Online Appendix for "The Impact of NAFTA on Prices and Competition: Evidence from Mexican Manufacturing Plants"

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A Data appendix

A.1 Example of products in the EIM

Table A1 displays the examples of EIM products at different levels of aggregation.

Table A1: Example of EIM Products

CMAP94 Code	Product Code	Description
31		Food and Beverages Sector
3112		Manufacturing of Dairy Products Subsector
311201		Processing and Packaging of Milk Industry
	311201001	Condensed Milk
	311201002	Dehydrated Milk
	311201003	Pasteurized Milk
	311201004	Pasteurized and Homogenized Milk
	311201005	Rehydrated Milk
	311201006	Ultra-Pasteurized Milk
		⋮
34		Paper Industries Sector
3410		Manufacturing of Cellulose and Paper Subsector
341021		Paper Manufacturing Industry
	341021001	Airmail Paper
	341021002	Bond Paper
	341021003	Copy Paper
	341021004	Paper for Textbooks
	341021005	Newsprint
	341021011	Corrugated paper for boxes
	341021012	Liner paper
		⋮

Note: CMAP94 corresponds to the Mexican Classification of Activities and Products. The first column shows the CMAP94 code for sector, subsector, or class. The second column includes the full 8-digit CMAP94 product code. The third column shows the product description.

A.2 Construction of variables from the EIA

To construct plants' capital stock from the information in the EIA, we use the perpetual inventory method. We use the book value reported in the 1994 survey as an initial value. According to this method, K^z_{jt},the capital of type z from plant j during period t, evolves according to:

$$K^z_{jt} = (1 - \delta_z)K^z_{jt-1} + I^z_{jt-1},$$

where δ_z is the depreciation rate of capital of type z, and $I^z_{j,t-1}$ is investment at time $t-1$ from plant j on type z capital.

We choose the classification of capital that matches both the 1994–2003 and 2003–2008 surveys. The types of capital used are:

- Machinery and production equipment, deflated by the total machinery and equipment price deflator.
- Transportation equipment, deflated by the national price deflator of transportation equipment.
- Construction of buildings and land, deflated by the total construction price deflator.
- Other fixed assets, including office equipment and others items such as computers, deflated by the total investment price index.

We use the mid-point of the Mexican fiscal depreciation band from Iacovone (2008), listed in Table A2, as δ_j during the construction of the capital stock variable.

Table A2: Capital depreciation rates

Type of Fixed Assets	Fiscal Depreciation Band	Applied Depreciation Rate
Machinery and Equipment	5-15%	10%
Buildings	3-8%	5.5%
Transportation Equipment	15-25%	20%
Office Equipment and Others	7-35%	21%

Note: This table includes the fiscal depreciation bands from the Mexican Ministry of Finance.

Our production function estimation requires real inputs of capital, labor, and materials. To construct these measures, we augment EIA data with price indices from various sources. INEGI provides price deflators for domestic intermediate inputs. Data are published monthly for the 4-digit NAICS classification, and thus they are one level of aggregation higher than our class definition. Each NAICS code is matches with the CMAP94 class using the concordance provided by INEGI.[1] By doing this, we match 86% of CMAP94 classes with a 4-digit NAICS. For the remaining 14% that we could not match directly, we use the intermediate input price index that more closely matched the corresponding NAICS classification.[2] For imported intermediates, we follow Iacovone (2008) and use the U.S. intermediate input price deflator for exported, non-agricultural supplies and materials (excluding fuels and building materials), adjusted for exchange rate fluctuations.[3] We use investment price deflators by type provided by INEGI to convert investment flows into real

[1] This concordance is available at http://www.inegi.org.mx/est/contenidos/proyectos/SCIAN/presentacion.aspx

[2] The majority of unmatched industries occur because the price series exists only after 2011. These classes were too small earlier such that an intermediate input price series could not be constructed appropriately.

[3] The input price deflator is available from the U.S. Bureau of Labor Statistics. Exchange rate data come from the Bank of Mexico.

terms. Since investment price deflators are unavailable by industry, we use deflators at the national level. INEGI provides separate deflators for non-residential construction, production equipment excluding transportation equipment, and transportation equipment.

A.3 Sampling of EIM and EIA and their summary statistics

For the two surveys, INEGI chooses the sample of plants in the following way. First, the 206 classes are ranked in decreasing order based on total value of production at factory gate prices from the industrial census of 1993. The most important activities, jointly representing 85% of manufacturing output, are then selected. Other classes of special interest in defining national accounts are also added, even if their contributions are small.

Second, within each class, plants are ranked in decreasing order based on production value at factory gate prices. Plants are sequentially added to the sample until the total number of plants accounts for approximately 85% of the class's output value. All plants larger than 100 employees are also included, regardless of whether the 85% threshold has already been reached. For highly concentrated classes, in which the 85% threshold is reached by adding fewer than 15 plants, all plants are included.

While these surveys are skewed toward the largest plant, they cover a large percentage of value added in manufacturing in the formal sector. Since the informal sector accounts for on average 11% of value added in manufacturing in Mexico, the share of value added of formal establishments in manufacturing not covered by the sample is very small.

Table A3 shows the average number of plant–product pairs per sector, together with the average number of products per plant. Table A4 displays the summary statistics for plants in each sector.

Table A3: Average number of plant–product pairs per sector

Sector	# of Products			Avg. # of Products Per Plant		
	Total	Domestic	Exported	Total	Domestic	Exported†
	(1)	(2)	(3)	(4)	(5)	(6)
Food and Beverage	2,963	2,622	340	3.66	3.23	1.55
Textile Manufacturing	548	417	131	2.36	1.78	1.13
Apparel Manufacturing	1,240	1,091	149	3.00	2.64	1.13
Wood and Furniture	610	547	63	4.13	3.70	1.57
Paper Industries	850	752	98	2.62	2.33	1.16
Chemical Industries	2,908	2,348	561	4.11	3.31	1.66
Non-Metallic Minerals	839	708	130	2.86	2.40	1.67
Metallic Manufacturing	1,105	809	296	3.17	2.30	1.66
Machinery & Equipment	890	666	225	2.76	2.06	1.17

Note: Columns 1–3 show the average number of plant–product pairs per sector for all years in the sample. Columns (4)–(6) show the average number of products per plant for all years in the sample.
†Average number of exported products for exporter plants.

Table A4: Plant-level summary statistics

Sector	# of Plants			Average (Thousands of Dollars)				
	Total	Exporter	Single	Employees	Sales	VA/Employees	Materials	Capital
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food and Beverage	814	224	151	378.9	35,823.9	164.7	16,230.4	7,363.1
Textile Manufacturing	235	118	85	248.9	13,339.1	56.3	5,568.6	4,116.2
Apparel Manufacturing	410	135	143	148.9	4,864.8	25.5	2,217.0	771.4
Wood and Furniture	150	42	43	133.6	4,681.2	15.2	2,457.6	1,136.5
Paper Industries	318	81	165	210.5	16,761.4	45.5	6,907.1	5,543.5
Chemical Industries	707	339	167	244.0	24,221.0	48.6	10,123.2	6,940.8
Non-Metallic Minerals	292	79	125	212.1	19,815.1	67.6	2,938.7	9,455.3
Metallic Manufacturing	354	183	123	242.7	32,703.9	36.6	18,443.7	8,752.3
Machinery & Equipment	325	192	96	467.0	78,896.3	26.3	44,954.4	15,835.7

Note: Includes sector-level averages of plant-level variables across all years in the sample. Units in Columns (5)–(8) are in 1994 U.S. dollars, converted from Mexican pesos using the average 1994 exchange rate.

A.4 Concordance between CMAP94 and HS

Constructing the concordance between the CMAP94 classification and the HS classification involves matching approximately 5,000 product codes from the CMAP94 classification to one or sometimes multiple HS codes. The matching is done using the CMAP94 product description provided by INEGI. The concordance table is available from the authors' webpages. The column labeled CMAP94 class code has the CMAP94 class identifier at the 6-digit level. The column labeled CMAP94 Product Code has the unique product identification number within each class. Finally, the column labeled HS Code has the HS product code. Note that a product in the table is a unique class–product code combination. For example, the product toy airplane has a class code 390006 corresponding to Toys plus a unique product identifier within the class of 012, and corresponds to an HS 6-digit code 950390.

A.5 Constructing the tariff measures

Our main data source for the tariff data is from the WITS. Tariff data for Mexico before 1995 are only available for the year 1991. However, since Mexican tariffs remained unchanged from 1991 to 1993 (Faber, 2014), we use the 1991 tariff schedule as the schedule for 1993. To construct the tariff schedule for the year 1994, we rely on the institutional details of NAFTA. In particular, we use the fact that under NAFTA tariffs on goods coming from the U.S. were either set to zero in 1994 or declined by a constant yearly magnitude from 1993 to 1995. For example, if the NAFTA tariff of a product was 15% in 1993 and 5% in 1995, we assume that the tariff was 10% in 1994. By contrast, if the tariff was already 0% in 1995, we assume that the tariff was set at 0% in 1994.

To construct the measure of intermediate input tariffs described in the main text of the paper, we use two concordances to match the IO tables (recorded in NAICS classification) with the CMAP94 classification. To do this, we first use a concordance between the NAICS classification and the International Standard Industrial Classification (ISIC), and then use the second concordance to match the ISIC classification to the CMAP94 classification. Both concordances are provided by INEGI.

Table A5 reports the summary statistics for the three measures of tariffs that we construct. The table shows that across the three measures, tariffs declined significantly under NAFTA.

Table A5: Summary statistics for tariff rates

	1993			2008		
	Mean	Median	S.D.	Mean	Median	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
Output Tariffs	14.8	15.0	4.3	0.2	0.0	1.0
Intermediate Input Tariffs	9.4	9.2	2.3	0.1	0.0	0.0
U.S. Tariffs	5.2	4.3	4.5	0.1	0.0	0.5

Note: The table shows the mean, median, and standard deviation of the tariffs in 1993 and 2008 in percentage points.

In Tables A6 and A7, we show the correlation matrix for our tariff measures at different levels of aggregation. First, in Table A6, we report the correlation between the constructed tariff measures at the product or class level.[4] As the table shows, the three tariff measures are positively correlated.

Table A6: Correlations between tariff measures (product or class-level)

	Output Tariffs	Input Tariffs	U.S. Tariffs
Output Tariffs	1.00		
Input Tariffs	0.83*	1.00	
U.S. Tariffs	0.60	0.62*	1.00

Note: The table shows the correlation matrix for our three measures of tariffs at the product and class level for the years 1994–2008.
∗: Output and U.S. tariffs are aggregated to the class level to compute the correlation between input tariffs.

For the main analysis in our paper, we use these constructed tariff measures and compute the tariffs for each plant–product pair (regression (1) in motivating facts and regression (7) in the main analysis). It is therefore crucial to have enough variation left at the plant–product level to identify the coefficients separately for each tariff measure. In Table A7 we report the tariff measures' correlation coefficients that are constructed at the plant–product level. The correlation coefficients become even smaller, suggesting that there is enough residual variation to identify the coefficients on tariffs in the main specification.

[4]Since the output and U.S. tariffs vary at the product level and input tariffs vary at the class level, we report the correlation that involve input tariffs by first aggregating output and U.S. tariffs at the class level.

Table A7: Correlations between tariff measures (plant–product level)

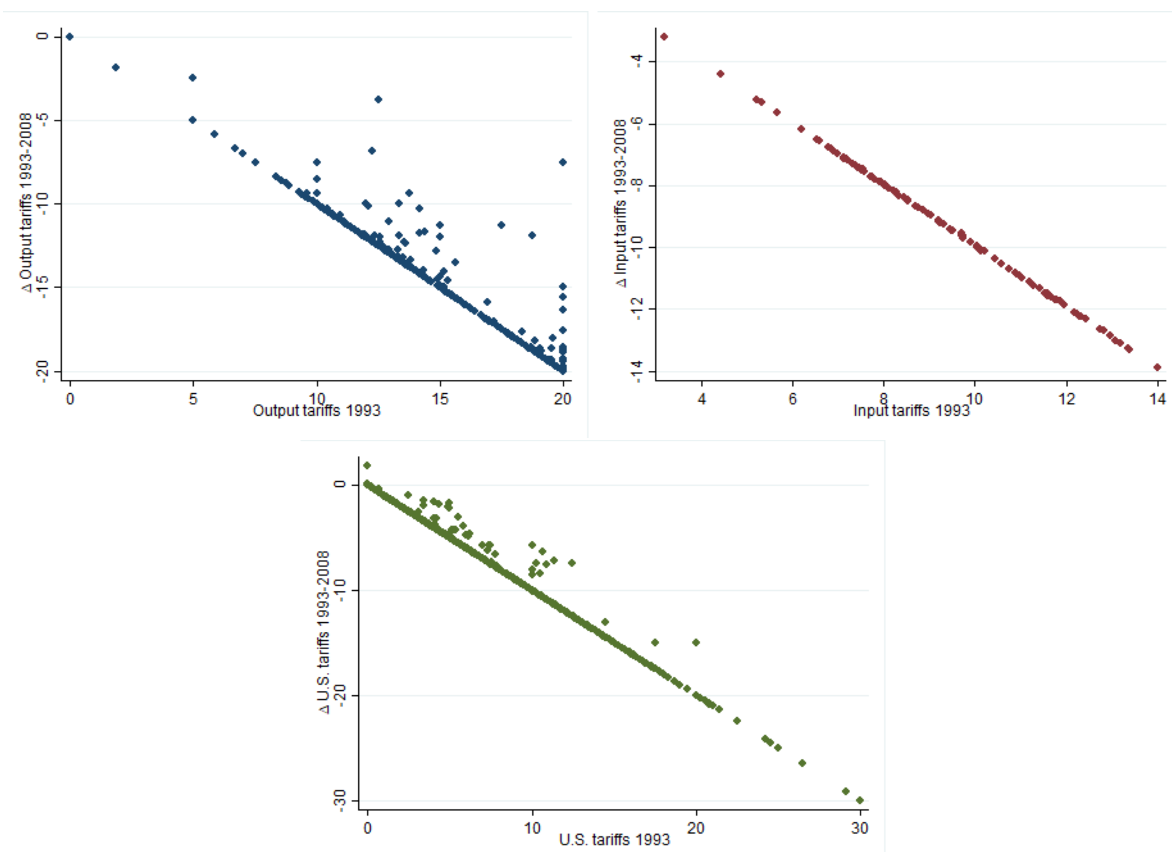
	Output Tariffs	Input Tariffs	U.S. Tariffs
Output Tariffs	1.00		
Input Tariffs	0.24^{*}	1.00	
U.S. Tariffs	0.32	0.21^{*}	1.00

Note: The table shows the correlation matrix for our three measures of tariffs at the plant–product and plant–class level for the years 1994–2008.

$*$: Output and U.S. tariffs are aggregated to the plant–class level to compute the correlation between input tariffs.

Finally, we show in Figure A1 the scatter plots of tariff levels in 1993 (before NAFTA), and tariff changes between 1993 and 2008. The negative correlation of all three tariff measures shown in the figure indicates that declines in tariffs under NAFTA were greatest in products that had large initial tariffs before NAFTA. The graphs provide further evidence against the hypothesis that tariffs were set to protect specific products or industries. If this were the case, then products with higher initial tariffs would be expected to face a lower subsequent tariff decline.

Figure A1: Scatter plots of the 1993 tariff level and the changes between 1993 and 2008



B More details of the empirical framework

Here, we provide details of the framework outlined in Section 4.1. We do so by first listing the framework's key assumptions and then providing additional details for each of the steps presented in Section 4.1.

Assumptions Consider the production function of product i from plant j in sector s at time t:

$$Q_{ijt} = F_i(M_{ijt}, L_{ijt}, K_{ijt}; \beta_s)\Omega_{jt}.$$

Let W^M_{ijt}, W^L_{ijt}, and W^K_{ijt} be the corresponding prices of materials, labor, and capital inputs, respectively.

Assumption 1: The production function is product-specific.

Assumption 2: $F_j(\cdot)$ is continuous and twice differentiable with respect to material inputs. Material inputs are static so they can be adjusted freely, without dynamic considerations.

Assumption 3: The Hicks–Neutral plant-level productivity Ω_{jt} is log-additive and plant-specific.

Assumption 4: All expenditures on inputs are attributable to products.

Assumption 5: State variables of the plant are $\mathbf{s}_{jt} = \{N_{jt}, \mathbf{K}_{ijt}, \Omega_{jt}, \mathbf{G}_j, \mathbf{r}_{ijt}\}$, where N_{jt} denotes the number of products, $\mathbf{G}_j$ denotes the location of the plant, and $\mathbf{r}_{ijt}$ are all payoff-relevant, serially correlated variables such as tariffs.

Assumption 6: Plants minimize short-run costs, taking output quantity and input prices as givens.

Unobserved plant-level productivity To control for unobserved productivity, we follow the proxy methods developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) and use a control function based on a static input demand equation for materials. We use single-product (and destination) plants in the estimation, and therefore we simplify the notation at the plant level in what follows. Reference to plant j thus refers to a product in the following procedures. We assume that demand for materials takes the form:

$$\hat{m}_{jt} = m_t(\omega_{jt}, \hat{k}_{jt}, \hat{l}_{jt}, p_{jt}, ms_{jt}, D_j, G_j, EXP_{jt}, \tau^{output}_{jt}, \tau^{input}_{c(j)t}, \tau^{US}_{jt}),$$

where $\hat{m}_{jt}$, $\hat{k}_{jt}$, and $\hat{l}_{jt}$ denote expenditures on materials, capital, and labor deflated by their respective industry price index, ms_{jt} is the market share of plant j, D_j is a product dummy, G_j is a plant's state, EXP_{jt} is a plant's export status at time t, τ^{output}_{jt} is the tariff applied to the product produced by plant j, $\tau^{input}_{c(j)t}$ is the tariff applied to the intermediate inputs used by plant j, and τ^{US}_{jt} is the U.S. tariff applied to the product produced by plant j. Under the assumption that demand for materials is increasing with productivity, we invert the demand function to arrive at a control function for productivity:

$$\omega_{jt} = h_t(\mathbf{\hat{x}_{jt}}, \mathbf{z_{jt}}),$$

with $\mathbf{\hat{x}_{jt}} = (\hat{m}_{jt}, \hat{l}_{jt}, \hat{k}_{jt})$ and $\mathbf{z_{jt}} = (p_{jt}, ms_{jt}, D_j, G_j, EXP_{jt}, \tau_{jt}^{output}, \tau_{c(j)t}^{input}, \tau_{jt}^{US})$. We use second-order polynomials on $\mathbf{\hat{x}_{jt}}$ and $\mathbf{z_{jt}}$ to approximate the unknown function $h_t(\cdot)$ in order to control for unobserved productivity.

Selection correction To resolve selection bias associated with estimations using single-product-single-market producers, we use the probability of remaining as a single-product-single-market plant as a control. We assume, as in Mayer, Melitz, and Ottaviano (2014), that the number of products increases with productivity. Let the state vector of plant j at time t be:

$$\mathbf{s}_{jt} = (N_{jt}, K_{jt}, \Omega_{jt}, G_j, EXP_{jt}, \tau_{jt}^{output}, \tau_{c(j)t}^{input}, \tau_{jt}^{US}),$$

where N_{jt} denotes the number of products produced by plant j at time t, and K_{jt} is the capital stock. Denote by $\bar{\omega}_{jt}(\mathbf{s}_{jt})$ the productivity cutoff associated with the introduction of a second product as a function of state variable $\mathbf{s}_{jt}$. Define the indicator variable $\mathcal{I}_{jt} = 1$ if a plant remains single-product. We can then write the probability of remaining single-product as:

$$\begin{aligned} Pr(\mathcal{I}_{jt} = 1) &= Pr(\omega_{jt} \leq \bar{\omega}_{jt}(\mathbf{s}_{jt}) | \bar{\omega}_{jt}(\mathbf{s}_{jt}), \omega_{jt-1}) \\ &= \kappa_{t-1}(\bar{\omega}_{jt}(\mathbf{s}_{jt}), \omega_{jt-1}) \\ &= \kappa_{t-1}(\hat{x}_{jt-1}, \mathbf{z}_{jt-1}) \equiv SP_{jt}, \end{aligned}$$

where the last equality comes from substituting the control function of productivity in $t-1$ and $\mathbf{z_{jt}} = (p_{jt}, ms_{jt}, D_j, G_j, EXP_{jt}, \tau_{jt}^{output}, \tau_{c(j)t}^{input}, \tau_{jt}^{US})$. In practice, we estimate this probability using the fitted values from a probit estimation.

Estimation We assume that productivity follows a first-order Markov process, with the law of motion:

$$\omega_{jt} = g(\omega_{jt-1}, \tau_{jt-1}^{output}, \tau_{jt-1}^{input}, \tau_{jt-1}^{US}, EXP_{jt-1}, SP_{jt}, R\&D_{jt-1}) + \xi_{jt},$$

where SP_{jt} is the fitted probability of remaining single-product, $R\&D_{jt}$ is research and development expenditures, and ξ_{jt} is the innovation to productivity shock.

The specification for the law of motion of productivity allows tariffs and export status to influence productivity but does not assume that they will necessarily affect it. The data will tell us if there is any significant correlation between productivity and these variables. We also allow research and development expenditures to affect productivity. We estimate the parameters of the production function and input price control function by constructing moments based on innovation to productivity shock ξ_{jt}. To do this, we first express ω_{jt} as a function of the data and parameters. Plugging in the input price and productivity control functions into the production function, we can write equation (5) as:

$$q_{jt} = \phi_{jt}(\mathbf{\hat{x}}_{jt}, \mathbf{z}_{jt}) + \epsilon_{jt},$$

where the function $\phi(\cdot) = f_j(\mathbf{\hat{x}_{jt}}; \beta_\mathbf{s}) + \Lambda(w_t(p_{jt}, ms_{jt}, D_j, G_j, EXP_{jt}; \delta_\mathbf{s}), \mathbf{\hat{x}_{jt}}; \beta_\mathbf{s}) + h_t(\mathbf{\hat{x}_{jt}}, \mathbf{z_{jt}})$ captures the output net of measurement error. Estimating this equation and recovering $\hat{q}_{jt} = \hat{\phi}_{jt}$ enables us to dispose of ϵ_{jt}. In practice, we form second-order polynomials on $\mathbf{\hat{x}}_{jt}$ and $\mathbf{z}_{jt}$ to proxy $\phi(\cdot)$ and estimate the fitted values. Once we have a measure of the output net of measurement error, we can express productivity directly as a function of the data and parameters as:

$$\omega_{jt}(\beta_s, \delta_s) = \hat{\phi}_{jt} - f_j(\mathbf{\hat{x}_{jt}}; \beta_\mathbf{s}) - \Lambda(w_t(p_{jt}, ms_{jt}, D_j, G_j, EXP_{jt}; \delta_\mathbf{s}), \mathbf{\hat{x}_{jt}}; \beta_\mathbf{s}),$$

where the input price control function has been evaluated in $\Lambda(\cdot)$. We approximate $\Lambda(\cdot)$ using a second-order polynomial on the elements of the input price control function $w_t(\cdot)$ and their interactions with input expenditures.[5] Finally, we form the moment conditions using the innovation to productivity shock:

$$\xi_{jt}(\beta, \delta) = \omega_{jt}(\beta, \delta) - E[\omega_{jt}(\beta, \delta)|\omega_{ijt-1}(\beta, \delta), \tau^{output}_{jt-1}, \tau^{input}_{jt-1}, \tau^{US}_{jt-1}, EXP_{jt-1}, SP_{jt,} R\&D_{jt-1}].$$

Following Ackerberg, Caves, and Frazer (2015), we estimate both the parameters of the production function β and the input price control function δ by GMM using the moment conditions:

$$E[\xi_{\mathbf{jt}}(\beta_\mathbf{s}, \delta_\mathbf{s})\mathbf{I}_{jt}] = 0, \tag{1}$$

where the instrument matrix $\mathbf{I_{jt}}$ includes lagged materials, current capital, current labor, and their higher order interactions. It also incorporates lagged market shares, lagged tariffs, lagged prices, lagged export status, and the interaction of lagged prices with inputs and market shares. We also include a time trend and its square to control for aggregate macroeconomic trends.

Estimation yields consistent estimates of the parameters of the production function β and input price control function δ. Identification of these parameters comes from the timing assumptions on productivity. We assume that labor and capital do not respond contemporaneously to the innovation to productivity shock, but materials do, in order to construct the appropriate moment conditions. We follow de Loecker, Goldberg, Khandelwal, and Pavcnik (2016) and assume that input and output prices are contemporaneously correlated with innovation to productivity to construct the moments needed to identify the parameters of the input price control function.

In principle, one would ideally estimate the production function and input price control function at the product level, but in practice, we do not have enough observations of single-product plants that produce each product. Therefore, we follow the literature and estimate the production function and input price control function at the sector level. We use the following sectors in the estimation: food and beverage, textiles, apparel, wood and furniture, paper industries, chemical industries, non-metallic mineral products, metallic manufacturing, and machinery and transportation equipment.

[5] Estimating interactions between product and state dummies and input expenditures is infeasible, so they have been excluded.

Unobserved product-level input prices As explained in Section 4.1, we posit that a product with a higher market share conditional on its price should be of higher quality and therefore must be produced using more expensive inputs. This relationship motivates us to construct the following input price control function:

$$w_{ijt} = w_t(p_{ijt}, ms_{ijt}, D_i, G_j, EXP_{jt}; \delta_{\mathbf{s}}),$$

where p_{ijt} is the logarithm of the price of product i, ms_{ijt} is the market share of product i, D_i is a product dummy, G_j is a plant's state, EXP_{jt} is a plant's export status at time t, and δ_s is a sector-specific parameter vector that we estimate.

Unobserved input expenditures by product We denote the log of the share of input expenditures for product–market i of plant j by ρ_{ijt}, and assume them to be the same across inputs. Since all of the inputs are assumed to be allocated to the production of products, the ρ_{ijt} of plant j have to satisfy:

$$\sum_{i \in J_j} \exp(\rho_{ijt}) = 1,$$

where J_j is the set of products produced by plant j.

To solve for input expenditure shares $\rho^x_{ijt} = log\left(\frac{W^X_{ijt} X_{ijt}}{\hat{X}_{jt}}\right)$ for multi-product plants, we purge quantities from measurement error as before by constructing $\hat{q}_{ijt} = E[q_{ijt}|\phi_{ijt}]$. Using the assumptions above, we can write the production function as:

$$\hat{q}_{ijt} = f(\hat{\mathbf{x}}_{jt}, \hat{\beta}_{\mathbf{s}}, \hat{w}_{ijt}, \rho_{ijt}) + \omega_{jt}.$$

For a functional form $f(\cdot)$, we can rearrange the equation as:

$$\hat{q}_{ijt} - f_1(\hat{\mathbf{x}}_{jt}, \hat{\beta}_s, \hat{w}_{ijt}) = f_2(\hat{\mathbf{x}}_{jt}, \hat{\beta}_s, \hat{w}_{ijt}, \rho_{ijt}) + \omega_{jt}.$$

Given estimates of the input price control function and the production function, the left-hand side of this equation is data, and the right-hand side depends on unknowns ρ_{ijt} and ω_{jt}. The equation must hold for each product from each plant. Since input expenditure shares must sum to 1, the following system of equations must hold for each plant j that produces I products at time t:

$$\begin{aligned}
\hat{q}_{1jt} - f_1(\hat{\mathbf{x}}_{jt}, \hat{\beta}_{\mathbf{s}}, \hat{w}_{1jt}) &= f_2(\hat{\mathbf{x}}_{jt}, \hat{\beta}_{\mathbf{s}}, \hat{w}_{1jt}, \rho_{1jt}) + \omega_{jt} \\
&. \\
&. \\
\hat{q}_{Ijt} - f_1(\hat{\mathbf{x}}_{jt}, \hat{\beta}_{\mathbf{s}}, \hat{w}_{Ijt}) &= f_2(\hat{\mathbf{x}}_{jt}, \hat{\beta}_s, \hat{w}_{Ijt}, \rho_{Ijt}) + \omega_{jt} \\
\sum_{j=1}^{J} exp(\rho_{ijt}) &= 1.
\end{aligned}$$

We have a system of $I+1$ equations in $I+1$ unknowns, I ρ_{ijt} and ω_{jt}. Numerically solving these equations, we get estimates of $\hat{\rho}_{ijt}$ and productivity $\hat{\omega}_{jt}$ that we can use to recover the markups as:

$$\hat{\mu}_{ijt} = \hat{\theta}^M_{ijt} \left(\frac{P_{ijt} Q_{ijt}}{exp(\hat{\rho}_{ijt}) \hat{M}_{it}} \right),$$

and then use the prices to construct marginal costs.

C Additional empirical results

C.1 Interaction with import status dummy

To explore the potential heterogeneity of how input tariff reductions affect plants' output prices, we consider a variation of specification (1) whereby input tariffs are interacted with the plant-level dummy on import status. For both domestically sold goods and exported goods, we find a statistically insignificant coefficient on the interaction term. This result suggests that all plants, regardless of their direct import status, experienced lower input costs through input tariff reductions. One may rationalize this result through increased import competition among the input suppliers. A reduction in input tariffs may have induced domestic suppliers of these inputs to cut prices, thereby indirectly benefiting non-importers. Another way to rationalize this result is through plants' usage of indirect imports through their domestic suppliers. Dhyne, Kikkawa, Mogstad, and Tintelnot (2021) find that firms that do not directly import also rely heavily on inputs that originate abroad through domestic supply networks.

Table C1: Impact of tariffs on prices, interaction with import status

	Domestic	Exported
	(1)	(2)
$\log\left(1+\tau^{output}_{it}\right)$	0.04^b	0.04
	(0.02)	(0.03)
$\log\left(1+\tau^{input}_{c(j)t}\right)$	0.03^b	0.07
	(0.01)	(0.06)
$\log\left(1+\tau^{input}_{c(j)t}\right) \times IMP_{jt}$	0.01	-0.03
	(0.01)	(0.05)
$\log\left(1+\tau^{US}_{it}\right)$	0.01	-0.04^b
	(0.02)	(0.02)
N	$143,717$	$27,642$

Note: The dependent variable is the log of prices. Column (1) uses the sample of domestic products and Column (2) the sample of exported products. Regressions include plant–product and sector–year fixed effects. Standard errors are clustered at the class level.
Significance: a (1%), b (5%), and c (10%).

C.2 Alternative sample and specification

In our main specification, we regress prices and their components on tariffs separately for domestic and exported goods. Here, we explore the sensitivity of the results in Table 1 and 5 by first focusing on plants that never export any of their products throughout the sample period. We report the results in Table C2. We find that the results are both quantitatively and qualitatively similar to those in Table 5. This conclusion remains the same when we additionally include domestically sold products from plants specializing between markets: these plants sell certain products solely in the domestic market and other products solely in the export market (Table C3).

Table C2: Never exporting plants

	Domestic		
	$\log P_{ijt}$	$\log MC_{ijt}$	$\log \mu_{ijt}$
	(1)	(2)	(3)
$\log\left(1+\tau_{it}^{output}\right)$	0.02	0.01	0.01
	(0.02)	(0.02)	(0.03)
$\log\left(1+\tau_{c(j)t}^{input}\right)$	0.03^{a}	0.10^{b}	-0.07
	(0.01)	(0.04)	(0.04)
N	80,301	80,301	80,301

Note: We focus on plants that never exported any of their products throughout the sample period. Dependent variables are the logs of prices, marginal costs, and markups. The regressions exclude outliers in the top and bottom 1% of the markup distribution within each sector. Regressions include plant–product and sector–year fixed effects. Standard errors are clustered at the class level.
Significance: a (1%), b (5%), and c (10%).

Table C3: Products that are sold only in the domestic market

	Domestic		
	$\log P_{ijt}$	$\log MC_{ijt}$	$\log \mu_{ijt}$
	(1)	(2)	(3)
$\log\left(1+\tau_{it}^{output}\right)$	0.04^{b}	0.03	0.01
	(0.02)	(0.02)	(0.03)
$\log\left(1+\tau_{c(j)t}^{input}\right)$	0.03^{b}	0.09^{c}	-0.06
	(0.01)	(0.05)	(0.05)
N	116,140	116,140	116,140

Note: On top of the sample considered in Table C2, we include plants that serve both markets but target different products to the different markets. Dependent variables are the logs of prices, marginal costs, and markups. The regressions exclude outliers in the top and bottom 1% of the markup distribution within each sector. Regressions include plant–product and sector–year fixed effects. Standard errors are clustered at the class level.
Significance: a (1%), b (5%), and c (10%).

Next, we focus on the sample of plants that sell products domestically and to the export market. In this sample, we include plants that sell the same products to both markets as well as plants that sell different products to different markets. We report the results in Table C4, and find that they are very similar to those in Table 5.

Table C4: Plants serving both markets

	Domestic			Exported		
	$\log P_{ijt}$	$\log MC_{ijt}$	$\log \mu_{ijt}$	$\log P_{ijt}$	$\log MC_{ijt}$	$\log \mu_{ijt}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(1+\tau_{it}^{output}\right)$	0.06^{b}	0.03	0.03			
	(0.02)	(0.04)	(0.04)			
$\log\left(1+\tau_{c(j)t}^{input}\right)$	0.07^{a}	0.15^{b}	-0.07	0.04^{c}	0.28^{a}	-0.24^{a}
	(0.02)	(0.04)	(0.04)	(0.02)	(0.07)	(0.07)
$\log\left(1+\tau_{it}^{US}\right)$				-0.03^{c}	0.07	-0.10^{b}
				(0.02)	(0.04)	(0.04)
N	39,839	39,839	39,839	27,153	27,153	27,153

Note: We focus on plants that sell products domestically and to the export market. Dependent variables are the logs of prices, marginal costs, and markups. The regressions exclude outliers in the top and bottom 1% of the markup distribution within each sector. Regressions include plant–product and sector–year fixed effects. Standard errors are clustered at the class level.
Significance: a (1%), b (5%), and c (10%).

Finally, we focus on the sample of plant–product pairs that serve both the domestic and export markets, and pool this sample in one regression specification where the outcome variables are regressed on the three tariffs, with plant–product–year fixed effects. We interact the tariffs on the exported product dummy and present the resulting coefficients in Table C5.

Table C5: Plant–product pairs that serve both markets

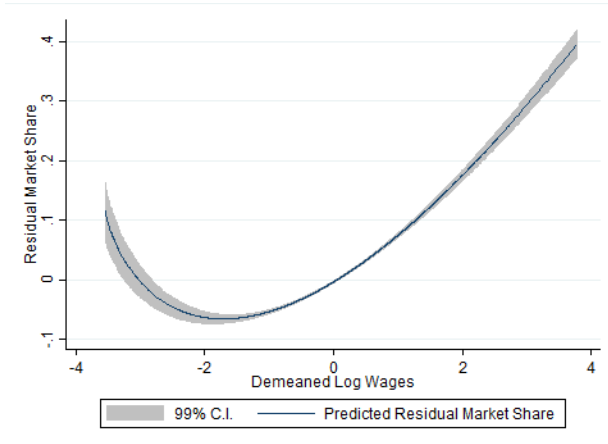
	$\log P_{ijt}$	$\log MC_{ijt}$	$\log \mu_{ijt}$
	(1)	(2)	(3)
$\log\left(1+\tau_{it}^{output}\right) \times EXP_{ijt}$	0.01	0.02	-0.01
	(0.05)	(0.05)	(0.05)
$\log\left(1+\tau_{c(j)t}^{input}\right) \times EXP_{ijt}$	-0.11^{b}	0.23^{a}	-0.33^{a}
	(0.05)	(0.07)	(0.05)
$\log\left(1+\tau_{it}^{US}\right) \times EXP_{ijt}$	-0.03	0.01	-0.03
	(0.02)	(0.04)	(0.04)
N	54,014	54,014	54,014

Note: The regression result is based on the sample of plant–product pairs that serve both the domestic and export markets. Regressions include plant–product–year fixed effects. Standard errors are clustered at the class level.
Significance: a (1%), b (5%), and c (10%).

C.3 Quality and average wages

Figure C1 displays the relationship between the residuals from a regression of market shares on output prices and product dummies, and plant-level average wages.

Figure C1: Quality and average wages

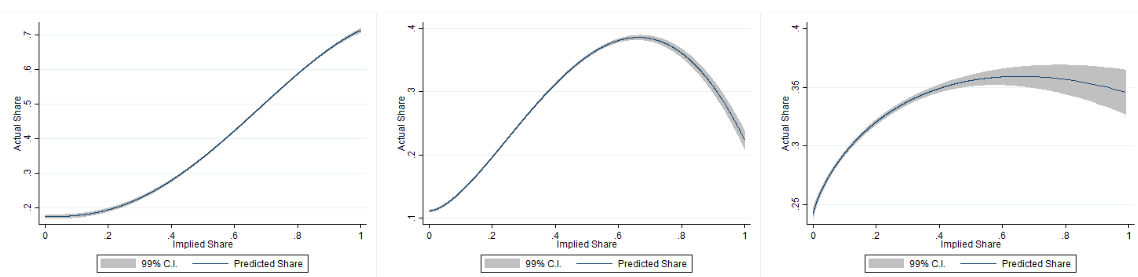


Note: The figure plots the the best-fitted polynomial of residuals from a regression of product market shares on prices and product dummies (y-axis) and the log of average wages demeaned by product–market fixed effects (x-axis) for the full 1994–2008 sample. Average wages were constructed by dividing total wage bill by total number of employees. The shaded area indicates a 99% confidence interval.

C.4 Actual and implied input expenditure shares

Figure C2 displays the relationships between the observed input expenditure shares at the plant level and the theoretical expenditure shares implied by the output elasticities under cost minimization.

Figure C2: Actual and implied input expenditure shares



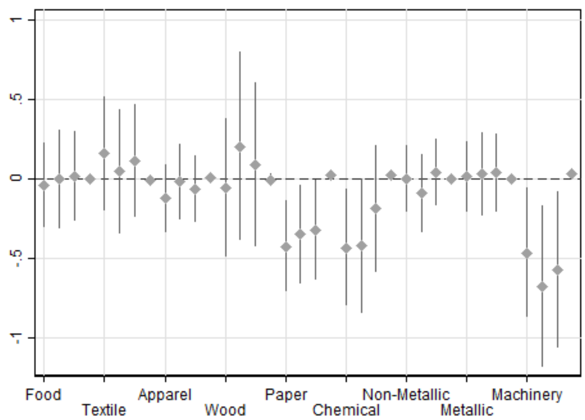
(a) Material inputs (b) Labor (c) Capital

Note: The figure shows the best-fitted polynomials of the observed share of input expenditures out of total expenditures in labor, capital, and materials (y-axis), and the input expenditure share implied by the estimated elasticities (x-axis). The shaded area indicates a 99% confidence interval.

C.5 Test of homotheticity in the production function

To test whether the estimated output elasticities satisfy the conditions under which the production function becomes homothetic, we compute the right-hand sides of equation (6) for each sector, and summarize the results in Figure C3. For six out of nine sectors, we find that all four conditions in equation (6) are satisfied.

Figure C3: Test of homotheticity

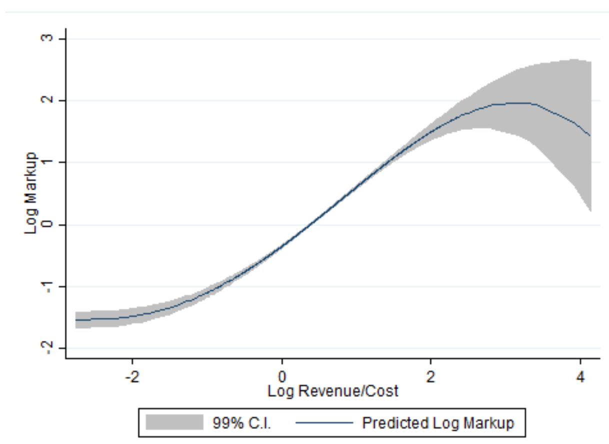


Note: The figure shows the values and the 95% confidence intervals of the right-hand sides of equation (6) for each sector using the estimated production function parameter values.

C.6 Validity of markup estimates

Figure C4 displays the relationship between the estimated markups aggregated at the plant level and the accounting measure of revenue over variable costs.

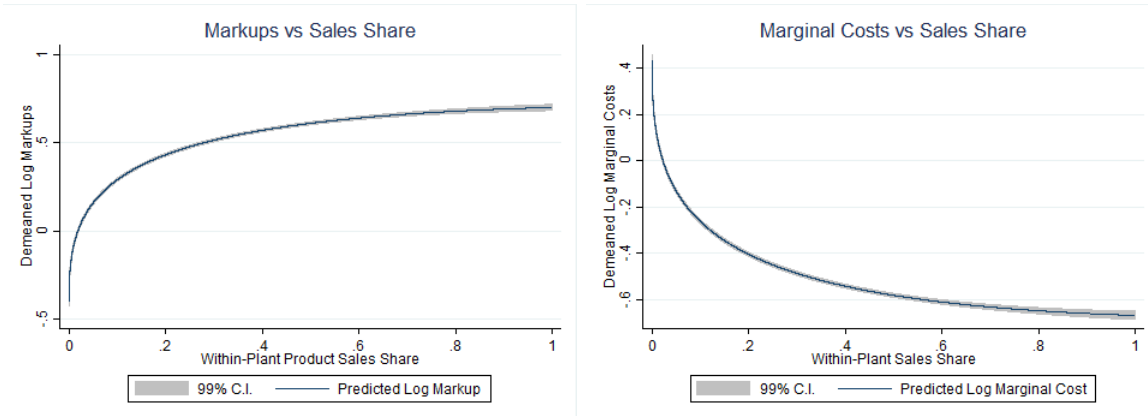
Figure C4: Estimated markups and accounting revenue over variable costs



Note: The figure shows the best-fitted polynomial of the logarithm of estimated markups (y-axis) and the log of the ratio of accounting revenue over variable costs (x-axis). The shaded area indicates a 99% confidence interval. The figure excludes outliers below the 1st and above the 99th percentiles of the markup distribution in each sector.

Figure C5 plots the relationships between within-plant product revenue share and the product's estimated markups (left panel) and the product's estimated marginal costs (right panel).

Figure C5: Relationships between sales shares and estimated markups and marginal costs



Note: The figure shows the best-fitted polynomials of the logarithm of markups and marginal costs, demeaned by product–market fixed effects (y-axis) and within-plant product sales share (x-axis). The figure excludes outliers below the 1st and above the 99th percentiles of the markup distribution in each sector. The shaded area indicates a 99% confidence interval.

C.7 The impact of tariffs on plant-level productivity

With the estimated productivity terms ω_{jt}, we explore how changes in tariffs affected measures of plant-level productivity. In addition, we test the identifying assumption made in Section 4.1 and Appendix B that plants' productivity shocks are orthogonal to changes in tariffs. The empirical framework used to estimate production functions and construct product-level markups allows us to recover a measure of productivity at the plant level. Since we estimate a quantity production function, the ω_{jt} recovered is a physical productivity (TFPQ). Therefore, we first use the TFPQ measure and estimate the following equation based on the specification used by López-Córdova (2003):

$$Y_{jt+1} = \alpha + \beta_1 \log\left(1 + \tau_{jt}^{output}\right) + \beta_2 \log\left(1 + \tau_{c(j)t}^{input}\right) + \beta_3 \log\left(1 + \tau_{jt}^{US}\right) + \gamma X_{jt} + \epsilon_{jt+1}, \qquad (2)$$

where for Y_{jt+1} we use the log of plant-level TFPQ, ω_{jt+1}. The terms τ_{jt}^{output}, $\tau_{c(j)t}^{input}$, and τ_{jt}^{US} are plant-level output, intermediate input, and U.S. tariffs, respectively. Output and U.S. plant-level tariffs are constructed as a sales-weighted average of the tariffs on products sold by plant j. X_{jt} is a vector of plant-level controls that include the plant's import and export status, the total industry sales of plant j excluding its sales, and the Herfindahl-Hirschman Index (HHI) of market concentration in the industry of plant j, as well as year, state, and sector fixed effects.

In the first column of Table C6, we find significant effects of lagged tariffs on productivity, consistent with our assumption on the law of motion of productivity. We find that declines in both output and U.S. tariffs led to increases in productivity, while declines in input tariffs led to a reduction in productivity. In the second column, we add the changes in tariffs and lagged TFPQ as the independent variables. We find here that the coefficients for the changes in tariffs are statistically insignificant on productivity in the following period. This is consistent with the argument made in Appendix B, where we posit that productivities at t are functions of lagged tariffs at $t-1$. This argument also leads to our identification assumption that the productivities are orthogonal to tariff changes from $t-1$ to t.

In contrast to TFPQ, revenue TFP (TFPR) confounds productivity changes with movements in prices or markups (Foster, Haltiwanger, and Syverson, 2008). In the third column of Table C6, we consider this TFPR to be the dependent variable. In particular, we measure plant-level TFPR as $\omega_{jt} + \log P_{jt}$, where plant-level price P_{jt} is constructed by taking the quantity-weighted average of product-level prices. Comparing the first and the third columns, we find that measuring productivity with TFPR can lead to a different prediction of how productivity responded to tariff reductions.

Table C6: Productivity on tariffs

	$\log\text{TFPQ}_{jt+1}$		$\log\text{TFPR}_{jt+1}$
	(1)	(2)	(3)
$\log\left(1+\tau_{jt}^{output}\right)$	-0.18[a]	-0.01[c]	0.18[a]
	(0.03)	(0.00)	(0.04)
$\log\left(1+\tau_{c(j)t}^{input}\right)$	0.92[a]	0.04[a]	−1.16[a]
	(0.13)	(0.01)	(0.16)
$\log\left(1+\tau_{jt}^{US}\right)$	-0.10[b]	-0.00	0.09
	(0.05)	(0.00)	(0.06)
ω_{jt}		0.97[a]	
		(0.00)	
$\Delta\log\left(1+\tau_{jt}^{output}\right)$		-0.02	
		(0.01)	
$\Delta\log\left(1+\tau_{c(j)t}^{input}\right)$		0.01	
		(0.05)	
$\Delta\log\left(1+\tau_{jt}^{us}\right)$		0.01	
		(0.01)	
R^2	0.11	0.94	0.34
N	33,510	32,587	33,510

Note: The dependent variable for the first two columns is the plant-level TFPQ of ω_{jt+1}, and the dependent variable for the last column is the plant-level TFPR. The output and U.S. tariffs are aggregated to the plant level. In all specifications, plant's import and export status, the total industry sales of plant j excluding its sales, the Herfindahl-Hirschman Index (HHI) of market concentration in the industry of plant j, state, and sector–year fixed effects are controlled for.
Significance: a (1%), b (5%), and c (10%).

C.8 Differences in marginal costs across destinations

We ask whether the estimated marginal costs differ between domestic and exported varieties within plant–product pairs. Table C7 reports the regression result where we regress the estimated marginal costs on a dummy indicating whether the product was exported, controlling for plant–product and sector–year fixed effects. We find a positive and statistically significant coefficient, implying that within plant–product pairs, exported varieties have higher marginal costs than those sold domestically.

Table C7: Marginal cost on export status

	(1)
EXP_{ijt}	0.21^a
	(0.02)
Plant–Product FE	✓
Sector–Year FE	✓
Within R^2	0.006
N	172,555

Note: The dependent variable is the estimated marginal costs for each plant–product pair, and the independent variable is an indicator of whether the product is exported.
Significance: a (1%), b (5%), and c (10%).

To verify that the above differences in marginal costs reflect the differences in input expenditures for production, we then regress plants' expenditures for each plant–product pair on its share of output that is exported or on its export status dummy, while controlling for its output quantity, input price index, and plant–product fixed effects. In Table C8, we find a positive coefficient on the export share and on the export status dummy, implying that varieties that are exported require larger input expenditures compared to the same products sold domestically.

Table C8: Material expenditures on export share

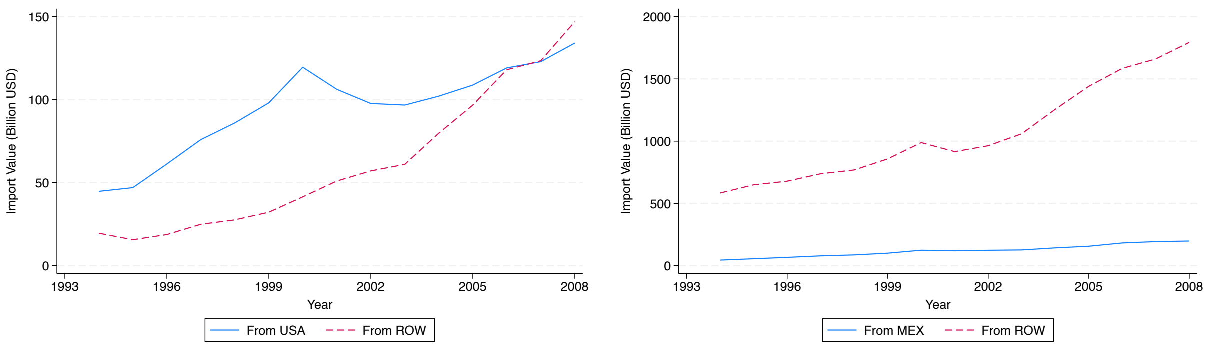
	(1)	(2)
Export share	0.73^a	
	(0.14)	
Export status		0.24^a
		(0.02)
Plant–Product FE	✓	✓
Sector–Year FE	✓	✓
Within R^2	0.36	0.35
N	15,815	15,868

Note: The dependent variable is the recovered material expenditures at the plant–product level. The independent variables are the share of exported output for each plant–product pair or the exported status dummy. Both specifications include log output quantity and the input price index as controls. We focus on the sample of single-product plants.
Significance: a (1%), b (5%), and c (10%).

C.9 Aggregate trade under NAFTA

Using trade data from the U.N. Comtrade database, we plot in Figure C6 the aggregate imports of both Mexico and the U.S. from each other and the rest of the world. The figures show that during the sample period, not only did the two countries increase trade with each other, but they also increased imports from the rest of the world.

Figure C6: Aggregate imports of Mexico and the U.S.



Note: The figures show the aggregate imports of the two countries from each other and the rest of the world.

C.10 The effects of competition on markups

The point estimates presented in Table 5 seem to suggest that declines in output tariffs did not have a statistically significant impact on the markup of domestic products. Considering only these point estimates as evidence of pro-competitive effects, however, is misleading, since the specification does not hold marginal costs fixed. If plants adjusted their markups in response to changes in marginal costs, the coefficient on output tariffs would capture not only the pro-competitive impact of tariffs on the markups, but also the impact through changes in marginal costs that are driven by changes in tariffs.

To test for effects of competition on markups, we follow de Loecker et al. (2016) and consider a specification in which we control for marginal costs. In particular, we estimate the following specification:

$$\log \mu_{ijt} = \alpha + \kappa_1 \left(1 + \tau_{it}^{output}\right) + \kappa_2 \left(1 + \tau_{it}^{US}\right) + g\left(\hat{mc}_{ijt}; \eta\right) + \xi_{ij} + \psi_{st} + \varepsilon_{ijt}, \tag{3}$$

where $g(\hat{mc}_{ijt}; \eta)$ is a polynomial of marginal costs used as a control. The specification also includes plant–product fixed effects, ξ_{ij}, and sector–year fixed effects, ψ_{st}. We use a third-order polynomial on marginal costs, but the results are robust to a linear or second-order polynomial. Measurement errors in marginal costs will lead to attenuation bias. We, therefore, also instrument the polynomial of marginal costs with its lagged polynomial and intermediate input tariffs. In using this instrument, we implicitly assume that input tariffs should affect markups only through the changes in marginal costs. This assumption implies that, once controlling for marginal costs, input tariffs have insignificant effects on markups—which we verify in the data. We consider the output tariffs to be the main independent variable when considering markups of domestic products, and U.S. tariffs to be the main independent variable when considering markups of exported products.

Table C9 shows the results from the estimation of equation (3). The first two columns show the results for domestic products, and the last two columns show the results for exported products. For each set of products, we present specifications both with and without the instrument. We find that once we control for marginal costs, the coefficient for the impact of output tariffs on markups becomes positive and statistically significant, suggesting that output tariff declines during this period had pro-competitive effects. Similarly, the fall in U.S. tariffs led to a rise in markups of exported products, once controlling for marginal costs. This result points to the anti-competitive effects of trade liberalization predicted by de Blas and Russ (2015).

Table C9: The pro-competitive effects of NAFTA

	Dependent Variable: $\log \mu_{ijt}$			
	Domestic		Exported	
	(1)	(2)	(3)	(4)
$\log\left(1+\tau_{it}^{output}\right)$	0.19^a	0.21^a		
	(0.02)	(0.02)		
$\log\left(1+\tau_{it}^{US}\right)$			-0.17^a	-0.11^a
			(0.02)	(0.03)
Instruments	No	Yes	No	Yes
First Stage F		5,821		622.7
Within R^2	0.24	0.79	0.28	0.77
N	143,717	124,148	27,642	22,754

Note: The dependent variables in Columns (1) and (2) are the logs of the domestic markup and the dependent variables in Columns (3) and (4) are the logs of the export markup. Both specifications include third-order polynomials on log marginal costs (coefficients not reported). In Columns (2) and (4), we instrument the marginal cost polynomial using its lag and intermediate input tariffs. The regressions exclude outliers in the top and bottom 1% of the markup distribution within each sector. Regressions include plant–product fixed effects and sector–year fixed effects. Standard errors are clustered at the product level.
Significance: a (1%), b (5%), and c (10%).

C.11 Pass-through of costs to prices

Here, we investigate the pass-through elasticity of costs to prices. Consider the following regression:

$$\log P_{ijt} = \alpha + \beta \log MC_{ijt} + \xi_{ij} + \varphi_{st} + \epsilon_{ijt},$$

where MC_{ijt} is the estimate of marginal cost, ξ_{ij} are plant–product fixed effects, and φ_{st} are sector–year fixed effects. If one observes marginal costs without error, then one should find $\beta = 1$ if plants charge constant markups. If plants charge variable markups, then the error term will be correlated with the marginal costs. As argued by de Loecker et al. (2016), if the demand elasticity that the plant is facing is increasing in the price, then a cost increase would lead to a higher demand elasticity, inducing the plant to charge a lower markup. In this case, the error term and the marginal cost will be negatively correlated, hence the estimated coefficient, β, would be less than one.

We estimate the above regression specification separately for the sample of domestic and exported products, and report the results in Table C10. To address the potential measurement error in the marginal cost terms, we also instrument them with input tariffs and lagged marginal cost. Consistent with the findings from de Loecker et al. (2016), we find incomplete pass-through in all the specifications, for both domestic and exported products.

Table C10: Pass-through regressions

	Domestic			Exported		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(MC_{ijt})$	0.78^a	0.83^a	0.84^a	0.77^a	0.82^a	0.83^c
	(.004)	(.004)	(.005)	(.008)	(.010)	(.010)
Within R^2	0.760	0.776	0.771	0.738	0.748	0.749
Instruments	-	$\tau^{input}_{c(j)t}$,$log\hat{mc}_{ijt-1}$	$\tau^{input}_{c(j)t}$,$log\hat{mc}_{ijt-2}$	-	$\tau^{input}_{c(j)t}$,$log\hat{mc}_{ijt-1}$	$\tau^{input}_{c(j)t}$,$log\hat{mc}_{ijt-2}$
N	$143,717$	$124,148$	$108,373$	$28,409$	$23,427$	$19,753$
F		6.6e5	2.4e5		8.8e4	2.7e4

Note: The dependent variable is the log of prices. Columns (1) and (4) show the OLS specification. Columns (2) and (5) instrument marginal costs using lagged value and intermediate input tariffs. Columns (3) and (6) instrument marginal costs with 2-year lag and intermediate input tariffs. Regressions include plant–product fixed effects and year fixed effects using data for the entire sample (1994–2008). Standard errors are clustered at the product level. Significance: a (1%), b (5%), and c (10%), respectively.

C.12 Aggregating outcome variables to the plant–product-level

To see how our results in Section 5 compare with those from de Loecker et al. (2016), we take the quantity-weighted averages of the outcome variables to aggregate our estimates to the plant–product level. We then regress plant–product-level outcome variables on the output and input tariffs. The results reported in Table C11 confirm those in Table IX of de Loecker et al. (2016) in the context of the Indian trade liberalization episode. Both declines in output tariffs and input tariffs led to declines in prices mostly through marginal costs.[6]

Table C11: Plant–product-level outcome variables on tariffs

	$\log P_{ijt}$	$\log MC_{ijt}$	$\log \mu_{ijt}$
	(1)	(2)	(3)
$\log\left(1+\tau^{output}_{it}\right)$	0.04^b	0.04^b	0.003
	(0.02)	(0.02)	(0.02)
$\log\left(1+\tau^{input}_{c(j)t}\right)$	0.04^a	0.10^b	-0.07
	(0.01)	(0.05)	(0.04)
Within R^2	0.002	0.002	0.0005
N	$145,505$	$145,505$	145,505

Note: The dependent variables are aggregated to the plant–product level by taking quantity-weighted averages across destination markets. Regressions include plant–product fixed effects and sector–year fixed effects. Standard errors are clustered at the class level.
Significance: a (1%), b (5%), and c (10%).

[6]When adding the U.S. tariffs as the independent variable, the coefficients for all three dependent variables were insignificant.

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