domestic consumer;
4. 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, $j \in [0, 1]$;
5. 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, $j \in [0, 1]$;
6. Composite good market clears, where the supply of the domestic consumer is equal to the total demand by domestic input firms:
$$N = \int_0^1 N^d_j \, dj$$
7. Labor market clears, where the fixed labor supply of the domestic consumer is equal to the labor

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

demand of domestic input firms and final good firms:

$$L = \int_0^1 \ell_j^d \, dj + \int_0^1 \ell_j \, dj$$

8. Price index for final consumption good and composite good, P, given by:

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

4.3 Interpreting delivery times: λ

This section describes how to relate the parameter λ, which represents delivery times, to the data. The introduction of this parameter to the model is a main part of the theoretical contribution. This parameter allows for different lengths of delivery times for inputs,[23] and can include delivery delays.[24] How we can relate and tailor it to the data is crucial for the analysis of its relationship to sourcing and inventory decisions.

Given a number of days in a period in the model, T, λ represents the proportion of days of the period the firm is able to use the order to produce. Equation (12) shows the relationship between the delivery days observed in the data and the parameter for delivery times in the model. If the delivery time is longer than the length of the period, then the delivery time is capped at one period delay, which which is commonly used in the literature. If not, then it is equal to the proportion of days of

[23]In the literature models have a fixed one period delays. The delivery time is then fixed to the assumed length of the period in these models.

[24]Delivery delays include arrivals before or after the expected delivery day.

the period the firm has the input in its warehouse.[25]

$$\begin{aligned}\lambda_j^d &= \max\left(0\ ,\ \frac{T-\text{days}_j^d}{T}\right)\\ \lambda_j^f &= \max\left(0\ ,\ \frac{T-\text{days}_j^f}{T}\right)\end{aligned} \tag{12}$$

For example, assume one period represents a month. If the delivery day equals to 25 days, then the delivery time λ equals to 5/30. On average, the input will be physically in the firm's warehouse for 5 days of the month. That proportion of days of the month, λ, that the firms has access to its order is added to its level of inventories and can be used to produced, as equation (5) shows.

The number of delivery days is defined by a distribution that will match the mean and variance of the observed delivery days in the data. The foreign and domestic inputs are calibrated to different delivery day distributions. This allows to model to describe how differences in delivery times impact firm's sourcing and inventory choices. The added flexibility in the model, compared with with standard models in the literature, allows me to use the model to quantify how inventories change through time as the mean and variance of delivery times varies without having to modify the length of a period.

4.4 Decision rules for different distributions of delivery times

This section characterizes the optimal decision rules of the final good firm for different distributions of domestic delivery times.[26] I compare key policy functions for two distributions of domestic delivery times: one with a high mean and variance ("long delivery times"), and another with a low mean and variance ("short delivery times"). I show the optimal decision rules for the orders of domestic inputs,

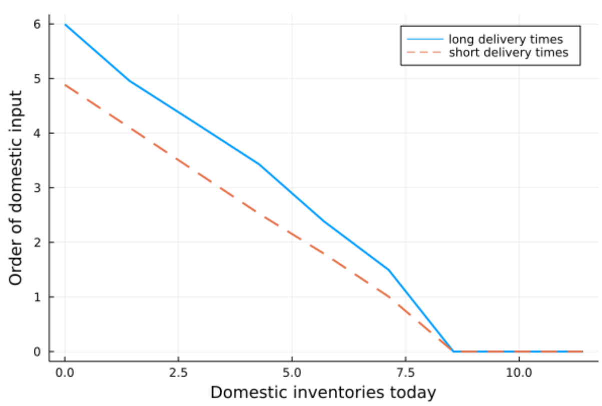
[25] There is an implicit assumption that the order is made on the first day of the period. This could be thought as a normalization, regardless of when the firm orders within the period. Alternately, we could assume there is a continuum of firms that order throughout the period. In this case, λ represents the proportion of firms for which the order arrives before the period ends and they are able to use the inputs to produce.

[26] The policy functions are obtained from the benchmark calibration detailed in section 5.1.

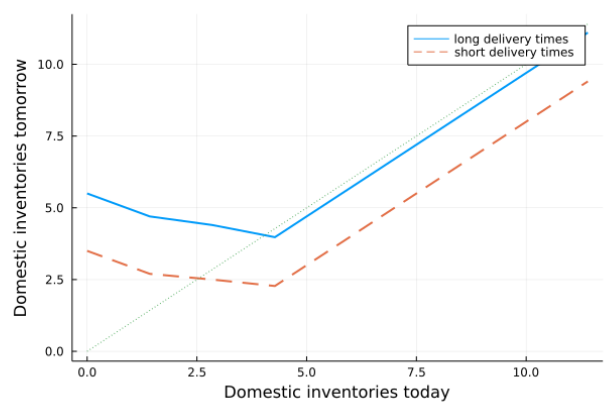
n^d, domestic inventories, s'^d, use of domestic inputs in production, x^d, and final good prices, p.[27] The figures show the optimal decision rules for values of domestic inventories. An analysis of the policy functions for different types of idiosyncratic shocks can be found in the appendix C.[28]

Figure 8 shows that orders and inventories are higher when inputs face longer delivery times. Orders are made before shocks are realized, so the firm chooses to order according to the expected value of the demand and delivery time shocks. Orders are decreasing in the amount of inventories, but as inputs face longer delivery times firms need to order more in advance to be able to meet their demand every period. Figure 8b shows the inventory decision rule for a specific idiosyncratic shock, one with a relatively high demand and low delivery time shock (low availability of inputs).[29] The firm will choose to store a higher level of inventories when inputs face longer delivery times, since the firm needs to insure against the added exposure to demand volatility and enter the period with a higher amount of inputs.

Figure 8: Orders and inventories are higher when inputs face long delivery times



(a) Order of domestic input for domestic inventories



(b) Domestic inventories for domestic inventories

Note: The Figure shows the policy functions for the order of domestic inputs (panel a) and the domestic inventories tomorrow (panel b), for values of domestic inventories today. The solid line represent the policy function for a distribution of with high mean and variance of domestic delivery times ("long delivery times"), and the dashed line represents the policy function for a shorter and less volatile distribution of delivery times ("short delivery times").

Figure 9 shows that the firm is more severely constrained in the amount of inputs to produce

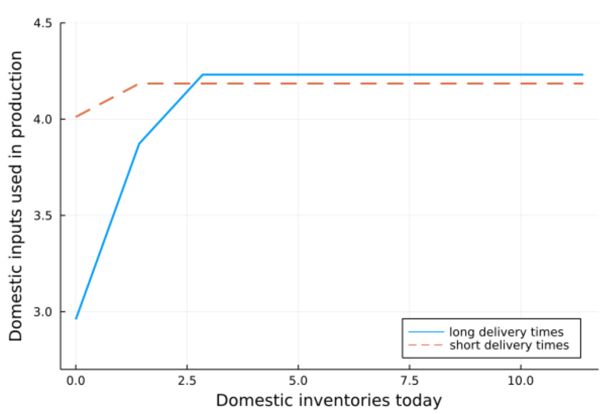
[27]Details on the methodology to solve the problem are also in the appendix B of the paper.

[28]This appendix provides further detail and explanation on the problem of the final firm.

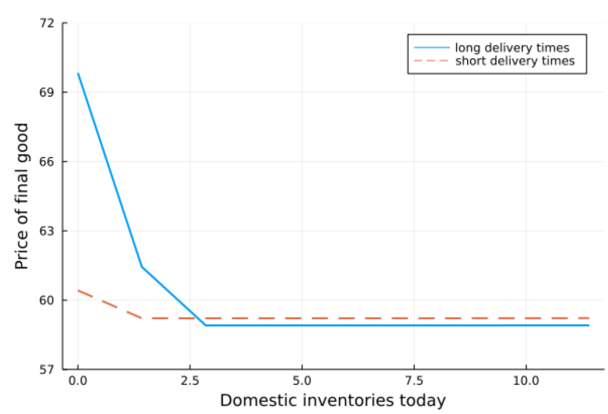
[29]Note decisions rules (except orders of inputs) are specific to the idiosyncratic shock for demand and delivery times. Throughout the section, the policy functions are given for a relatively high demand and low delivery time shock (low availability of inputs).

when facing longer delivery times. If the firm enters the period with low inventories, then the firm will be constrained in the amount of inputs they can use to produce (see equation (5)), as shown in Figure 9a. Firms will be more constrained if facing longer delivery times, since they have access to a lower proportion of the order. Otherwise, if the firm enters the period with high inventories, then it is able to meet its unconstrained demand. The firm will demand a higher level of input to produce when facing longer delivery times. Why? Since the firm behaves monopolistically, it will choose to produce less and set higher prices – which will give a higher profit – when facing shorter delivery times. In a way, as they are less constrained in delivery times, they are able to extract larger profits by producing less and charging a higher price of the final good. Figure 9b shows the price of the final good. When the firms is constrained in the amount of inputs they need to produce, the price will rise. When constrained, prices will rise more sharply with longer delivery times. When unconstrained, the firm will charge a higher price when delivery times are shorter, which allows the firm to obtain higher profits.

Figure 9: Firms are more constrained in their inputs when they face longer delivery times



(a) Domestic input for domestic inventories



(b) Final good price for domestic inventories

Note: The Figure shows the policy function for the use of of domestic inputs in panel a and the final good price in panel b for values of domestic inventories today. The solid line represent the policy function for a distribution of with high mean and variance of domestic delivery times ("long delivery times"), and the dashed line represents the policy function for a shorter and less volatile distribution of delivery times ("short delivery times").

4.5 Decision rules for different price of foreign inputs

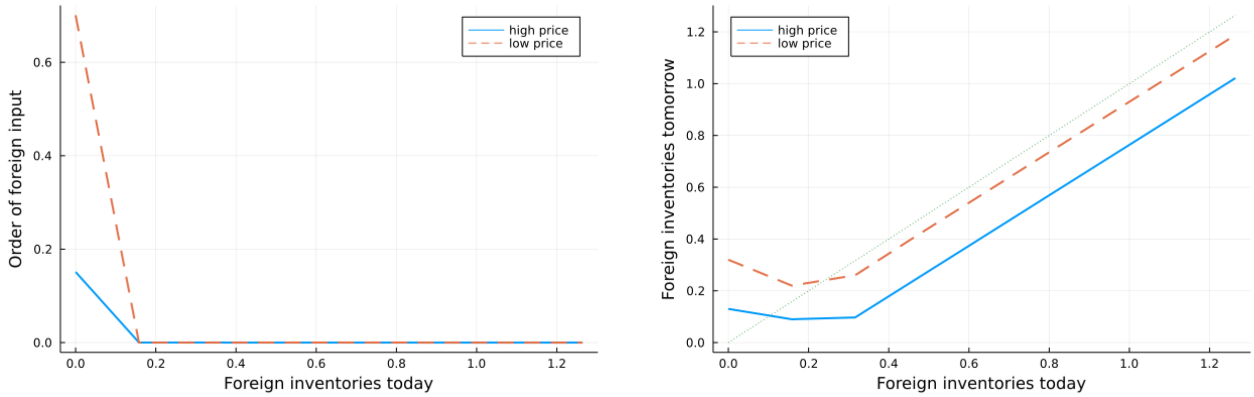
This section characterizes the optimal decision rules of the final good firm for different prices of the foreign input. I compare the optimal decision rules for the order of foreign inputs, n^f, foreign inventories, s'^f, use of foreign inputs in production, x^f, and final good price, p.[30] The figures in the section show the optimal decision rules for a high and a low value of the price of the foreign good, p^f. Policy functions, which the exception of the order of foreign inputs, are demand and delivery times shock specific. Figures in this section show the decision rules for a high idiosyncratic demand and low availability of input shock.[31]

Order of inputs and inventories of foreign inputs is higher when the price of foreign inputs is low. Similar to the order of domestic inputs describes in the previous section, the order of the input is decreasing in the amount of inventories, and they are made before the idiosyncratic shocks are realized. Figure 10a shows that when the foreign input price is low then the firm substitutes towards foreign inputs, and thus demand more of them. The orders of foreign input are higher, and the firms need to store more inventories to face the risk of sourcing a larger proportion of foreign inputs, as Figure 10b shows.

If the price of foreign inputs are low, then the firms will demand and use more of the foreign input to produce, and will be able to set lower prices of the final good. If the firm enters the period with low inventories, then the firm will be constrained in the amount of inputs they can use to produce. As inventories increase, the firm is able to use more of the inputs until it reaches the unconstrained demand. Figure 11a shows the orders for low and high foreign input prices. With low price of foreign input firms substitute towards foreign input and then use more of the foreign input to produce. Additionally, with low foreign inputs, the firm is able to set a lower price of the final good as shown in Figure 11b.

[30] The policy functions are obtained from the benchmark calibration detailed in section 5.1.
[31] Optimal decision rules for different idiosyncratic demand and delivery time shocks can be found in appendix C.

Figure 10: Orders and inventories are higher when the price of foreign inputs is low

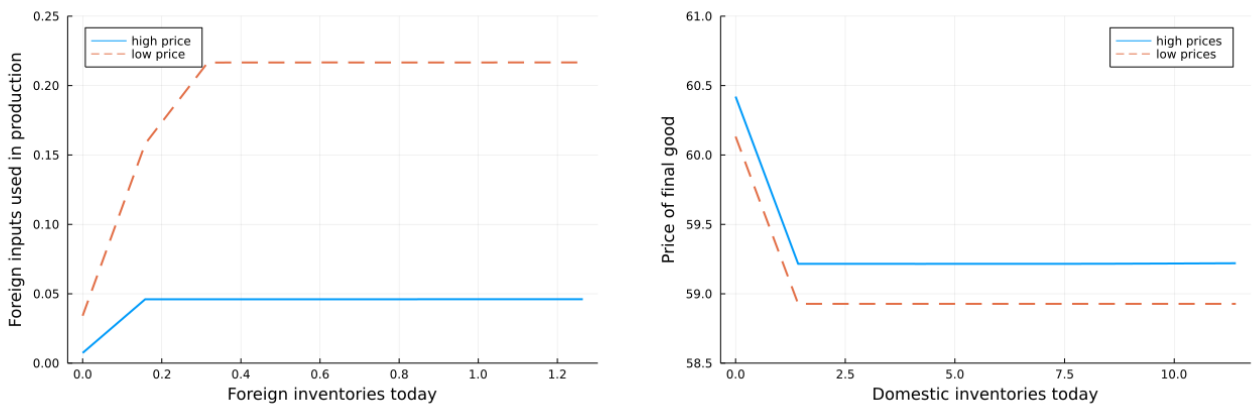


(a) Order of foreign input for foreign inventories

(b) Domestic foreign for foreign inventories

Note: The Figure shows the policy functions for the order of foreign inputs (panel a) and the foreign inventories tomorrow (panel b), for values of foreign inventories today. The solid line represents the policy functions for a high value of the price of the foreign input, and the dashed line for a lower value of the price of foreign inputs.

Figure 11: Firms demand more foreign input and set lower prices when foreign input price is low



(a) Foreign input for foreign inventories

(b) Final good price for domestic inventories

Note: The Figure shows the policy functions for the use of foreign inputs (panel a) and for the price of final goods (panel b), for values of foreign inventories today. The solid line represents the policy functions for a high value of the price of the foreign input, and the dashed line for a lower value of the price of foreign inputs.

4.6 Discussion of the mechanism of the model

The mechanism of the model is centered around the tradeoff between price and delivery times, and how firms choose to insure against demand and delivery time shocks. Final good firms have to decide how much of each of the inputs to use in production. To do so, they take into account the relative price of the inputs, and the delivery times each inputs faces. Depending on the amount of risk the firms face, they chose the amount of inventories for each of the inputs.

In this model firms insure themselves according to the expected shocks for demand and delivery time shocks. Depending on the realized history of shocks, in the equilibrium stationary distribution some firms are constrained in the amount of inputs they need to meet their demand. No firm has full insurance against all shocks, and if firms experience a surge in demand or high delays in their inputs, they will be constrained in the amount of inputs they have to produce. In this case, firms will charge a price high enough that the consumer demands only their available stock.

How do the decision rules change as foreign input prices and delivery times change through time? Inventories rise as firms increase their reliance on inputs that face high delivery times. Assume the price of the foreign input falls. Then firms will increase their reliance on the foreign input to produce. If the risk associated to the delivery times of foreign inputs is greater than for domestic inputs, then firms will face the additional risk from substituting domestic for foreign inputs. To insure themselves against this additional risk, firms increase their inventory stock.

Additionally, inventories increase if the mean and (or) variance distribution of delivery days increases. If firms face longer delivery times, then firms need to store more inventories and firms are more constrained in the amount of inputs they need to produce. As delivery times increase, or become more volatile, firms will need to 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.

5 Quantifying frictions

In this section I calibrate parameters of the model presented in the previous section to match moments of the U.S. manufacturing industry. Then, I use data on delivery times and imported inputs to calibrate the two opposing forces: shorter delivery times for domestic inputs and cheaper inputs from China for the period of 1992 to 2018. Details regarding the solution method can be found in appendix B.

5.1 Benchmark calibration

The baseline version of the model is calibrated to U.S. manufacturing. One period in the model corresponds to a month in the data. The calibration consists of selecting a set of parameters so that the stationary distribution averages coincide with the relevant moments in the data.

5.1.1 Calibrated parameters

I match two key moments of the aggregate U.S. manufacturing industry: (i) the share of inputs from China in 1992, and (ii) the initial decline in input inventories over output from 1992 to 1997. To match these moments I use the weight of the domestic inputs in the technology function of the final good firms, θ in equation (4), and the variance of the demand shocks, σ_ν. Panel A in Table 3 reports the value for the parameters and the moments matched.

To match the share of inputs from China in 1992 which equals to 1.1%, I set the weight for the domestic inputs in the technology function of the final good firms, θ, equals 0.99. For this initial period I normalize the price of domestic inputs to equal the price of foreign inputs. In this case, the share of foreign inputs used for production will be roughly equal to the technology parameter, $1-\theta$.[32]

I assume the demand shocks are distributed log normal with mean zero, $\log(\nu_j) \sim_{iid} \mathcal{N}(0,\ \sigma_\nu)$. I calibrate the variance of the demand to match the annual decline in the trend of input inventories over output, which in the data correspond to the work-in-process inventories, from 1992 to 1997 of 3.6%.[33] To do so, I use data on the decline in domestic delivery days from 1992 to 1997, and compute the resulting decline in inventories in the model. I use the variance of demand to discipline the implied change in input inventories to match the observed annual average decline of 3.6% for those five initial years.

Data on delivery times comes from the diffusion index for future delivery times published by the

[32] Roughly equal and not completely equal because the distribution of delivery times is not the same across inputs. Since domestic inputs are more readily available and thus less costly, then there will be a slight substitution towards the use of domestic inputs.

[33] I apply an HP filter to the input inventory over output time series, and then take the average of the growth rates from 1992 to 1997, which equals -3.6%.

Federal Reserve Bank of Philadelphia in the *Manufacturing Business Outlook Survey*.[34] Delivery times for domestic goods decline on average 7.5% per year from 1992 to 1997, and the calibrated variance of demand equals $\sigma_v = 0.463$. Note the variance of demand accounts for any source of uncertainty the firms is facing, which in the model has been collapsed into demand volatility.[35]

5.1.2 Estimated parameters

I estimate the (i) distribution of the domestic delivery times, (ii) the distribution of delivery times for inputs from China, and (iii) intermediate input share in the technology function of final good firms outside the model. Panel B in Table 3 shows the value for these estimated parameters. The parameter α represents the share of intermediate inputs used in production, according to the technology function of final good firms in equation (4). I inform this parameter using data on the value of intermediate inputs over total output in 1992 using data reported in the *Input-Output Tables* from the Bureau of Economic Analysis. The share is relatively constant across manufacturing industries and time.

Delivery times for inputs from China. To estimate the delivery times for U.S.-China trade I use data for the mean of delivery days and the average length of delays. On average, 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. Throughout the period of analysis, the value of imports from China that arrived via air increased from 10% of total inputs in 1992 to around 30% in 2018.[36] For the analysis in the paper, I take the average of air and ocean throughout the period from 1992 to 2018.

Estimates of delivery times and delays are obtained from *Freightos*, an online freight shipping marketplace platform thats specializes in the U.S.-China route. Ocean transportation from China takes around 25 days to arrive to the West Coast, and 35 days to the East Coast. Delivery days associated with ocean transportation on this route vary around +/- 10 days. For air transportation, the mean of

[34] More on this data and assumption in subsection 5.2.1 below.

[35] As in Alessandria, Kaboski, and Midrigan (2010a) all the uncertainty a firm is facing is modeled through demand volatility, which takes into account other risks, such as productivity shocks, that the firms faces.

[36] Data on the trend of method of transportation for total U.S. imports and imports from China is shown in appendix I.

delivery times is around 10 days, with a possible early or late arrival of 3 days.

To match the transportation patterns in the data, I assume for the distribution of delivery days from China is a mixture of the distribution of two log-normal probability distributions.[37] Informed by the pattern of transportation for inputs from China, I mix the distributions using 0.8 for the ocean distribution, and 0.2 for the air distribution.

$$g(d^f) \;=\; 0.8\, g_{ocean}(d^f) \;+\; 0.2\, g_{air}(d^f) \tag{13}$$

The geometric mean of each of the log-normal distributions equals the mean of delivery days in the data. The standard deviation is assumed to be such that around 95% of the distribution lies within the observed early/late deliveries in the data. These assumptions imply a distribution for China's ocean and air transportation, $\log(d_{ocean}) \sim \mathcal{N}(30, 6)$.[38], and $\log(d_{air}) \sim \mathcal{N}(10, 2)$. Last, the distribution of days, d^f, is related to the parameter for delivery times in the model, λ^f, through equation (12). Assuming a monthly model, $T = 30$, the parameter equals $\lambda^f = \max(0, 1-d^f/30)$, where λ^f represents the proportion of the days in the month that the firm has access to the order to produce within that period. If delivery days, $d^f = 20$ days, then $\lambda^f = 1/3$, which are the ten days of the month the firm has the inputs in the warehouse and is able to use them to produce.

Delivery times for domestic inputs. I assume a log-normal distribution for the domestic delivery days, $\log(d_t^d) \sim \mathcal{N}(day_t^d, 0.1 day_t^d)$. Due to lack of data, I assume the geometric mean of the distribution equals $day^d = 15$ days in 1992, and that the variance is a fixed proportion of the mean, equal to 10%. I test the assumption on the number of days and delays on deliveries for domestic inputs used in production in the sensitivity section of this paper. This paper focuses on the trend in inventories, and while the initial assumption on the level of the mean and variance of the distribution of domestic delivery times is important, the decrease of the mean and variance is the most informative for the trend in inventories over output in the model.

[37] I assume log-normal distributions for delivery days because they start at zero, and have long right tails that allow for possible long delays.

[38] I assume half of the imported input arrive to the West Coast, and half to the East Coast.

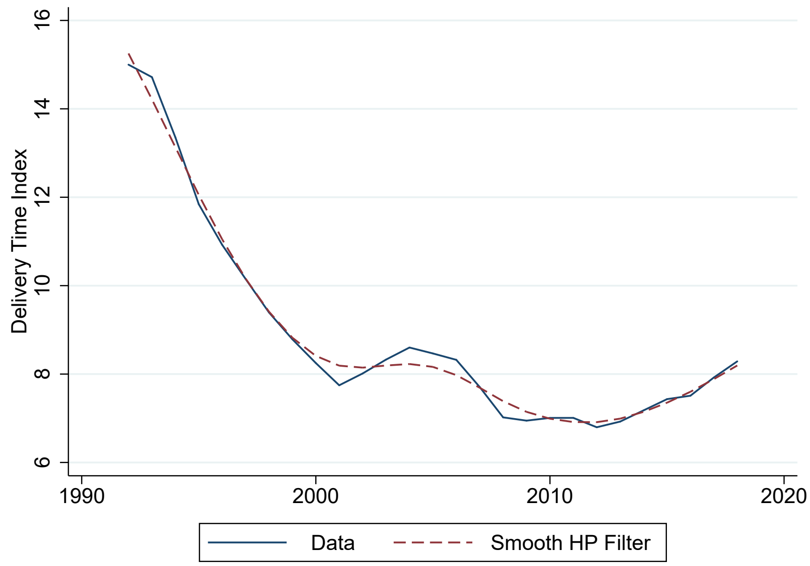


Figure 12: Decrease in domestic delivery times

Note: The Figure shows the declining trend of the domestic delivery times, according to the index published by the Federal Reserve Bank of Philadelphia in their *Manufacturing Business Outlook Survey*. I assume an initial level of delivery time equal to 15 (days), and use the index to compute the changes across time. Additionally, the dashed line shows the trend using the Hodrick-Prescott (HP) filter.

Following the literature, I model improvements in transportation and information technology as a decrease in the delivery times for domestic inputs. To inform the change of domestic delivery days for 1992 to 2018, I use the diffusion index for future delivery times published by the Federal Reserve Bank of Philadelphia in their *Manufacturing Business Outlook Survey*. The future delivery time index forecasts the change in delivery time over the next six months for reporting manufacturing firms. I use the trend of the index[39] to compute the changes along the period of analysis. While the index reports total delivery times (foreign and domestic) of inputs sourced by U.S. manufacturing firms, I assume the trend applies only for domestic delivery times. In the calibration, the majority of the goods are sourced domestically, and I use data for U.S. - China trade to inform the distribution of foreign delivery times.

To match the initial decline in inventories over output from 1992 to 1997, I use the diffusion index for future delivery times and feed the change in the trend to the distribution. The decline in delivery

[39] I compute the trend of the delivery times by assuming an initial level, use the delivery time index to compute the changes across time, and last apply the HP filter to obtain the trend of the series.

times is observed in Figure 12. I assume the day_t^d has average annual decline of 7.7% for the first five years. Then I use the variance of demand to discipline the decrease in the inventory over output given by the changes in the distribution of domestic delivery times.

5.1.3 Predetermined parameters

The reminder of the parameters of the model are set to values found in the literature and their values are detailed in Panel C in Table 3. I set the discount factor, β to $0.96^{1/12}$ which corresponds to a 4% interest rate. To set the storage costs, δ, I draw from the literature that documents inventory carrying costs for the U.S.[40] They estimate annual carrying costs to be from 19 to 43 percent of firm's value of inventories, which imply a monthly carrying cost from 1.5% to 3.5%.[41] I choose the storage cost to be in the middle of the range, $\delta = 2.5\%$.

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 elasticity of substitution between domestic and foreign inputs, σ, is also set to 1.5, which is the mean of the elasticities reported in the literature for the U.S. manufacturing industry according to Bajzik, Havranek, Irsova, and Sxhwarz (2019). The elasticity between domestic and foreign inputs is an important parameter in the model, and crucial to match the data on the increase towards foreign inputs used in production. Robustness checks on this parameter are detailed in the sensitivity section, and more information on the overall importance and relevance for the calibration is given in the next section.

5.2 Opposing trends of delivery times

To answer to what extent do delivery times explain the reversal in U.S. manufacturing inventory trend, this section explains the calibration strategy for the two opposing forces of delivery times that I observe in the data. The first is the decrease in delivery times for inputs due to transportation and information technology. The second is driven by the decrease in cost of inputs form China, which

[40] See Richardson (1995).
[41] The values and analysis or carrying costs are taken from Alessandria, Kaboski, and Midrigan (2010a) paper.

Table 3: Moments for U.S. manufacturing industry and parameters

Monthly model, $T = 30$

Panel A. Calibrated parameters

Parameter		Value	Moment	Model	Data
Weight domestic inputs	θ	0.99	share foreign inputs 1992	1.0%	1.1%
Variance of demand	σ_v	0.463	Δ_{avg} input inventory/output	−3.6%	−3.6%

Panel B. Estimated parameters

Parameter		Value	Comment
Domestic delivery times	day^d	15	days for 1992 $\log(d^d) \sim \mathcal{N}(day^d, 0.1\ day^d)$
Foreign delivery times			$g(d^f) = 0.8 g_{\text{ocean}} + 0.2 g_{\text{air}}$
Input share	α	0.63	α = total intermediates/industry output

Panel C. Predetermined parameters

Parameter		Value	Comment
Elasticity of sub. x^f, x^d	σ	1.5	Bajzik, Kavranek, Irsova, and Schwarz 2019
Elasticity of sub. y	ϵ	1.5	International business cycle literature
Monthly interest rate	β	$0.96^{1/12}$	4% annual interest rate
Monthly storage rate	δ	0.025	30% annual rate

increased the reliance on inputs from China which have long delivery times and delays. I will show how I model and calibrate the two trends, and the next section will detail their effect on inventory holdings for U.S. manufacturing firms.

I solve for the transition paths from 1992 to 2018 for the final good firms, taking into account the two delivery time trends. I calculate the partial equilibrium stationary distribution of the economy for each year in the transition path. In this sense, firms are constantly surprised by the change, and do not know that the future changes.

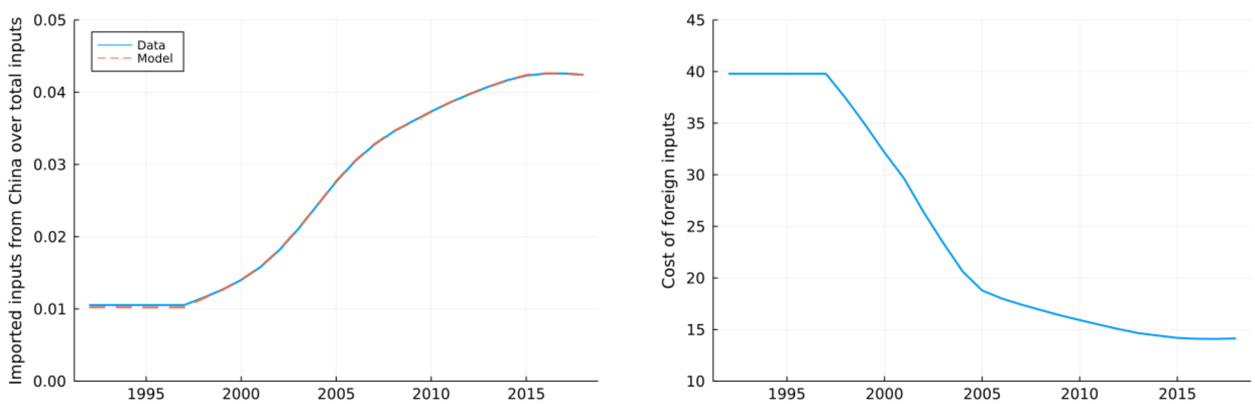
5.2.1 Improvements in transportation and information technology

Following the literature, I model improvements in transportation and information technology as a decrease in the delivery times for domestic inputs. I continue with the same methodology used in the benchmark calibration and described in section 5.1.2. Figure 12 shows the trend of domestic delivery days for the entire period of analysis. In this period, delivery times decrease at an annual average rate of 2.2%, where there is a steeper decline from 1992 to 2011, and then delivery times exhibit a small increase from then onwards.

5.2.2 Increase in inputs from China

The increase in delivery times faced by U.S. manufacturing firms is driven by the increase in inputs that are sourced from China. To match this trend in the model, I calibrate the cost of foreign inputs, $\tau_t p_t^f$, to match the share of imported inputs in the period 1992 to 2018.[42] The cost of foreign inputs decreases 3.8% annually to match the increase in share of inputs from China of 3 percentage points. Figure 13a plots the increasing share of imported inputs over total inputs from China for the model and data. Figure 13b plots the implied decrease in the cost of foreign inputs required to perfectly match the share of foreign inputs.

Figure 13: Calibrated cost of foreign inputs to match rise in inputs from China



(a) Imported inputs over total inputs

(b) Implied foreign input price, τp^f

Note: The Figure shows the perfectly matched share of imported inputs from China over total inputs from 1997 to 2018 in Panel a. Panel b shows the implied price of foreign inputs needed to match the share of imported inputs from China.

For this calibration strategy, the trend in inventories is robust to different levels of the elasticity of substitution between domestic and foreign inputs, σ. The elasticity of substitution governs the magnitude of the change in the cost of foreign inputs. For different values of the elasticity, the resulting decline in the cost of foreign inputs needed to match the rise in inputs from China would

[42] I assume this share of inputs from China used in production remains constant from 1992 to 1997, due to lack of data for imported intermediate inputs (BEA report data on intermediate inputs used in production across industries from 1997 onwards).

differ. But, since the calibration strategy aims to match the rise in imported inputs, regardless of the decline in the cost of inputs, the resulting change in inventories is not as sensitive to the elasticity of substitution.

6 Results: quantitative implication of delivery times

This section details the main quantitative findings of the paper. Using the calibrated trends for domestic delivery times and the relative price of inputs from China I analyze the inventory over output trend in the model. I find the model can explain 61% of the decrease from 1992 to 2004,[43] and 34% of the increase from 2005 to 2018. The first subsection details the results of the benchmark model, and the second subsection has a decomposition of the two trends: (i) the decline in domestic delivery times and (ii) the rise in imported inputs from China, and and their impact on firms choice for inventory holdings.

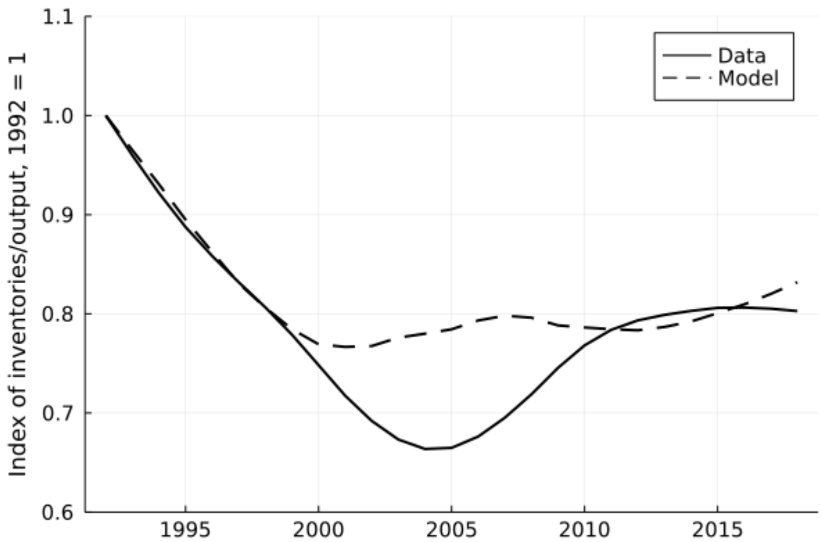
6.1 Inventory trend

The interaction between demand volatility and stochastic delivery times for inputs is an important source of risk for U.S. firms. The opposing forces generate a similar trend in the ratio of inventories over output in the model as is observed in the data. Figure 14 shows the growth of inventories over output for the model and the data, normalizing the level of inventories over output to one for the initial year of the analysis, 1992. Note the initial decrease in inventories from 1992 to 1997 is a targeted moment. In the model, the steep decline in domestic delivery times throughout the period generates a decrease in inventories from 1992 to 2001. After 2001, the increase in inventories lead by the reduction in the cost of inputs from China is large enough to overcome the effect of the decrease in domestic delivery times. Inventories in the model continue to increase from 2002 onwards. The turning point in the model coincides with China's entrance to the World Trade Organization, where U.S. firms

[43] In the benchmark calibration I match the trend of inventories over output from 1992 to 1997, but the remaining trend is a non-targeted moment.

increased sharply the amount of inputs they sourced from China.

Figure 14: Trend of inventories over output: model vs data



Note: The Figure shows the comparison between the trend in inventories-to-output from 1992 to 2018 of data and model results. The initial five year period is matched, but from 1997 to 2018 the inventory trend in an un-targeted moment. The two opposing forces generate a similar trend in the ratio of inventories over output in the model as is observed in the data.

The first section of Table 5 shows the annual growth rates for the periods of 1992 to 2004 and 2005 to 2018 for the ratio of inventories over output. In the data, inventories decrease at a 3.4% rate, whereas in the benchmark model inventories decease at a 2.0% rate. The delivery times channel is able to explain around 61% of the data trend. The trend in the data is reversed in 2005, where inventories increase at an annual rate of 1.4%. The decrease in the cost of foreign inputs, with the simultaneous decrease in domestic delivery times in the model implies an annual increase in inventories of 0.5% from 2005 to 2018, and explains a third of the observed inventory increase.

The share of foreign inventories over total inventories increased throughout the period of analysis. Figure 15 shows the share foreign inventories in the model which represented 2.5% of total inventories in 1992 and grew to 13.3% in 2018. The change in this share is due to the two opposing trends in the analysis. On one hand, firms have quicker access to domestic inputs, which allows to hold less domestic input inventories, ad increases the share of foreign inventories. Column four in Table 5 shows that domestic inventories over output decreased at an annual average rate of 1.2% from 1992 to 2018.

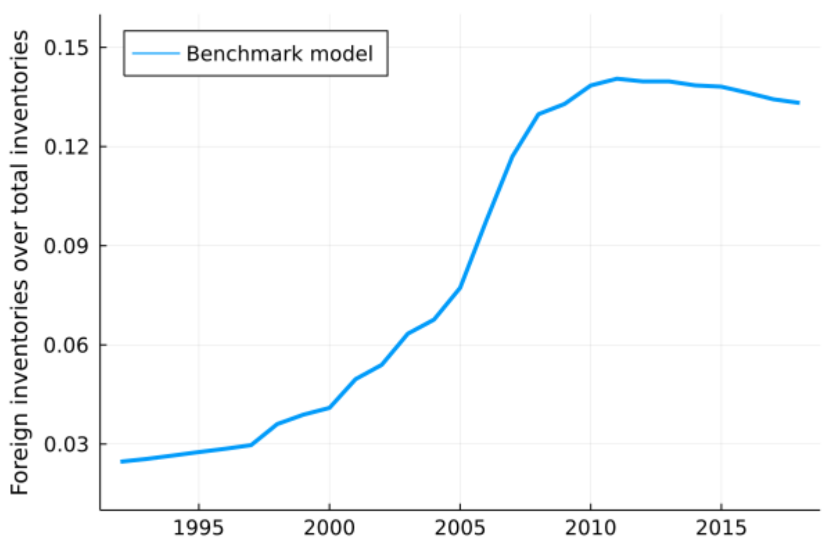
Table 4: Model vs data – inventories over output

Average annual growth rates: inventory/output	Total		Foreign	Domestic
	92 − 04	05 − 18	92 − 18	92 − 18
Data	−3.4%	1.4%		
Benchmark model	−2.0%	0.5%	6.3%	−1.2%
Delivery time channel	61%	34%		
Improvements in technology	−2.3%	−0.1%	−0.01%	−1.1%
Rise in inputs from China	0.2%	0.7%	6.3%	−0.1%

Average annual growth rates reported in the Table are computed from the average level of inventories and output of the simulated stationary distributions for each year in the period of analysis.

Additionally, the reduction in the cost of inputs from China increased firms' reliance on foreign inputs, therefore increasing the need for foreign inventories. Moreover, these inputs face longer delivery times and delays than domestic inputs. Thus firms need larger amount of foreign inventories to insure the production process. The ratio of foreign inventories over output increased at an annual average rate of 6.3% in the period of analysis, as shown in column three in table 5. The rise in foreign inventories is large enough to overcome the decrease in the domestic input inventory from 2002 onwards, driving the trend of total inventories over output.

Figure 15: Foreign inventories over total inventories in the model: 1992 to 2018



Note: The Figure shows the share of foreign inventories over total inventories observed in the model. Although there is no data to compare this share with, it shows the increase in importance of foreign inventories due to the increase in reliance on foreign inputs.

Firms choose to modify their level of inventories to insure against changes in the risk they are facing. In this sense, I define the cost associated with the changes in inventories as the cost of insurance against additional risk. Equation (14) shows the cost of insurance which equals the ratio of the change in inventories over output times the storage cost of holding the inventory in the warehouse. In the initial period, the improvements in transportation and information technology have an associated annual average savings of -0.5% due to the decrease in the cost of holding inventories.

$$\text{Cost insurance}_t = \frac{\delta\left(\text{inventories}_t - \text{inventories}_{t-1}\right)}{\text{output}_t} \tag{14}$$

Similarly, the cost of insuring against the risk of sourcing inputs form China represents on average an annual 0.12% of output in the period of 2005 to 2018. As the price of inputs from China decreases, firms substitute towards the riskier and cheaper inputs that take longer to arrive, and need to increase their insurance via inventories. Throughout this period, output grows at an annual average rate of 0.04%, driven by the decrease in the domestic delivery times and the reduction in the cost of inputs from China. Part of the increase is dampened by the increase in the cost of holding the additional inventories.

Table 5: Cost of insurance via change in inventories

Average annual growth rates

	Cost of insurance		Output growth	
	$92-04$	$05-18$	$92-04$	$05-18$
Benchmark model	-0.5%	0.12%	0.05%	0.04%
Improvements in technology	-0.6%	-0.01%	-0.01%	0.00%
Decline in cost of inputs from China	0.06%	0.14%	0.06%	0.05%

Average annual growth rates are computed from the average level of inventories and output of the simulated stationary distributions for each year in the period of analysis. Cost in inventories is computed using equation (14).

Other motives for inventory holding. Firms choose to stock inventories for many reasons. This paper focuses on the role of delivery times for domestic and foreign inputs.[44] Another important channel is changes in firm level risk. In the model, this risk is represented by demand volatility. An

[44] Another interesting extension includes adding fixed costs of ordering foreign inputs, motivated by the fact that trade is lump and there are administrative barriers to sourcing foreign inputs. The added friction will further increase the level of foreign inventories firms need to stock and increase the impact of the increase in inputs from China.

increase in firm-level idiosyncratic volatility could potentially explain the remaining trend in inventories. Other sources of uncertainty, such as productivity shocks, would have the same mechanism as increasing the variance of demand in the current framework.

A channel that has been studied by the literature is how changes in the short term inventory holding react to trade policy uncertainty. The recent increase in trade policy uncertainty documented by Caldara, Iacovello, Molligo, Prestipino, and Raffo (2020), could be another reason for firms to increase their inventory holdings expecting potential increases in import tariffs.

Other potential channels are changes in the interest rates and storage costs firms face. These two parameters govern the disincentives to hold inventories. Low interest rates decrease the cost of holding inventories, which would lead to an increase in inventories. Appendix J has more details and data on these additional channels, and future work will include exploring these other channels within the framework developed in this paper.

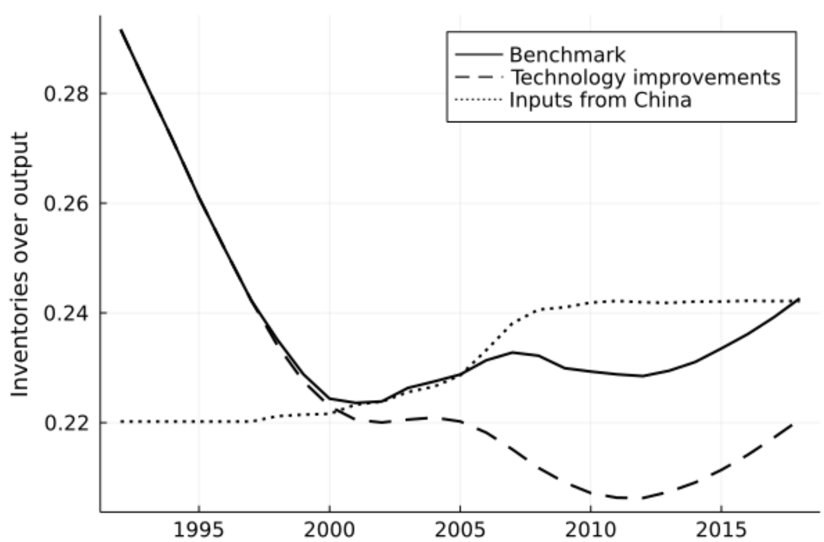
6.2 Decomposition of the effects on inventories

To understand how the trend for domestic delivery times and the relative price of inputs from China interact in the benchmark model, this section has a decomposition analysis for each trend. The second section of Table 5 shows the annual growth rates when considering only one trend, and Figure 16 shows the trend of inventories over output for the benchmark model, and for each of the opposing forces.

Inventory over output decreases at an annual average rate of 1.1% when including only the improvements in transportation and information technology. In this case, I assume the price of foreign inputs remains at the initial level of 1992, and I use the change in the delivery times index for domestic inputs. Similar to the trend of domestic delivery times, inventories have a sharper initial decline of 2.3% from 1992 to 2004, and then the decrease slows down to 0.1% for the remaining of the period. Incentives to hold domestic inventories decrease, therefore domestic inventories over output decline at a 1.1% annual average rate. Furthermore, foreign inventories in this case decrease slightly through this period, since firms are substituting slightly towards domestic inputs since they become relatively cheaper in terms of their cost of delivery times. The cost of insurance decreases at a 0.3% annual average rate throughout the period.

When considering only the reduction in the price of inputs from China, inventories over output grow at an annual rate of 0.4% on average for the entire period. In this case, I fix the domestic delivery times to the mean observed in 2005, which is around 8 days. Then I use a similar methodology as before, where I calibrate the price of foreign inputs to match the rise in imports from China. Inventories over output have a sharper increase after China joins the World Trade Organization in 2001, and grow at an annual average rate of 0.7% from 2005 to 2018. Excluding improvements in technology that decreased delivery times boosts the increase in inventories, and this channel is able to explain 51% of the increasing trend in inventories from 2005 to 2018. Throughout this period, foreign inventories grow at a similar rate as the benchmark model and domestic inventories decrease only slightly. In this case, the change in domestic inventories is only due to the substitution effect towards foreign inputs. The annual cost of insurance represents 0.1% of output on average, higher than the benchmark due to the steeper increase in inventories.

Figure 16: Decomposition of delivery time trends in inventories



Note: The Figure shows the trend of inventory-to-output ratio for three different model scenarios. The solid line represents the benchmark model, the dashed line the inventories from a model taking into consideration only the improvements in transportation and information technology. Last, the dotted line represent the trend of inventories from a model with only the decrease in foreign input prices.

Both trends are necessary for the model to generate a similar trend to the one in the data of inventories over output for the U.S. manufacturing industry. 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. This process overcomes the decrease in domestic inventories in 2002, and drives the increase in the trend of total inventories over output for the rest of the period.

7 Conclusion

This paper documents the reversal in the long term decline of the ratio of U.S. manufacturing inventories over output. After a decades-long decline, U.S. manufacturing inventories over output have been increasing since 2005. The increase is observed across manufacturing industries and types of inventories. Inventories are an important source of insurance against risk, both against changes in their demand and to ensure a smooth production process. This paper explores the change in the trend in inventories through the increase in delivery times for inputs as U.S. firms created global supply chains. In particular, U.S. firms are increasingly relying on inputs from China which face long delivery times and delays. This process indirectly increased their exposure to volatility in demand, through longer delivery times, and directly increased risk in the availability of inputs through potential delays, leading to greater incentive to hold inventories.

I introduce a novel dynamic trade model that features different and stochastic delivery times for inputs. In the presence of demand volatility, firms face a tradeoff in their sourcing decisions between the relative price of inputs and the delivery times for each input. I calibrate the model to match two opposing trends. First, improvements in transportation and information technology made inputs more readily available for firms in the production process. However, as firms substituted more expensive domestic inputs with short delivery times for cheaper inputs from China, they increased their exposure to long delivery times and delays. I find that the initial decrease in delivery times explains 61% of the decline in inventories from 1992 to 2004, and the increase in reliance on inputs which face longer delivery times explains 34% of the increase from 2005 to 2018.

Last, firms choose to stock inventories for many reasons. This paper focuses on the role of delivery times, and the impact global value chains have in the level of risk firms face. This particular channel is able to generate a similar trend in inventories to that observed in the data, and explains a third of the increase in the trend of U.S. manufacturing inventories over output. Moreover, the current frameworks allows for further work in the importance of delivery times in trade, and possible extensions for the consideration of other channels to explain the remaining trend in inventories.

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A Additional data sources and methodology

This section provides additional information on the data sources used in the paper, and details additional data sources.

Inventory data. All of the inventory data used on this paper comes from the *Manufacturers' Shipments, Inventories, and Orders* survey published by the U.S. Census Bureau. Additional sources and details and found here.

Manufacturers' Shipments, Inventories, and Orders 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

Manufacturing and Trade Inventories and Sales is a survey published by the U.S. Census Bureau which has data on monthly inventories and sales from 1992 to today, for the total business sector, and further detail by each business: wholesale, retail, and manufacturing.

The define the type of business as follows:

- Wholesaler (Wholesale) - A business that sells to retailers, contractors, or other types of businesses (including farms), but not to the general public (or at least not in any significant amount).
- Retailer (Retail) - Business that sell goods in small quantities directly to consumers.
- Manufacturers (Manufacturing) - Establishments in the manufacturing sector are often described as plants, factories, or mills, and characteristically use power-driven machines and material-handling equipment. Manufacturing establishments may process materials, or may contract with other establishments to process their materials for them. Both types of establishments are included in manufacturing.

NBER-CES Manufacturing Industry Database The database published by the NBER contains annual industry-level data from 1958 to 2012 on output, sales, and inventory stocks (among others), for six digit NAICS industries.

Import data. Schott (2008) has a dataset available in their website (thank you for making it accessible for everyone!) which includes annual U.S. HS-level imports and exports for the period 1989 to 2018. The data was purchased from the U.S. Census Bureau, and it has 10 digit HS industry data for imports and export, by method of transportation and country of origin.

Intermediate input data.

Input-Output Tables. Data on domestic and foreign intermediate inputs used in production by industry are published in the *Input-Output* tables by the Bureau of Economic Analysis. 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 combine the industries 311 and 312, 313 and 314, and 315 and 316 together to form only 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.

Data on the intermediate inputs used in production by country of origin is more difficult to find.

To obtain these variables, I follow a similar methodology used by the Bureau of Economic Analysis to obtain 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:

$$\frac{\text{Country } i \text{ imported inputs in } j}{\text{Total inputs used in } j} = \frac{\text{Imports from } i \text{ in } j}{\text{Total imports of } j} \frac{\text{Imported inputs from } j}{\text{Total inputs used in } j} \tag{15}$$

Broad Economic Categories. The United Nations defines the *Classification by Broad Economic Categories*, which have three basic classes of goods according to the System of National Accounts: capital goods, intermediate goods, and consumption goods. The BEC classification system can be matched to the HS industries.

B Solving the model

In this section I provide details concerning the algorithms used to solve the model. First subsection details the algorithm used to solve for a general equilibrium stationary distribution, which is used in the benchmark calibration of the model. Second subsection contains details on the benchmark calibration methodology. Las subsection details the methodology used for the calibration of the two opposing trends for delivery times.

B.1 Solving for the general equilibrium stationary distribution

I assume I know the parameters of the model $\{\beta, \epsilon, \alpha, \sigma, \delta, L, \mu_\lambda^f, \sigma_\lambda^f, \mu_\lambda^d, \sigma_\lambda^d, (\gamma_a, \theta_a, \sigma_{\nu_a}, \tau_a, p_a^f)_{\forall a}\}$. Note since I abstract from modeling the foreign input producers, in this sense we can think about the cost of foreign inputs, $\tau_a p_a^f$ as an extra parameters in the model. Then I follow the structure detailed below.[45]

1. I start with an initial guess for the consumption of the representative consumer, the composite good, and sectoral output prices, $(C^g, N^g, (p_a^g)_{\forall a})$. I normalize the wage to one, $w = 1$.[46]

2. Given the values for $(C^g, N^g, (p_a^g)_{\forall a}), w = 1)$, I find the implied sectoral output, $(y_a)_{\forall a}$, the consumption price index, P, and the price of the domestic inputs, p^d, according to the equations below.

$$\begin{aligned}
\frac{1}{P} &= \prod_a \left(\frac{\gamma_a}{p_a}\right)^{\gamma_a} \\
y_a &= \frac{\gamma_a \, P \, (C+N)}{p_a} \\
p^d &= \frac{P^{\,\alpha} \; w^{\,1-\alpha}}{\alpha^{\,\alpha} \; (1-\alpha)^{\,1-\alpha}}
\end{aligned}$$

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

$$\begin{aligned}
V(s^d, s^f) &= \max_{n^d, n^f} \; E[\tilde{V}(n^d, n^f)(s^d, s^f, \; \eta)] \qquad \text{where } \eta = (\nu, \; \lambda^d, \lambda^f) \\
\tilde{V}(n^d, n^f)(s^d, s^f, \; \eta) &= \max_{\{p, x^d, x^f, \ell\}} \; p \, y\,(p) - w\,\ell - p^d\, n^d - \; \tau_a\, p_a^f\, n^f + \beta\, V(s'^d, s'^f)
\end{aligned}$$

   (a) 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).[47]

[45] The general structure of the code follows Johnson C. and Moxnes (2019).

[46] I choose to normalize wages, in accordance to Walras' law.

[47] Also I could have created a grid for n^d, n^f, but I use a non-linear solver that is a bit faster than solving for each point in the n grid.

i. Step one: given $(n^d, n^f, s^d, s^f, \eta)$ I solve for the four options that can happen: 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.

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

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

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

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

C. 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.

$$x^f = s^f + \lambda^f n^f$$

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

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

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

$$y = x^\alpha\,\ell^{1-\alpha}$$

$$p = P\left(\frac{y}{\nu\,y}\right)^{\frac{1}{\epsilon}}$$

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

D. 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.

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

ii. Step two: Which case is the optimum one, the one that defines the policy functions? Given $(n^d, n^f, s^d, s^f, \eta)$:

A. 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.

B. 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.

C. 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.

D. 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.

(b) 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 $\tilde{V}(n^d, n^f)(s^d, s^f, \ \eta)$ (function of n^d, n^f, for each value of

$(s^d, s^d, \eta))$.

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

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

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

(e) Step five: given the solved 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 $V(s^d, s^f)$ of the final good firm.

$$V(s^d, s^f) = \ E_\eta\Big[\ p^*\, y\,(p^*) - w\,\ell^* - p^d\, n^{*d} - \ \tau_a\, p_a^{f*}\, n^{*f} + \beta\, V(s'^{*d}, s'^{*f})\Big]$$

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

$$\begin{aligned} \ell_j^d &= \frac{(1-\alpha)\, p_j\, x_j^d}{w} \\ N_j^d &= \frac{(\alpha)\, p_j\, x_j^d}{P} \end{aligned}$$

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

6. Finally I update the initial guess for $(C^g, N^g, (p_a^g)_{\forall a})$ 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. Part of the resources of the consumer is the profits of the continuum of final good firms, $\int_0^1 \Pi_j dj$.

$$
\begin{aligned}
p_a &= \left(\int_{I_a} v_j \; p_j^{1-\epsilon} \; dj \right)^{\frac{1}{1-\epsilon}} \qquad \forall a \\
N &= \int_0^1 N_j^d \; dj \\
C &= \frac{w \; L \; + \int_0^1 \Pi_j dj}{P}
\end{aligned}
$$

B.2 Benchmark calibration

This subsections provides additional information on the assumptions and solution method used to calibrate the initial general equilibrium model. The benchmark calibration matches U.S. manufacturing data for the year 2005, the turning point of the inventory trend. For the aggregate manufacturing sector, I need to match the weight of the domestic inputs in the final good firm technology function, θ, to the share of foreign inputs. To do so, I assume the price of foreign inputs equals the price for domestic inputs. In this case, the weight for domestic input approximately equals the share of domestic inputs sued for production in the data.

The second moment I need to match is the level fo inventory over output for the aggregate manufacturing sector. To match that moment I use the variance of demand. I compute model's inventory over output level from the general equilibrium stationary distribution. If it is lower that in the data, I increase the demand variance. Otherwise I decrease the variance. Since more volatility in demand imply a higher level or risk in the model that firms need to insure against using inventory, I use the bisection method to match the moment.

When I split the unit continuum of final good firms into different sectors, then I have two moments by sector to match. The method described above to match the share of foreign inputs used in production can still be used here. For all sectors a, I equal $\tau_s p_a^f$ to the domestic input price, and let each θ_a equal the share of domestic input used in production for each sector. Matching the level of inventories over output for each sector is not as easy as before. In this case I use the simulated method of moments to match the variance of demand of each sector to the inventory over sales observed across sectors, in general equilibrium. A similar bisection analysis can be made within sector, but having the general equilibrium loop makes the adjusting more complicated.

B.3 Calibrating opposing forces of delivery times

This section provides further detail on the calibration of the two opposing trends of delivery times for inputs. The first trend of delivery times is based on the improvements in transportation and information technology which are documented in the literature. These improvements allowed for a decrease in the delivery times U.S. firms face. For simplicity, I assume the per period change in the distribution is for domestic inputs only, since they represent the majority of the inputs that firms use to produce. I model the reduction in the domestic delivery times as the decrease in the mean and variance of the distribution of delivery times. Then for every period, I compute the partial equilibrium stationary distribution. I hold fix the aggregate consumption variables and prices from the benchmark calibration, and do steps three, four, and five detailed in the subsection above, B.1.

The increasing trend in delivery times comes indirectly from the reduction in the cost of foreign inputs. As the price reduces, firms increase their reliance on the foreign inputs which whose distribution of delivery times has a longer mean and variance (longer delivery times and longer delays). To model this mechanism, I calibrate the reduction in the price of foreign inputs across time and sectors, $\tau_{at}\, p_{at}^f$, to match the observed increase in imports in time and for each sector. This will happen while the distribution of domestic delivery times is also changing across time. This analysis is done for partial equilibrium, so a similar bisection method can be use to calibrate the price of foreign inputs. If the implied share of foreign inputs from the (partial equilibrium) stationary distribution is lower than in the data, then I further reduce the price of foreign inputs.

C Optimal decision rules for different idiosyncratic shocks

This section characterizes the optimal decision rules for the final good firm.[48] In equilibrium, firms will sometimes be constrained and unable to meet their demand. This is a direct effect of the frictions from positive and stochastic delivery times for inputs and firms having to plan in advance for their orders. If firms have a high demand shock, or have access to a low proportion of the order (or both), they will be constrained in the amount of inputs available for production. In consequence, they will stock out of inventories and increase the final good price so that the consumer demands only their available stock of the final good.

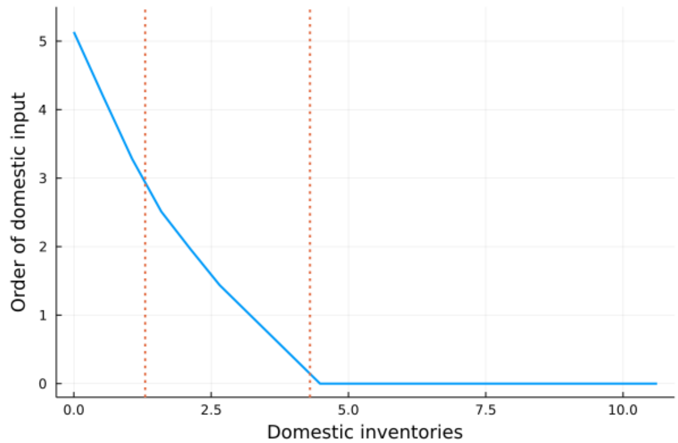
Figures in this section show the policy functions for orders of domestic inputs, use of domestic inputs for production, domestic inventories, and the final good price. Figures show the policy function for current domestic inventories, given a fixed level of foreign inventories and foreign order of input. The policy functions of the foreign inputs are similar and can be found in the appendix **??**.[49]

Orders are made before the shocks are realized, so firms choose to order according to the expected value of the demand and delivery time shocks. How much to order of each input will depend on the relative price of inputs, and the distribution of delivery times. Figure 17 shows the firm's decision to order domestic inputs, n^d, for the domestic inventories s^d, and a fixed level of foreign inventories, s^f. As the domestic inventories increases, the amount of domestic input they need to order decreases. The two vertical dotted lines show where the stationary distribution of the final good problem lies. In these case, firms in the stationary distribution will always order a positive level of inputs every period.

Given the timing constraint, depending on the realized shocks for the period firms will be constrained or unconstrained in the amount of inputs they are able to use for production. Additionally,

[48]The policy functions are obtained from the benchmark calibration detailed in section 5.1.
[49]Details on the methodology to solve the problem are also in the appendix B of the paper.

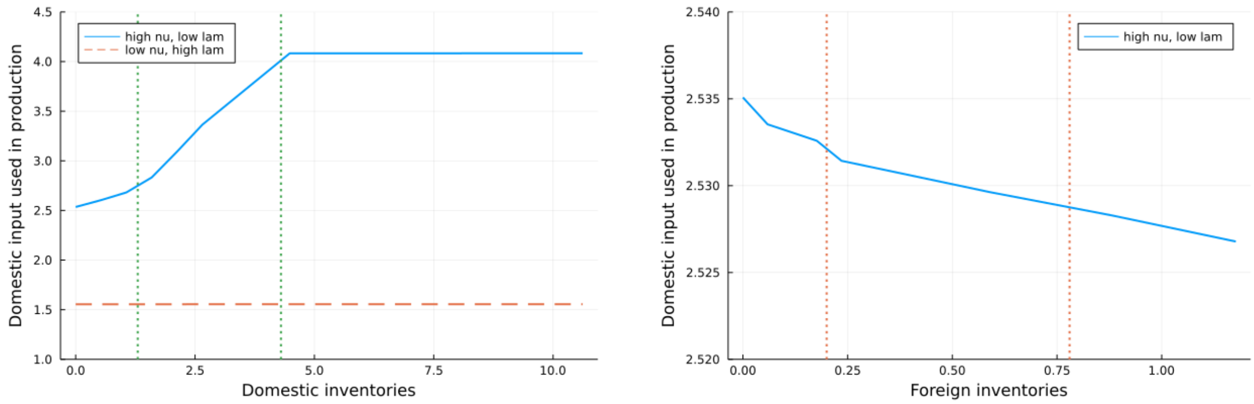
Figure 17: Order of domestic input before shocks are realized



firms will substitute between inputs depending on the inventory availability of each input. Figure 18a shows the use of domestic input for different realized shocks. The solid line represent the use of domestic input for a high demand and low access to input shock. In this case, within the stationary distribution, the firms are constrained (see equation 5) and are unable to use the amount of inputs they need to meet their unconstrained demand. In comparison, the dashed line shows the use of domestic input for a low demand and high access to input shock. In this case, the stock of inventories and the order is enough to use the amount needed to satisfy the unconstrained demand. Figure 18b shows the domestic input used to produce for foreign inventory levels, fixing the level of domestic inventory level. The solid line represents the case where there is a high demand and low access to input shock. The negative slope of the line shows the substitution between inputs for different inventory levels. For low levels of the foreign inventory, firms substitute the foreign inputs with domestic inputs. As firms have more foreign inventories, then they use more foreign inputs to produce. A key parameters that defines the slope of the line is the elasticity between foreign and domestic input, σ.

Final good prices adjust to make sure the consumer demands their available stock. Panel 19 shows the prices for different demand and delivery time shocks, given the demand they face by the consumer in equation 3. When final good firms are constrained, and unable to meet the unconstrained demand, prices rise as shown in the solid line. In the other case, when firms have enough inventories to produce, then the price is lower and defined by the demand function they face.

