Trade War and Ambient Air Pollution

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Abstract

I analyze the effect of the 2018 trade war on ambient levels of air quality in the United States of America. Domestic tariffs placed by the US on imported foreign goods and foreign tariffs applied to US exports by other countries have the potential to impact US production, which can translate into emissions and ambient pollution concentrations. Using the EPA's Air Quality dataset and satellite PM2.5 data, I implement a shift-share methodology and find that exposure to domestic tariffs does not result in any worsening of pollution conditions. Exposure to domestic and foreign tariffs do not have statistically different effects.

1 Introduction

After a century of trade liberalization, political fervor has once again turned to favor protectionism. Despite pushback from many economists, politicians have delivered on promises to increase barriers to trade. In 2018, the US raised tariffs on imports and trading partners levied tariffs on US exports in retaliation. With the actions of the second Trump administration, it is probable that more tariff hikes are on the horizon, though their magnitude and permanence are up in the air. These trade barriers will have widespread effects on the global economy. I address environmental quality as one of the second order effects that policy makers should consider in order to assess and levy efficient tariffs.

My research quantifies the impacts of trade barriers on air quality. If U.S. tariffs on imports stimulate domestic production, environmental quality may suffer from increased emissions. At the same time, tariffs placed by other countries on goods exported by the US could improve air quality by decreasing US production and emissions. