Supplemental Appendix

The Cost of Delivery Delays

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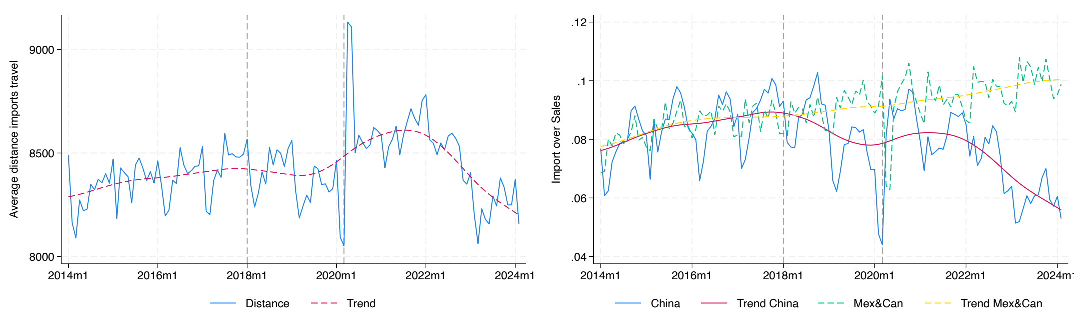
A1. Motivating Evidence

Our research question is motivated by two empirical observations. First, Figure A1 shows that the average distance U.S. imports travel has been decreasing, and in 2024, it reached the lowest point since 2014. We follow Ganapati and Wong (2023) and build a measure of the distance traveled by U.S. imports. The distance, D_t, combines information from the CEPII-BACI dataset on the average distance between countries and monthly import data from the U.S. Census Bureau by country of origin. The distance $D_t = \sum_i \frac{D_i M_{it}}{\sum_i M_{it}}$, where, D_{it} is the distance between country i and the U.S. and M_{it} is U.S. manufacturing imports from i at time t. The decline in distance is driven by the decrease in imports from China that started in 2018. Imports from China fall sharply due to the increase in tariffs imposed by the U.S. government in 2018.

Figure A1. : Decline in distance imports travel due to decline in imports from China



(a) Distance traveled by imports

(b) Decline in imports from China

Note: Panel (a) shows the decline in the average import weighted distance traveled by imports. Panel (b) shows the decline in imports from China and the constant rise in imports from Mexico and Canada, including their HP filtered trend.

The second empirical observation is that U.S. manufacturing inventories to sales ratio have increased from 2018 to 2024, as shown in Figure A2. Panel (a) shows the rise in manufacturing input inventories over sales, measured as the sum of material and supplies and work-in-process inventories, reported by the U.S. Census Bureau. In 2018, the average firm carried around 26 days of sales as input inventories, and by 2024, they carry an additional 3 days of sales in input inventories. Panel (b) shows the rise across the three types of inventories: finished goods, materials and supplies, and work-in-process inventories. The sharpest rise occurs in the materials and supplies inventories and then in work-in-process inventories.

A2. Model

The recursive problem for the final good producer is given by two Bellman equations, which correspond to the choices made within the timing constraint. For clarity, I drop the

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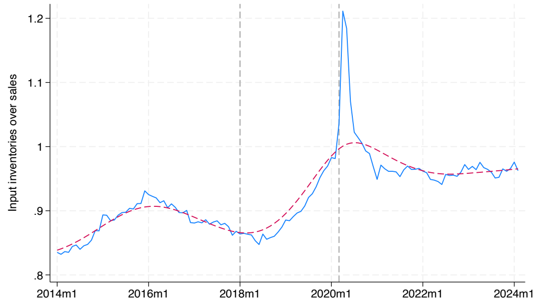
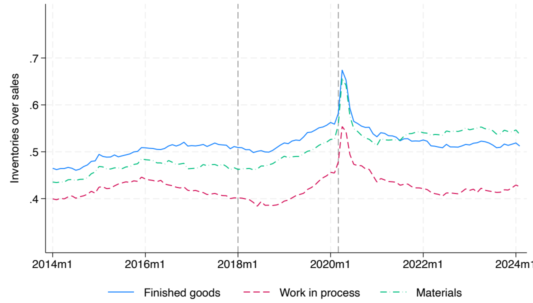
Figure A2. : Rise in manufacturing input inventories to sales



(a) Rise in input inventories over sales



(b) Rise across types of inventories

Note: Panel (a) shows the decline in imports from China and the constant rise in imports from Mexico and Canada, including their HP filtered trend. Panel (b) shows the rise in manufacturing input inventories over sales. Input inventories are the sum of materials and supplies and work-in-process inventories. All data comes from the U.S. Census Bureau.

subscript denoting the specific firm in the unit continuum, j. The value function, $V(s^c,\, s^f)$, defines the optimal order of inputs, given the initial inventories of each input. Then, after shocks are realized and given the order of inputs, firms decide on the amount of inputs and labor to use in production, and set prices. This problem is described by the value function $\tilde{V}(s^c,\, s^f\,, n^c,\, n^f,\, \eta)$, where firms maximize present and future profits subject to 6 constraints: the demand from the consumer, the production function, the two constraints for the two foreign inputs, and the law of motion for the close and far input inventories.

$$
\begin{aligned}
V(s^c,\, s^f) &= \max_{\{n^c, n^f\}} E_\eta \Big[\tilde{V}(s^c,\, s^f,\, n^c,\, n^f,\, \eta)\Big] \qquad \text{where } \eta = (\nu,\, \lambda^c,\, \lambda^f) \\
\tilde{V}(s^c,\, s^f\,, n^c,\, n^f,\, \eta) &= \max_{\{p, x^d, x^c, x^f, s'^c, s'^f\}} \; p\, y(p) - p^d\, x^d - p^c\, n^c - \; p^f\, n^f + \beta\, V(s'^c,\, s'^f) \\
&\quad \text{subject to} \\
&\quad y(p) \; = \nu\, Y\, (P/p)^\epsilon \\
&\quad y = \Big(\theta^{c\,\frac{1}{\sigma}}\; x^{c\, \frac{\sigma-1}{\sigma}} \; + \; \theta^{f\,\frac{1}{\sigma}}\; x^{f\, \frac{\sigma-1}{\sigma}} \; + \; (1-\theta^c-\theta^f)^{\frac{1}{\sigma}}\; x^{d\, \frac{\sigma-1}{\sigma}} \Big)^{\frac{\sigma}{\sigma-1}} \\
&\quad x^c \; \leq \; s^c \; + \; \lambda^c\, n^c \\
&\quad x^f \; \leq \; s^f \; + \; \lambda^f\, n^f \\
&\quad s'^c = (1 \; - \; \delta)\, (s^c \; + \; n^c \; - \; x^c) \\
&\quad s'^f = (1 \; - \; \delta)\, (s^f \; + \; n^f \; - \; x^f)
\end{aligned}
$$

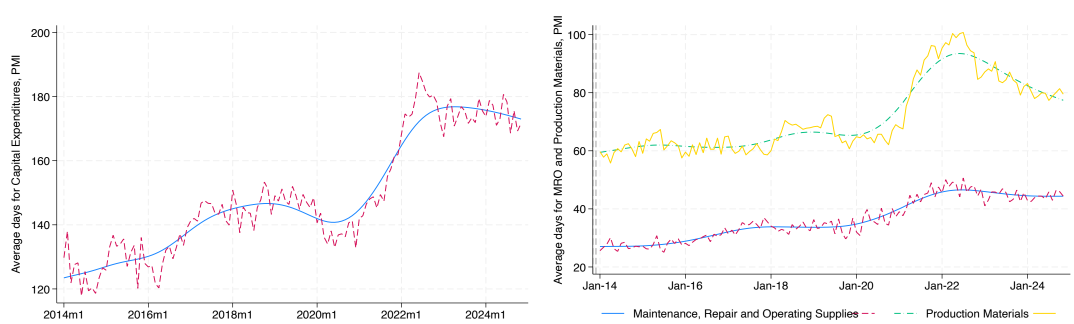
Firms behave monopolistically by setting prices. If a firm is unconstrained in the amount of inventories it needs to meet the demand, then the price it sets is equal to a markup over the cost-minimizing marginal cost. If the firm is constrained by the available input quantity, it distorts its optimal price by changing the input mix. The binding constraint forces the firm to a suboptimal pricing strategy. As a consequence of the risk of foregone profits, the interaction between positive delivery times and demand shocks creates incentives for firms to hold inventories. Since firms have to wait for their inputs to arrive, while their demand changes every period, they need to store some of these inputs as inventories to ensure they will be able to meet their demand. Additionally, firms hold inventories because delivery times are stochastic, and firms do not have certainty regarding when they will arrive. On the other hand, inventories are costly; they depreciate at a rate δ and firms face a discount rate β. The cost of holding inventories creates a trade-off between the relative price and delivery times across inputs.