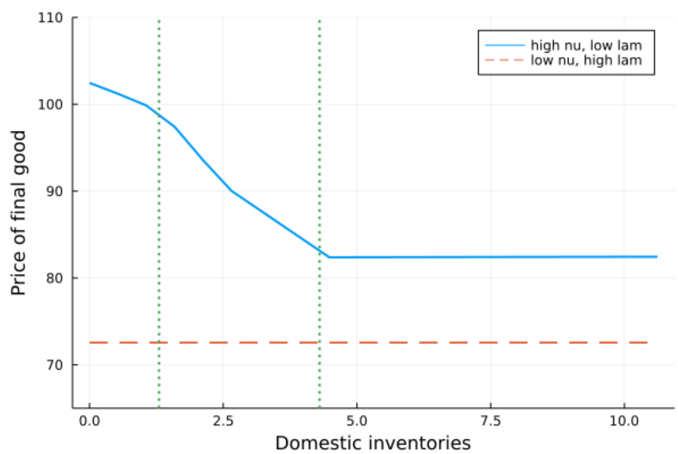
Figure 18: Domestic inputs can be constrained depending on shocks η



(a) Domestic input for domestic inventories

(b) Domestic input for foreign inventories

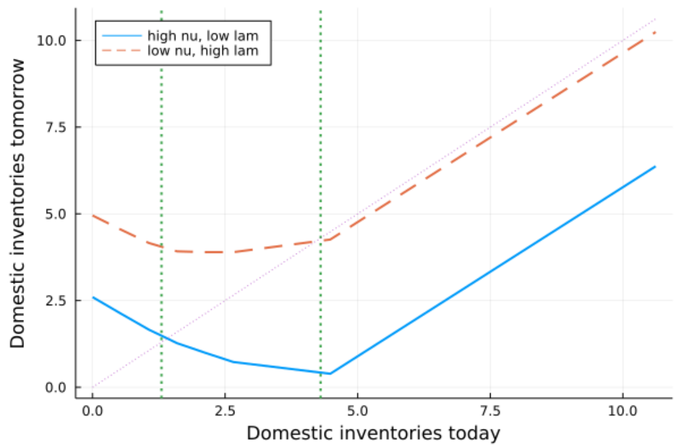
Figure 19: If constrained, price of final goods will adjust upwards



The level of inventories firms will have next period is determined by the order and the amount of inputs they use to produce, given equation 6. If firms are constrained in their use of inputs, then they will use all the available inputs today and stockout of inventories, as the solid line in panel 20 shows. In this case, inventories next period will be equal to the inputs that are in transit, $(1-\lambda)n$. Compared to the unconstrained case, noted by the dashed line in panel 20, inventories next period will be lower. This maps to the order of inputs next period, where if inventories they start the period with are low, they will order a high amount of the input.

Furthermore, if the parameters of the model change, the optimal decisions rule will be modified as well. As the distribution for delivery times and/or demand shocks changes, also the level of inventories firms choose to stock, and amount of times firms are constrained. If the mean of the distribution

Figure 20: Inventories of domestic inputs, s'^d



of delivery times, λ, is lower (low access to inputs), then firms will choose to stock more inventories. Additionally, if the distribution of delivery times is more volatile, firms will be more constantly constrained in their output, and prices will vary and increase more often. Similar reactions will occur as we change the distribution of demand shocks.

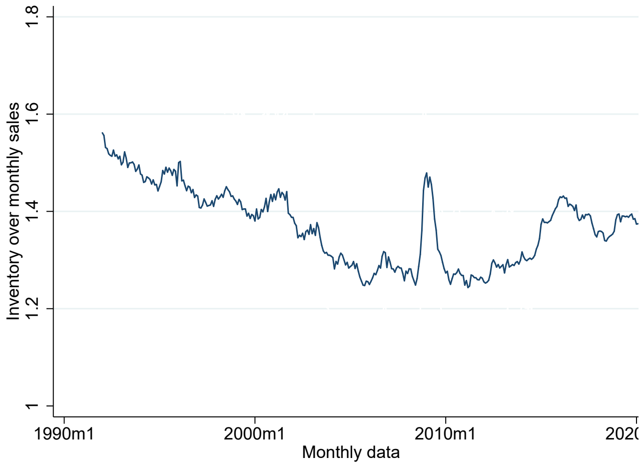
D Increasing inventories in total business

Figure 21a documents the trend in inventory over monthly sales for total business as defined by the U.S. Census Bureau in the *Manufacturing and Trade Inventories and Sales* survey. Total business are divided into wholesale, retail, and manufacturing industries. Figure 21b shows the trend for the inventories over monthly sales for each of the industries. This paper focuses on the manufacturing inventories, which show the starkest decrease and following rise.

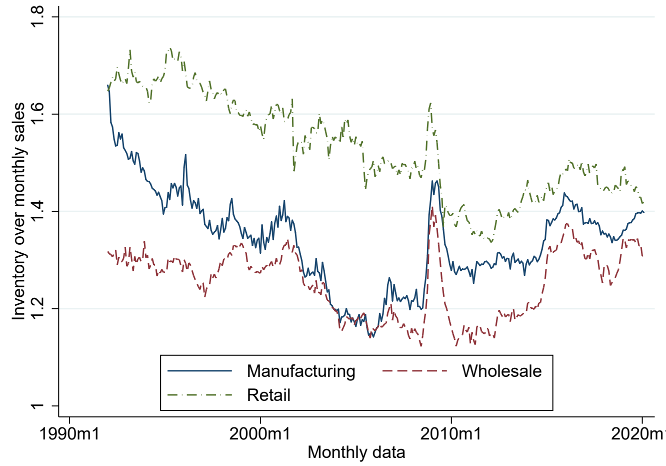
E Increasing manufacturing inventories for Canada and Japan

This section documents the increasing inventory trend for the manufacturing industries in Canada and Japan, shown in Figure 22. Data on inventories for Canada is obtained from the Statistics Canada, who publish *Manufacturers' sales, inventories, orders and inventory to sales, by industry.* Inventory

Figure 21: Increasing Business Inventories



(a) Total Business Inventories

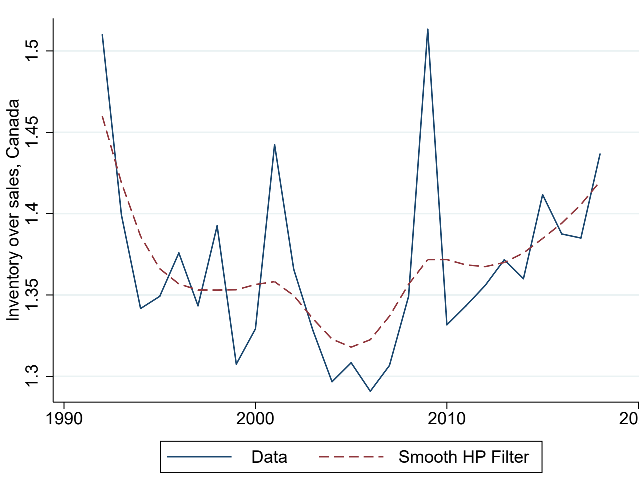


(b) Inventories across sectors

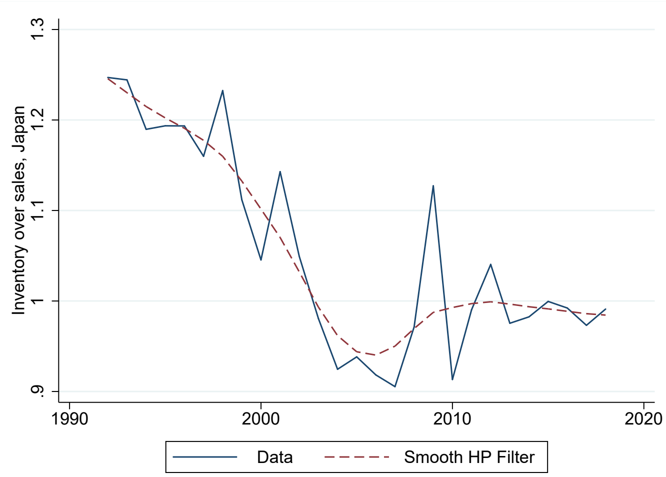
trend for Canada shown in Figure 22a is very similar to the one observed for the U.S., where after a sharp decline, inventories increase around 2005.

Data on inventories for Japan's manufacturing industry comes from the Ministry of Economy, Trade, and Industry, form their published report on who publish the *Indices of Industrial Production*. For Japan, inventory over sales stop decreasing around 2005 as shown in Figure 22b. There is an increase after 2005, and then inventories remain stable after 2010.

Figure 22: Increasing inventories for Canada and Japan



(a) Total Business Inventories



(b) Inventories across sectors

F Type of goods imported from China

This section presents alternative measures or methodologies to compute the intermediate inputs used in production that come from China. I present two additional methodologies that also provide possible explanations on the lag between the increase in inventories in the data and in the model. The current methodology to compute the share of intermediate inputs from China that U.S. firms use in production assumes that the amount of intermediate inputs from China is a fraction of the total imports that arrive from China, and this fraction is equal to the amount of total foreign intermediate inputs used in production - which does not vary across countries - according to the *Input-Output Tables* published by the Bureau of Economic Analysis.

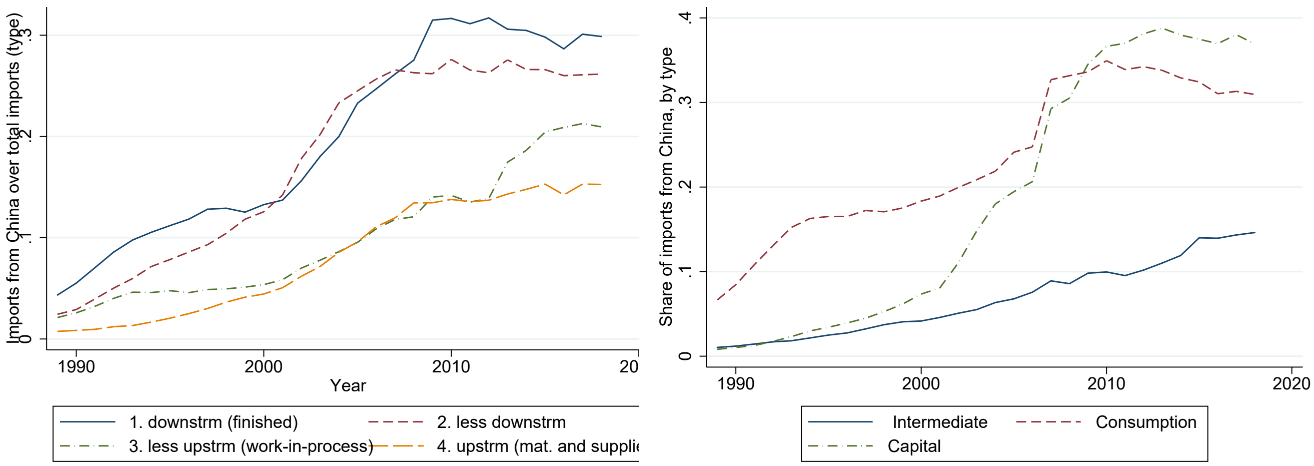
Another way of computing the goods which are intermediate inputs from China is to follow Antrás, Chor, Fally, and Hillberry (2012) methodology which computes the *upstreamness* measure of each industry. They define *upstreamness* as the average distance of a good from final use. Given their measure of this *upstreamness* index, I combine the NAICS industries into four types of commodities: commodities that have a high index are considered materials and supplies (upstream goods), and as the index decreases industries are considered as work-in-process, almost finished goods, and lastly finished goods.

Figure 23a shows the imports that arrives from China over the total imports by type of commodity for each of the four types of commodities I defined. Initially, in 1990, of the imported commodities, almost none was imported from China. In 2018 U.S. firms were importing from 15% to 30% of each of the commodities from China. Commodities that are more intermediate - work-in-process and materials and supplies - represent a lower share and the increase after 2001 was less steep, and took more time to get to the highest point. The second category of goods, what I names work-in-process goods, continues to increase until 2018.

This could indicate that it took firms some time to integrate China in their supply chain. Even though most of the increase in imports from China is observed right after 2001, the imports of intermediate goods took longer to increase. The slow increase of intermediate goods could explain why the reversal in the trend of inventories occurred until 2005.

Figure 23b shows the imports from China over the total imports by type of goods for the three categories defined in the *Broad Economic Categories*, published by the United Nations. Similarly to the methodology used to compute panel A, the share of intermediate inputs observe the slowest and continuous increase when compared to capital and consumption goods.

Figure 23: Increasing inventories for Canada and Japan



(a) Upstreamness Measure

(b) Broad Economic Categories

G Creation of global supply chains and inventories

This section provides evidence on the creation of global supply chains by U.S. firms, and its relation to inventories. To do so, I rely on a measure for global supply chains developed by Hummels, Ishii, and Yi (2001), which indicates the degree of integration of an industry with the use of imported inputs in producing goods that are exported, called vertical specialization. I use the *Input-Output* tables published by the Bureau of Economic Analysis to compute the trend of the vertical specialization index from 1997 to 2018 for U.S. manufacturing firms. Figure ?? shows the increase in the measure from 2001 onwards, which is evidence of the creation of global supply chains in the U.S.

$$\text{Vertical Specialization Index}_i = \frac{\text{Imported Intermediate}_i}{\text{Gross Output}_i} \frac{\text{Exports}_i}{\text{Gross Output}_i} \tag{16}$$

Figure 24: Measure of the creation of global supply chains

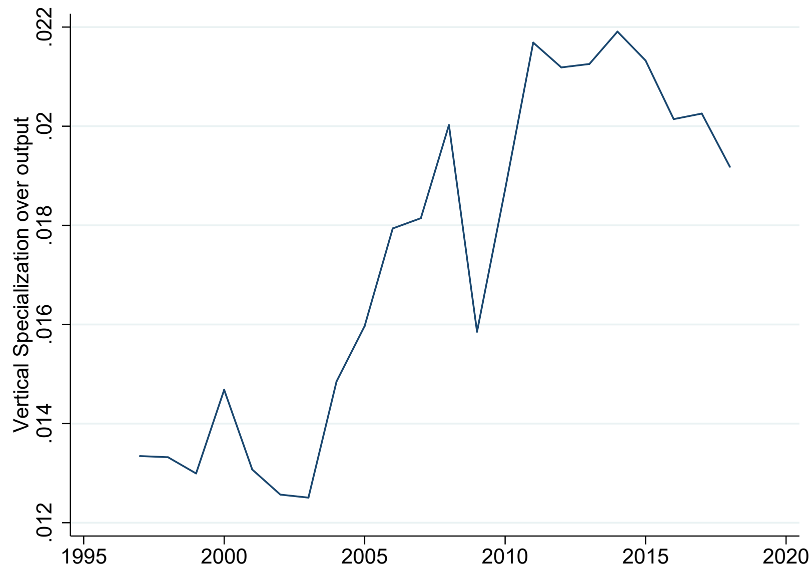


Figure 25: Vertical Specialization Index

Similarly to the relation between the share of imported inputs and inventories, industries who have a higher vertical specialization index tend to store more inventories. Figure 26a shows the positive relation between the average of vertical specialization index and the ratio of inventory over gross output for each manufacturing industry The correlation is equal to 0.74, and the relationship is strengthened when considering only work-in-process inventories with a correlation of 0.75, as shown in Figure 26b. As industries choose to integrate - import inputs, and export some of their output - their inventories increase in response to the added risk the integration poses.

Table 6 shows the results of the analysis using industry-level panel data to regress the change of inventories and the change of imported inputs, and vertical specialization controlling for the size of the industry using value added. I include year and industry fixed effects. There is a strong correlation between imported inputs and inventories, as an increase of 10% in imported inputs is associated with an increase in inventories of 5.9%. When controlling for the size of the industry, the increase in inventories is reduced to 3.4%, but still positive and significant. Results are similar for the vertical

Figure 26: Integrated industries have more inventories

(a) Total inventory, $\rho = 0.74$

(b) Work in process, $\rho = 0.75$

specialization index. When considering work-in-process inventories the relationships are strengthened and the correlations increase. When controlling for the size of the industry, a 10% increase in imported intermediates is associated with an increase in work-in-process inventories of 3.5%.

Table 6: Strong correlation between imported inputs and inventories

	ln(inventory)			ln(work-in-process)		
ln(imported inputs)	0.589	0.342		0.725	0.421	
ln(VS index)			0.291			0.353
ln(value added)		0.747	0.918		0.921	1.134
year, industry FE	✓	✓	✓	✓	✓	✓

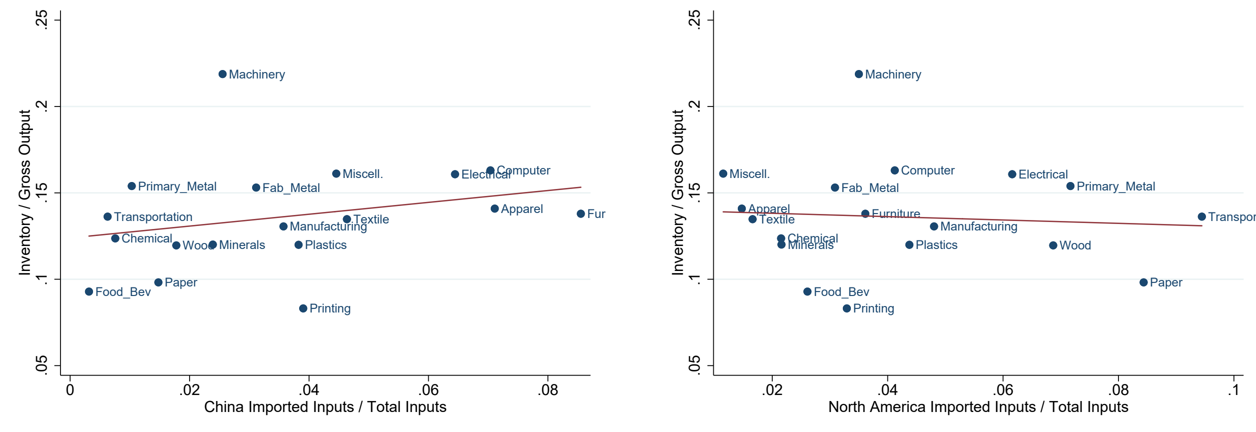
Data using NAICS 3 digit sectors, from 1997-2018, 396 observations

H Inventories and imported inputs by country of origin

This section provides evidence of the relationship between the distance between the country of origin and destination of the imported input to the level of inventories that the firm needs to holds. As the distance increases, then firms need to hold more inventory to insure against the added risk of longer delivery times and possibly longer and more frequent delays for the inputs.

Industries that import inputs from China tend to hold more inventory than industries who import inputs from Canada and Mexico. Figure 27a show the relationship for the industry averages for the intermediate inputs from sourced from China for the period 1997 and 2018, and Figure 27b for the inputs coming from Canada and Mexico.

Figure 27: Inventories and imports by country of origin



(a) Inputs from China, $\rho = 0.36$

(b) Inputs from Canada and Mexico $\rho = -0.28$

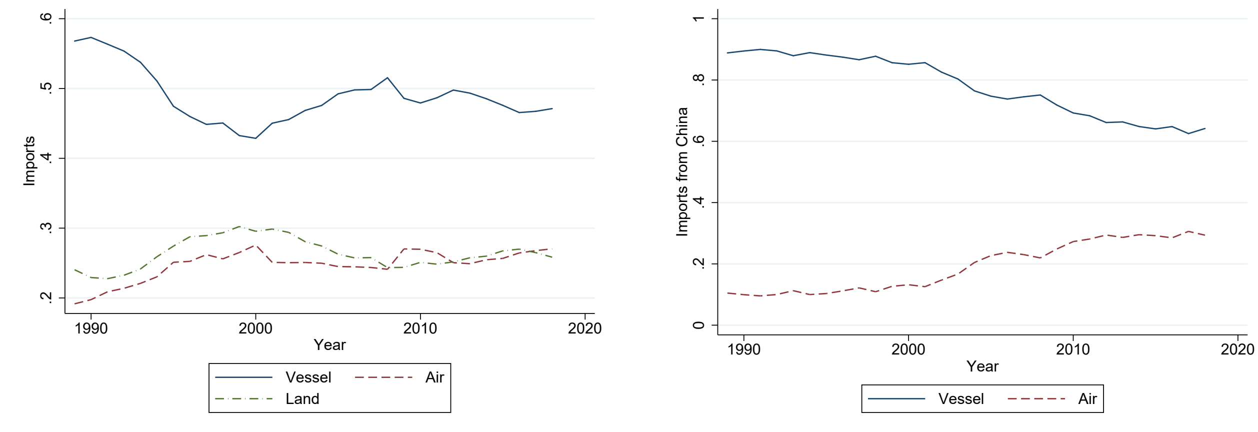
I Transportation methods for imports across time

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.

J Other channels that contribute to the rise in inventories

Firms decision to stock inventories depends on multiple factors. While this paper focuses on the risk from the interaction between a volatile demand and long and stochastic delivery time for inputs, this section explores other important factors. A key extension of the analysis is to explore how variations

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



(a) Transport method for US imports

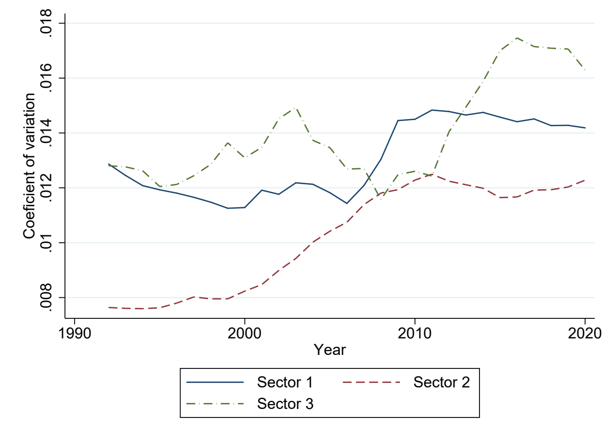
(b) Transport method for imports from China

on the volatility of demand affect firms inventory choices. Figure 29a shows the coefficient of variation, the standard deviation over sales, for monthly sales. This is a measure commonly used by the literature to observe firm-level uncertainty. Across sectors, the coefficient of variation rises over time. This channel could potentially explain the remaining increase in the inventory over sales ratio that the model does not explain.

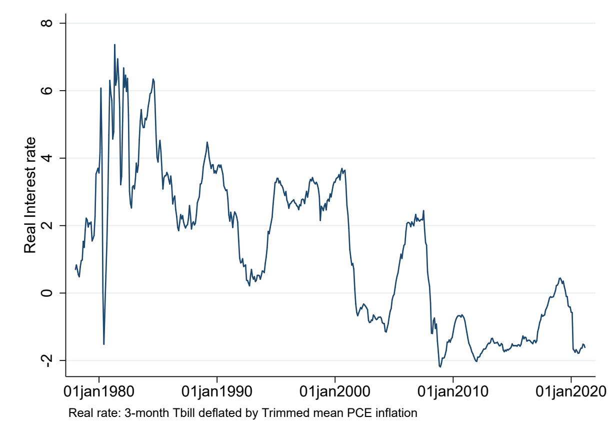
Another important channel that drives inventory levels is the interest rate the firms face. Maccini, Moore, and Schaller (2004) provode evidence on the long run relationship between long term interest rates and inventories. Figure 29b shows the real interest rate for the U.S. I compute the interest rate using the nominal three monthT-bill discounted by the trimmed mean PCE inflation rate published by the Federal Reserve Bank of Dallas[50]. After 2001 there was an important decrease in the real interest rate, which further decreased in 2009. Low interest rates decrease reduce the costs of storing inventories. U.S. manufacturing inventories after 2005 increase despite the consistently low interest rates, which sheds light on the force of the other potential channels driving the increase in inventories.

[50]The Trimmed Mean PCE inflation rate produced by the Federal Reserve Bank of Dallas is an alternative measure of core inflation in the price index for personal consumption expenditures (PCE). Calculating the trimmed mean PCE inflation rate for a given month involves looking at the price changes for each of the individual components of personal consumption expenditures. The individual price changes are sorted in ascending order from ?fell the most? to ?rose the most,? and a certain fraction of the most extreme observations at both ends of the spectrum are thrown out or trimmed. The inflation rate is then calculated as a weighted average of the remaining components. The trimmed mean inflation rate is a proxy for true core PCE inflation rate.

Figure 29: What drives inventories?



(a) Coefficient of variation of sales



(b) Real interest rate

K Time series: inventories increase with imported input intensity

In this section I explore the relationship between inventories and imported inputs across time and industries. I estimate the regression shown in equation (17). For each industry i in period t, y_{it} denotes inventories, x_{it} imported inputs, a_{it} value added, and α_j, α_t are the industry and year fixed affects. Table 7 shows the estimated coefficients, where Panel A shows the relationship between inventories and imported inputs, Panel B for inventories and inputs from China, Panel C for input inventories and imported inputs, and last Panel D for input inventories and inputs from China.

$$\log(y_{it}) = \beta_0 + \beta_1 \log(a_{it}) + \beta_2 \log(x_{it}) + \alpha_i + \alpha_t + \epsilon_{it} \tag{17}$$

Panel A of Table 7 shows the relationship between inventories and imported inputs across industries controlling for time, where an increase of 10% in the imported inputs is associated with an increase in total inventories of 6.3%, controlling for time (column [2]). This result holds when controlling for industries as well, and for value added. Column [7] shows that the coefficient equals 0.45 when controlling for value added and weighting using industry sales. Furthermore the relationship is strengthened using input inventory to estimate equation (17). If I weight the regression using industry sales, then a 10% increase in the share of imported inputs is associated with an increase in input inventories by 1.16 (column [4]), and an increase of 9.8% when controlling for value added in column [7].

Panel B and D replicates the results for the relationship of inventories and inputs from China. It shows the results hold for the relationship across sectors between inventories and inputs from China. Across industries, 10% in inputs sourced from China is associated with an increase in total inventories of 4.1%, and and increase of 5.2% in intermediate input inventories, controlling for time in column [2]. The relationship is also present when controlling for industry value added and year fixed effects. In this case, a 10% increase in the share of inputs from China increases total inventories by 2.0% and input inventory by 2.8%.

L Increasing inventories across manufacturing industries

Manufacturing inventories over sales have been increasing since 2005 across manufacturing industries. This section shows the trend for the 20 *North American Industry Classification System* three digit manufacturing industries, using monthly data from 1992 to 2018 for inventory over monthly sales.

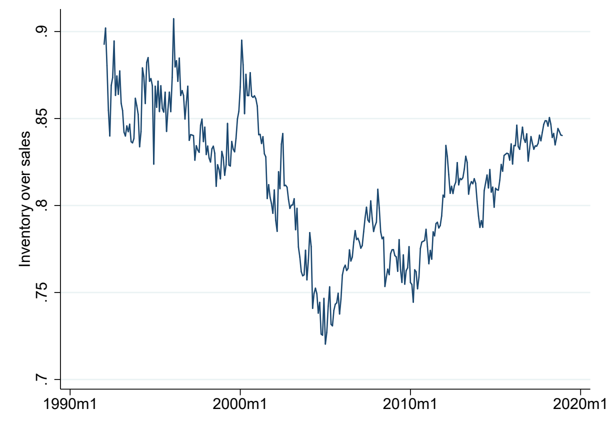
The only manufacturing industry whose inventory over sales ratio continue to decrease throughout the period is industry 322, *Paper Manufacturing* which represents 3% of total inventory and 4% of total output on average for the period 1997 to 2018. For the reminder of the manufacturing industries, inventory over sales ratio observe an increase or in some cases, the decline of inventories stops around 2005.

Table 7: Positive relation between inventories and imported inputs across time and industries

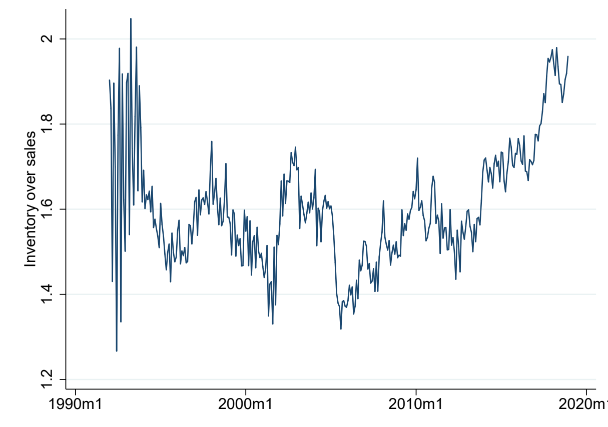
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Panel A				**log(inventory)**			
log(imported inputs)	0.89***	0.63***	0.59***	0.81***	0.35***	0.35***	0.45***
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
log(value added)					0.73***	0.75***	0.51***
					[0.03]	[0.03]	[0.02]
Year FE		✓	✓		✓	✓	
Industry FE			✓			✓	
Weighted using sales				✓			✓
R^2	0.89	0.89	0.89	0.88	0.94	0.94	0.95
N	374	374	374	374	374	374	374
Panel B				**log(inventory)**			
log(inputs China)	0.37***	0.41***	0.41***	0.20***	0.20***	0.21***	0.00
	[0.05]	[0.02]	[0.03]	[0.04]	[0.02]	[0.02]	[0.02]
log(value added)					0.87***	0.86***	0.97***
					[0.03]	[0.04]	[0.02]
Year FE		✓	✓		✓	✓	
Industry FE			✓			✓	
Weighted using sales				✓			✓
R^2	0.13	0.2	0.2	0.06	0.87	0.87	0.87
N	374	374	374	374	374	374	374
Panel C				**log(input inventory)**			
log(imported inputs)	1.13***	0.75***	0.72***	1.16***	0.43***	0.42***	0.98***
	[0.3]	[0.03]	[0.03]	[0.00]	[0.03]	[0.02]	[0.05]
log(value added)					0.90***	0.92***	0.25***
					[0.04]	[0.04]	[0.06]
Year FE		✓	✓		✓	✓	
Industry FE			✓			✓	
Weighted using sales				✓			✓
R^2	0.83	0.85	0.85	0.83	0.84	0.84	0.83
N	374	374	374	374	374	374	374
Panel D				**log(input inventory)**			
log(inputs China)	0.47***	0.52***	0.52***	0.32***	0.28***	0.28***	0.06
	[0.07]	[0.03]	[0.03]	[0.00]	[0.02]	[0.02]	[0.04]
log(value added)					1.03***	1.03***	1.23***
					[0.04]	[0.05]	[0.05]
Year FE		✓	✓		✓	✓	
Industry FE			✓			✓	
Weighted using sales				✓			✓
R^2	0.11	0.2	0.2	0.07	0.77	0.77	0.67
N	374	374	374	374	374	374	374

*D*ata for NAICS 3 digit industries. The table reports the regression results of the log of inventory over the log of imported inputs, for the 17 industries and the period of 1997 to 2018. I include controls for industry value added, and year and sector fixed effects. It includes a total of 374 observations.
Note $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

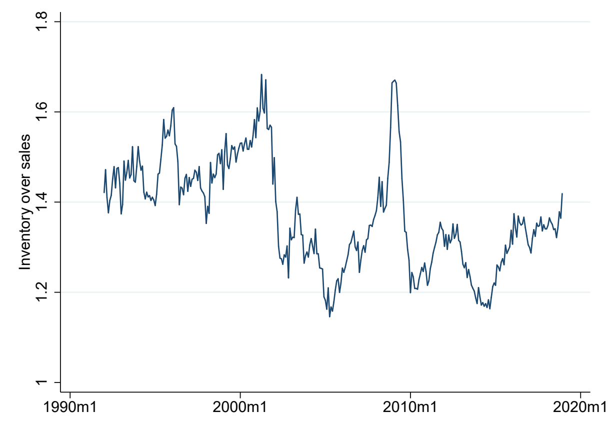
Figure 30: Increasing inventories for manufacturing industries