We assume there is a unit continuum of the input producers that produce each variety, j. We abstract from modeling the problem of the inputs firms, and take as given the input prices. This is equivalent to assuming a constant return to scale technology for the input firms, where $x^i_j = A^i \ell^i_j$ and thus $p^i = w^i/A^i$ for $i \in \{d, c, f\}$. All firms along the continuum have access to the same technology and do not face any shocks, so there is a unique price for the unit continuum of the inputs, p^d, p^c, p^f.

A3. Comparing our model-based to the ISM data

The Institute of Supply Management, ISM, reports average lead times used in their Manufacturing PMI Index. They report lead times for maintenance, repair, and operating supplies (MRO), production materials, and capital expenditures. Figure A3 shows the growth in lead times across the three time series reported. Lead time start rising in 2020 and remain high in 2024.

Figure A3. : Rise in lead times reported by the ISM



(a) Average lead times in capital expenditures

(b) Production materials, and maintenance, repair and operating supplies

Note: Panel (a) shows the average lead times for capital expenditures and their HP filtered trend, and panel (b) shows the times for production materials, and maintenance, repair and operating (MRO) supplies reported by the ISM.

We compare our model measure of delivery times to the data on lead times reported by the ISM. To do so, we replicate the ISM methodology in our model. We take a large number of draws, N of each of the domestic and foreign distributions of delivery times for each quarter between 2018 and 2024. Then we classify each draw in each of the time bins defined by the ISM, bin_j, $j \in \{5, 30, 60, 90, 180, 365 \text{ days or more }\}$. We take the average across the bins for each distribution of delivery times for inputs from China and ROW. Then, to compute our measure of average days, we take an import-weighted average across input, as follows.

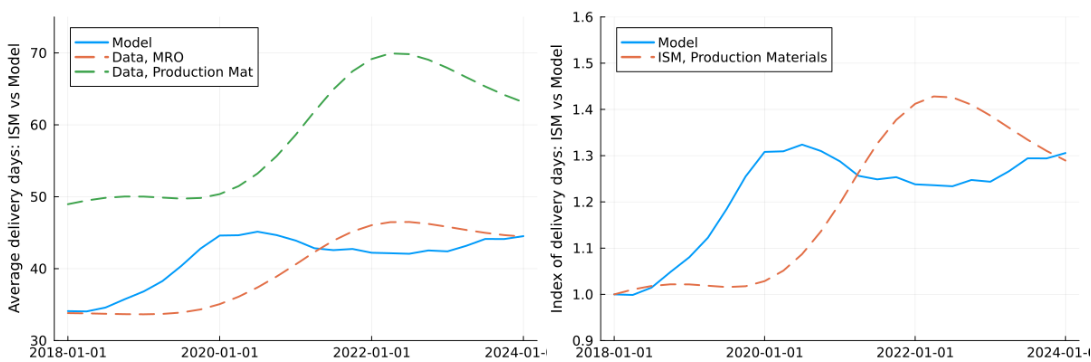
$$\text{days}^{\text{model}}_t = \frac{\text{imports}^c_t}{\text{total imports}_t} \frac{\sum_j \text{bin}_j \sum_{i\in \text{bin}_j}^N \text{days}^c_i}{N} + \frac{\text{imports}^f_t}{\text{total imports}_t} \frac{\sum_j \text{bin}_j \sum_{i\in \text{bin}_j}^N \text{days}^f_i}{N} \tag{A1}$$

where days^c_i and days^f_i are draws from the estimated log-normal delivery time distributions, and bin_j is the days in a given bin defined by ISM.

Figure A4 shows the model comparison to the two ISM series for maintenance, repair, and operating supplies (MRO), and production materials. Panel (a) shows the model delivery days computed using Equation (A1) and the lead times reported for MRO supplies and Production Materials. The model-based initial delivery times for imports equals 34 days, which is similar to the days reported for MRO supplies in 2018. The model-based days grow faster than the ISM days at the beginning, but the total growth from 2018 to 2024 equals 11 days for both the model and MRO days. A simple explanation for the different dynamics in the model and the data is that we do not include any aggregate change in demand. As a consequence, the increase in inventories partly driven by changes in aggregate demand during the Covid pandemic is loaded on delays in the model. As changes in demand subside, the model correctly captures the rise in delays that explains the new level of inventory-to-sales ratio.