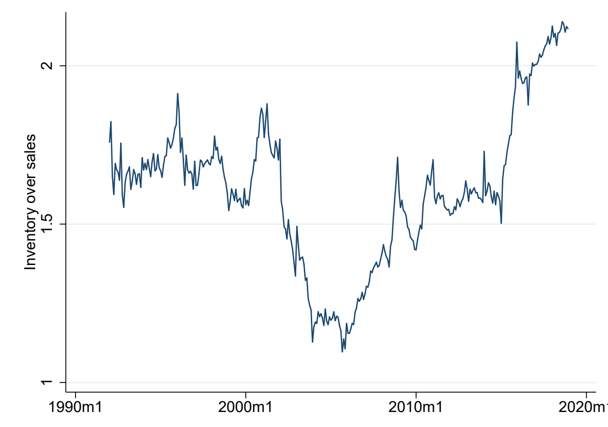
(a) 311, Food and Kindred Products



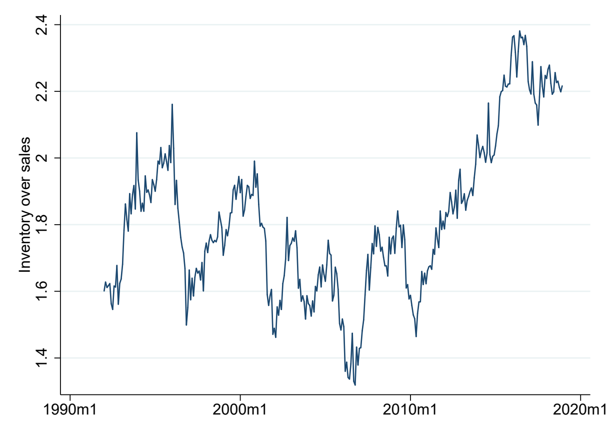
(b) 312, Beverages and Tobacco Products



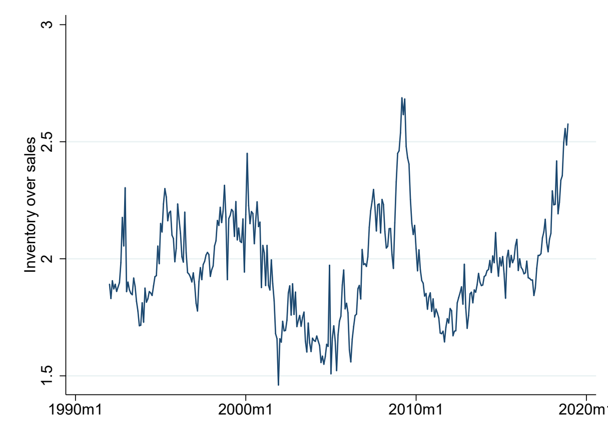
(c) 313, Textiles and Fabrics



(d) 314, Textile Mille Products



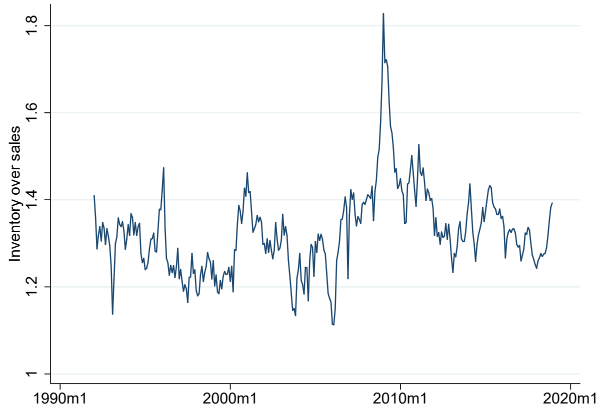
(e) 315, Apparel and Accesories



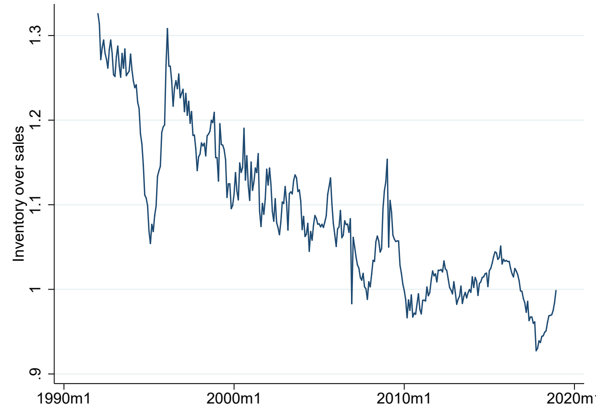
(f) 316, Leather and Allied Products

M Rise in inputs from China across industries

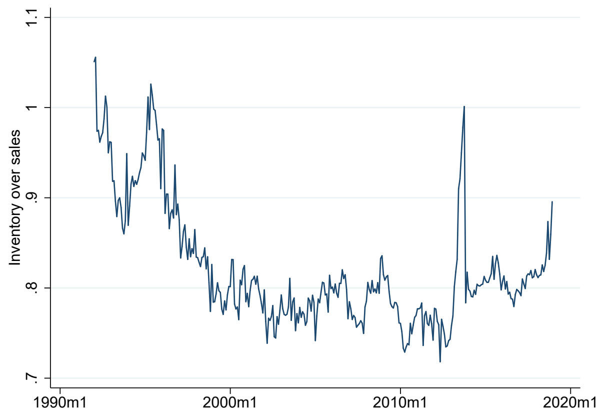
The rise in the share of foreign inputs over total inputs used in production is observed across manufacturing industries. The following figures show the increase of the total share of foreign inputs in



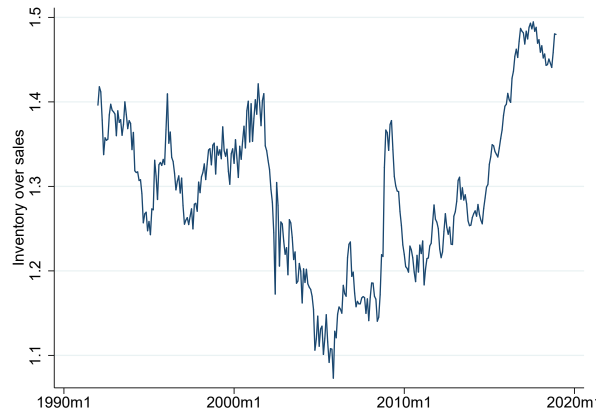
(g) 321, Wood Products



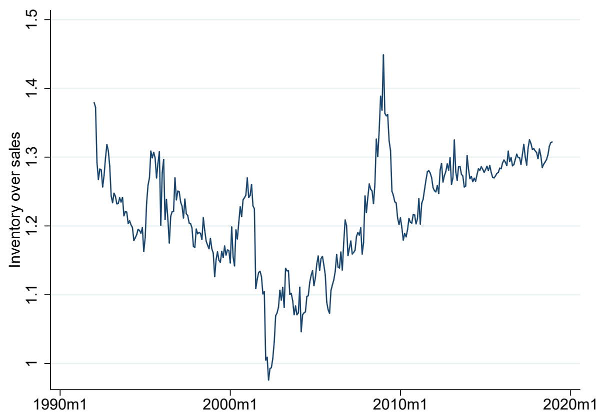
(h) 322, Paper



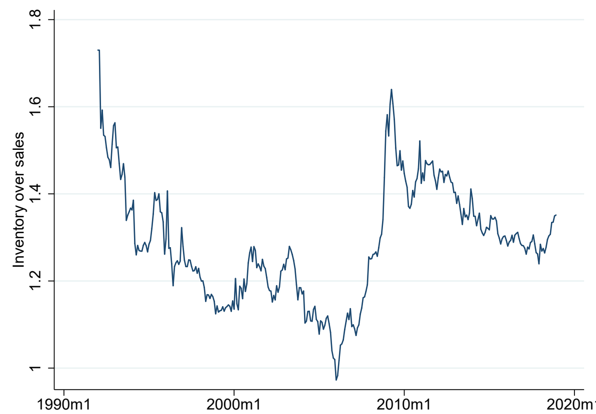
(i) 323, Printing and Related Activities



(j) 325, Chemicals

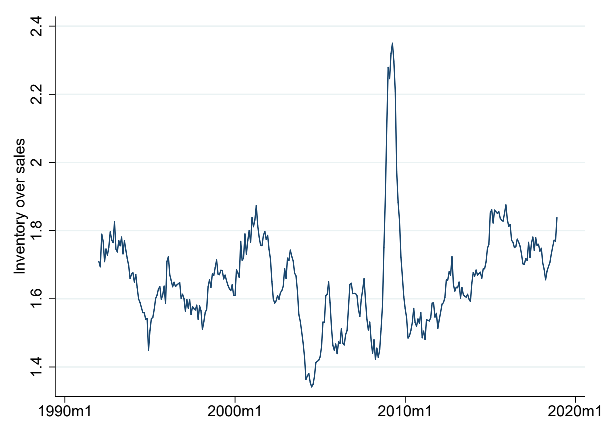


(k) 326, Plastics and Rubber Products

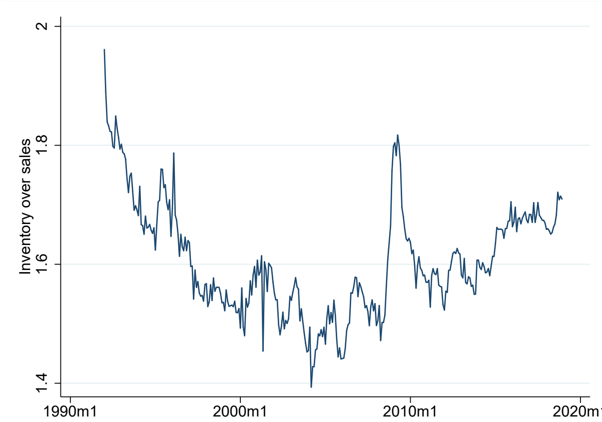


(l) 327, Nonmetallic Mineral Products

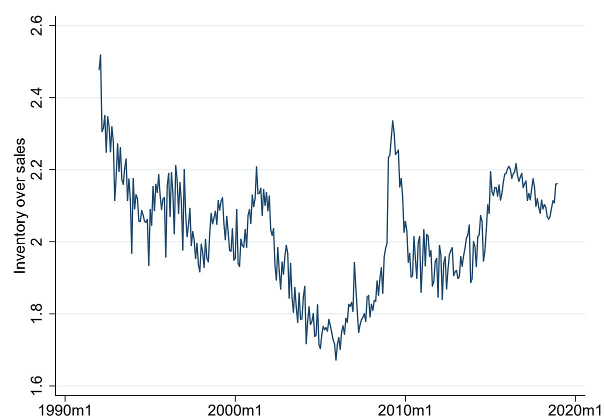
panel A and panel B shows the share of foreign inputs from the three main U.S. trade partners: China, Mexico, and Canada. I plot the share coming from Mexico and Canada together. The share of inputs over total inputs that comes from China has increased across manufacturing sectors.



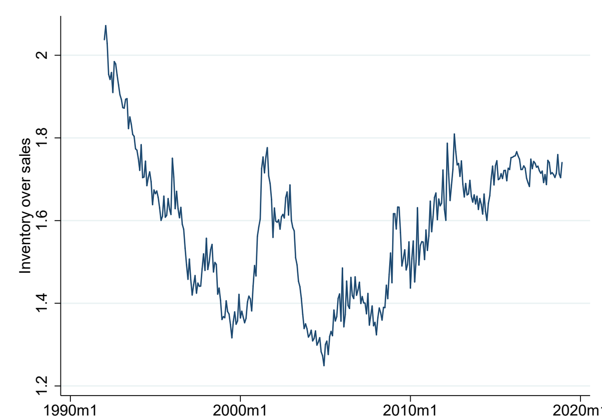
(m) 331, Primary Metal Manufacturing



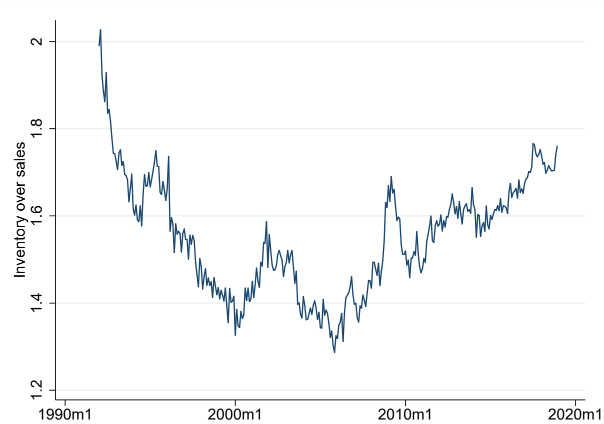
(n) 332, Fabricated Metals Products



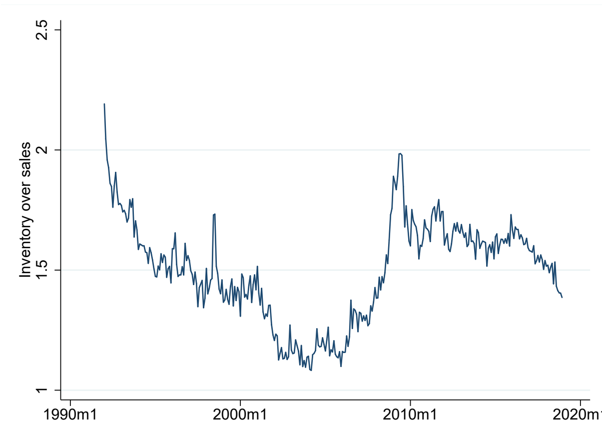
(o) 333, Machinery, except Electrical



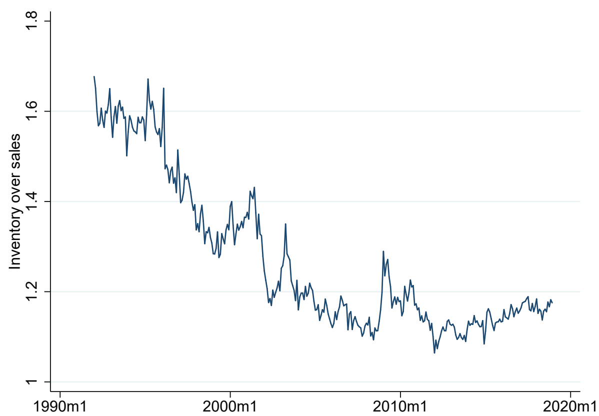
(p) 334, Computer and Electronic Products



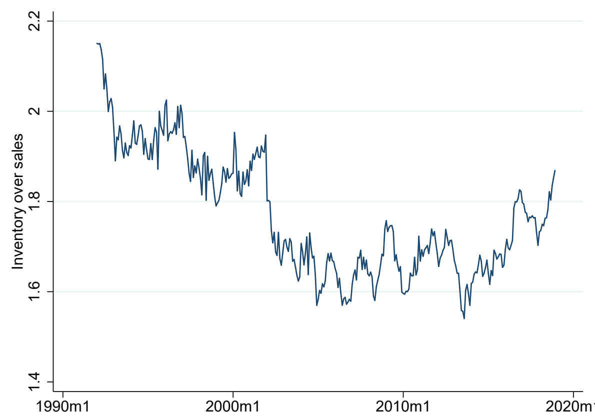
(q) 335, Electrical Equipment



(r) 336, Transportation Equipment

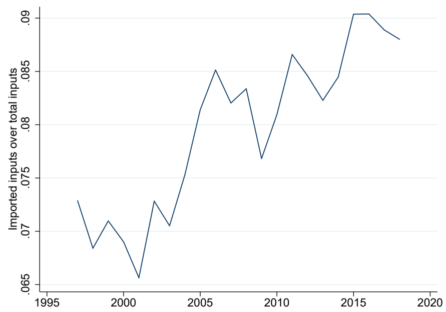


(s) 337, Furniture and Fixtures

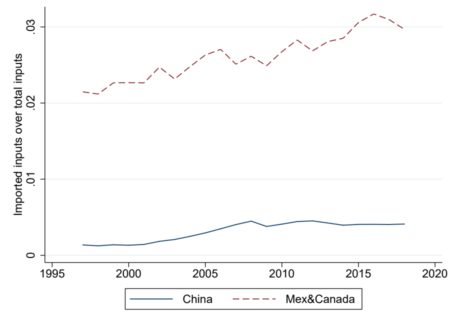


(t) 339, Miscellaneous Manufactured Products

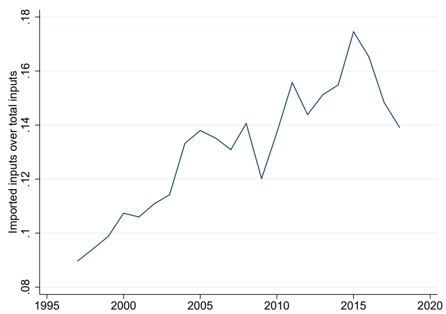
Figure 31: Rise in the share of foreign inputs driven by increase in inputs from China



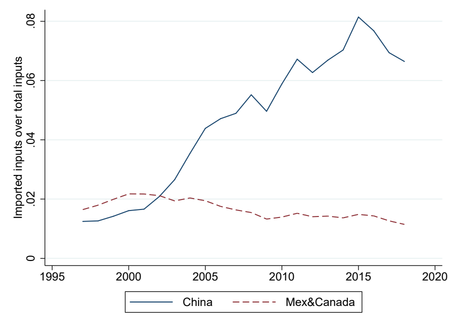
(a) 311+312, Food, Beverages, and Tobacco Products



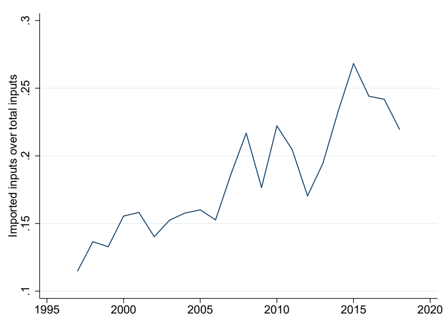
(b) 311+312, Food, Beverages, and Tobacco Products



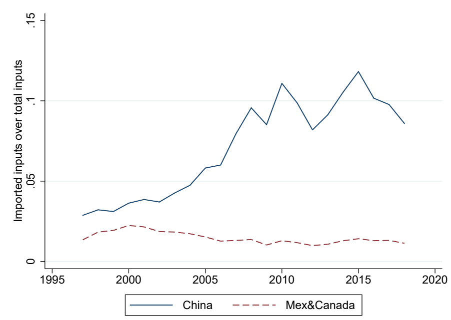
(c) 313+314, Textile Mills, Textiles, and Fabrics



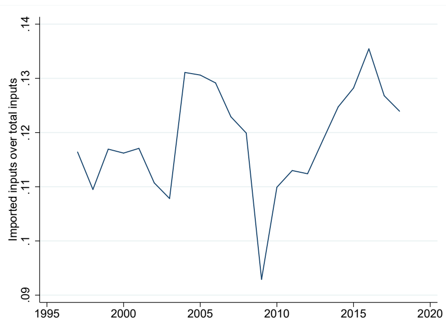
(d) 313+314, Textile Mills, Textiles, and Fabrics



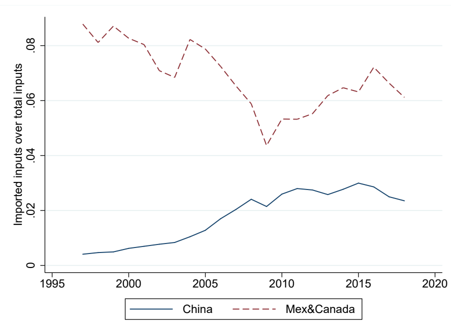
(e) 315+316, Apparel, Accessories, and Leather



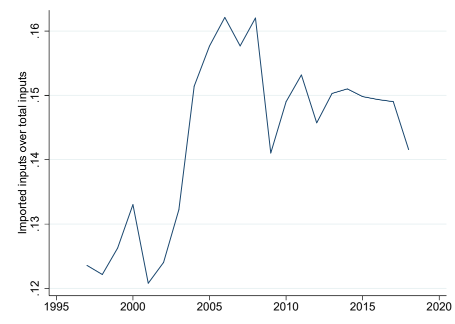
(f) 315+316, Apparel, Accessories, and Leather



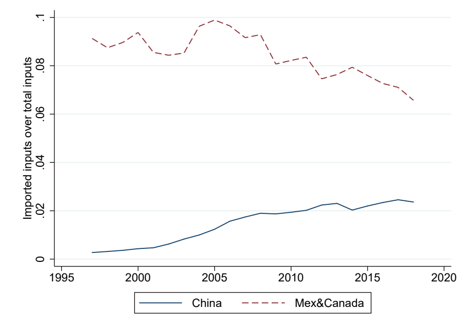
(g) 321, Wood Products



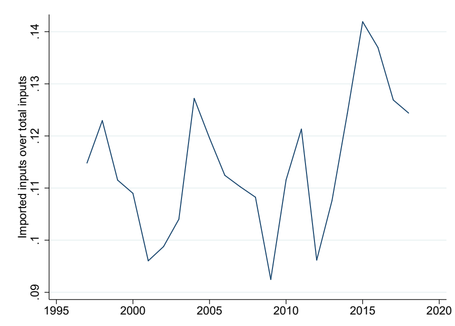
(h) 321, Wood Products



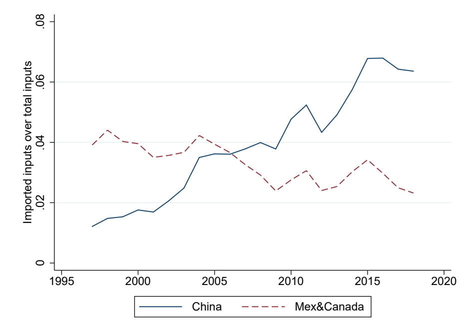
(i) 322, Paper



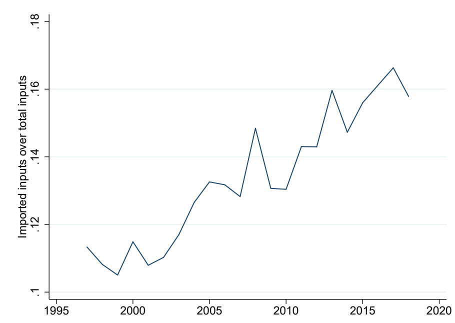
(j) 322, Paper



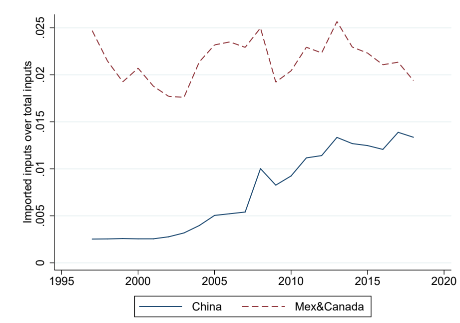
(k) 323, Printed Metals and Related Products



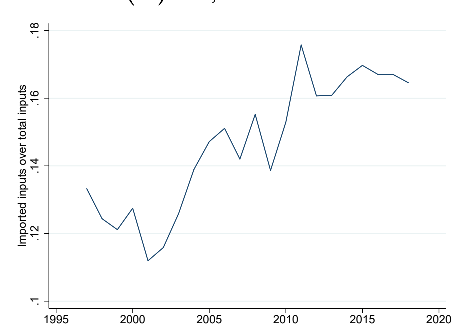
(l) 323, Printed Metals and Related Products



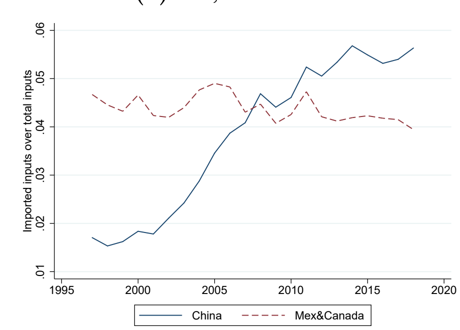
(m) 325, Chemicals



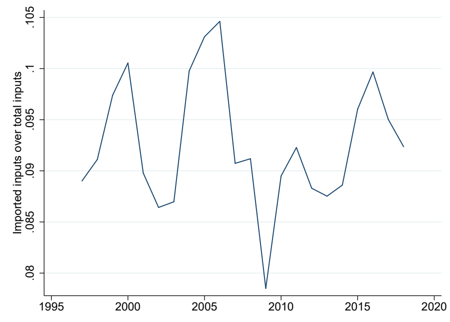
(n) 325, Chemicals



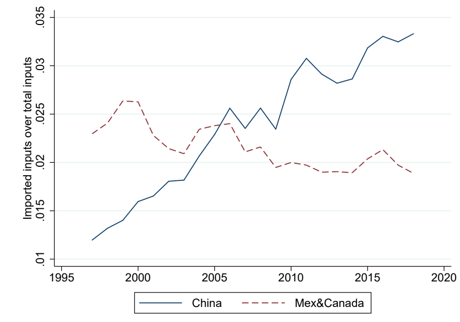
(o) 326, Plastics and Rubber Products



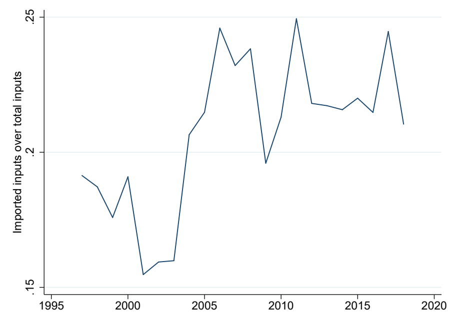
(p) 326, Plastics and Rubber Products



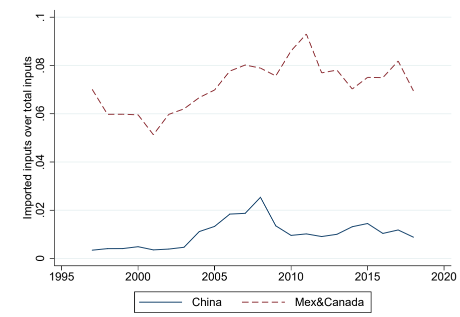
(q) 327, Nonmetallic Mineral Products



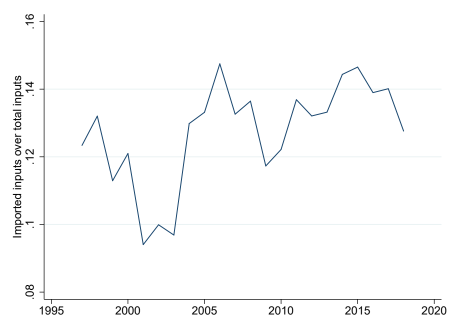
(r) 327, Nonmetallic Mineral Products



(s) 331, Primary Metal Manufacturing

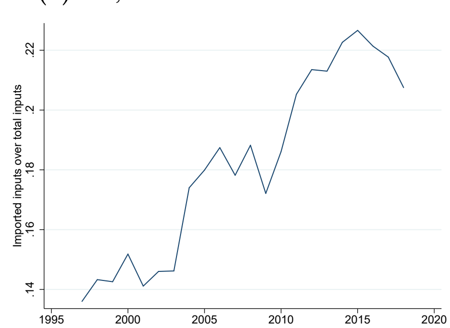


(t) 331, Primary Metal Manufacturing

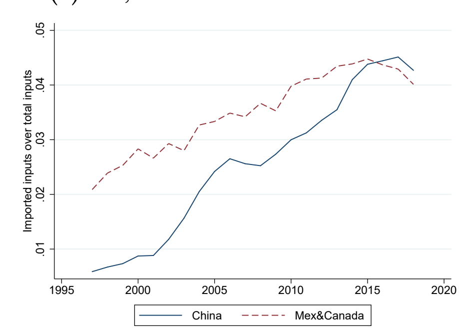


(u) 332,Fabricated Metals Products

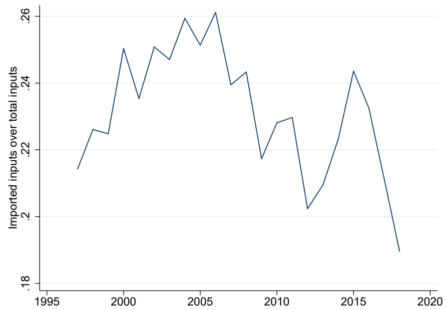
(v) 332,Fabricated Metals Products



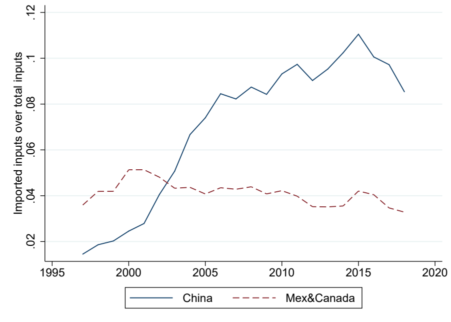
(w) 333, Machinery



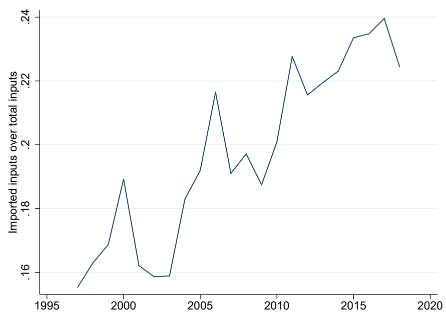
(x) 333, Machinery



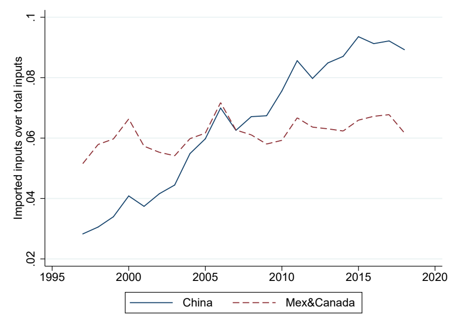
(a) 334, Computer and Electronic Products



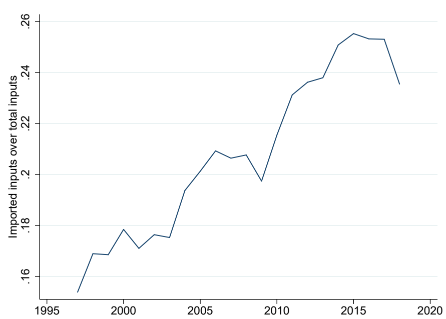
(b) 334, Computer and Electronic Products



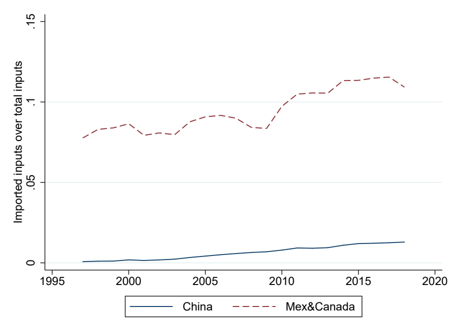
(c) 335, Electrical Equipment



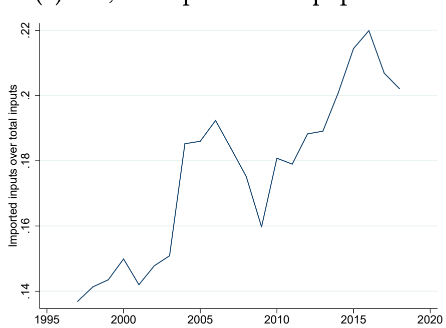
(d) 335, Electrical Equipment



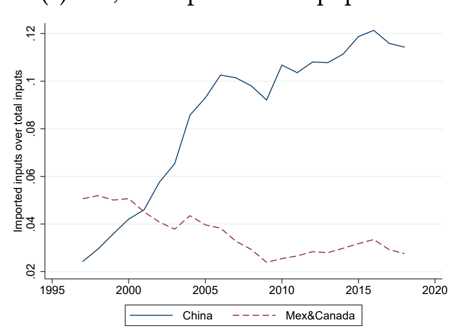
(e) 336, Transportation Equipment



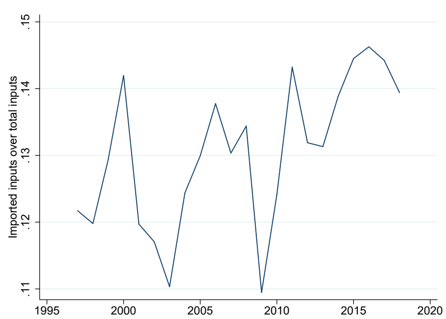
(f) 336, Transportation Equipment



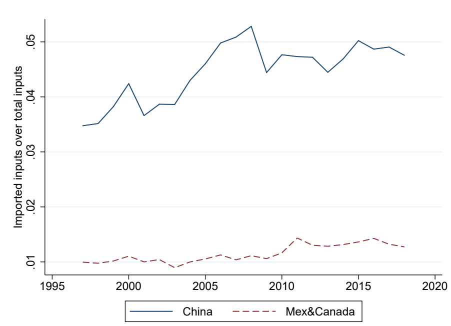
(g) 337, Furniture and Fixtures



(h) 337, Furniture and Fixtures



(i) 339, Miscellaneous Manufacturing



(j) 339, Miscellaneous Manufacturing