The lead times for Production Materials start at 49 days in 2018 and grow by 14 days. While the level is off by 7 days with respect to the Production Materials, the growth in both series equals 13 days and 11 days, respectively. Panel (b) shows the growth of the Production Materials lead times and our model-based measure of days.

Figure A4. : Comparing our measure on delivery days to ISM



(a) Measures of delivery days (b) Growth in delivery days

Note: Panel (a) shows the average lead times for our model-based days, and for the MRO supplies and production materials reported by the ISM. Panel (b) shows the growth in delivery days in the model and in the production materials series reported by the ISM.

A4. Robustness

In this section, we include a robustness exercise to include a larger increase in tariffs, than the 15pp we use in the main text. Here, we use the average increase in tariffs of 19pp increase. The results hold across both exercises.

We first recalibrate the benchmark model to fit the larger raise in tariffs. The weight of the inputs from China and ROW are equal to 0.084 and 0.44 respectively. The variance in demand equals 0.623, which are similar to our benchmark estimates. The key change is observed in the elasticity of inputs, σ, since it is calibrated to match the 3.23 percentage point decline in imports from China over sales observed from 2018 to 2024, given the rise in tariffs of 19 percentage points. In this case, the elasticity of substitution equals 3.97, which is lower than the 4.5 used before. The larger change in the price of inputs from China allows for a smaller elasticity.

For this tariff change, we need a 30-day additional delay for the foreign inputs to match the observed input inventory over sales. Delays rise since inputs are less substitutable, thus we need a larger change in the standard deviation of delivery times to match the inventory data. Table A1 shows the results across the different stationary distributions. The rise in a 30-day delay and an increase in tariffs for inputs from China of 19 percentage point leads to a drop in output of 8.5% and an increase in prices of 2.1%. Inventories are influenced by two opposing factors. On one hand, the increase in tariffs prompts firms to shift away from Chinese inputs, which have the longest delivery times, reducing the need for inventories. On the other hand, as delays grow, firms are compelled to hold more inventories per unit used. The impact of delays outweighs the substitution effect, resulting in an 11.2% increase in total inventories relative to sales. Isolating the effects of delays, we show that output drops by 2.4% and the final good prices increase by 0.4%. In this case, inventories rise 17%.

Table A1—: Quantify costs of tariffs and delays with a 19 percentage point increase

	(1) **2018 Benchmark**	(2) **Tariffs** $\uparrow \tau^c$	(3) **Delays** $\uparrow$ **delay**	(4) **2024** $\uparrow \tau^c$ **+ delay**	(5) **Tariffs vs 2018**	(6) **Delays vs 2018**	(7) **2024 vs 2018**
Tariff	$\tau^c p^c = 0.84$	$\tau^c p^c = 1.0$	$\tau^c p^c = 0.84$	$\tau^c p^c = 1.0$			
Change delays	Δ delay = 0	Δ delay = 0	Δ delay = 30	Δ delay = 30			
Output	0.919	0.860	0.897	0.841	-6.5%	-2.4%	-8.5%
Prices	1.345	1.369	1.351	1.374	1.8%	0.4%	2.1%
Inputs China/sales	0.088	0.055	0.087	0.055	-37.3%	-1.7%	-37.5%
Inventories China/sales	0.079	0.050	0.089	0.059	-36.8%	13.6%	-24.3%
Inputs ROW/sales	0.277	0.292	0.273	0.288	5.4%	-1.6%	3.7%
Inventories ROW/sales	0.210	0.222	0.248	0.262	5.7%	18.3%	24.8%
Inputs domestic/sales	0.368	0.387	0.374	0.392	5.2%	1.6%	6.6%
Inventories/sales	0.288	0.271	0.337	0.321	-5.9%	17.0%	11.5%

Columns 1 to 4 in the table report the average of the stationary distribution for different variables. Column one represents the benchmark economy of 2018 with the low initial tariffs and no additional delays. Column two isolates the effects of tariffs, and computes the steady state average of an economy with the raise in tariffs and low delays. Column three shows an economy with high delays and the initially low tariffs. Then, column four shows an economy with both the rise in tariffs and delays. The last three columns compares the economies relatively to the benchmark 2018 economy to show the effects of tariffs, in column 5, the effect of delays, column 6, and both changes in column 7.

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REFERENCES

Ganapati, Sharat, and Woan Foong Wong. 2023. "How far goods travel: global transport and supply chains from 1965–2020." *Journal of Economic Perspectives*, 37(3): 3–30.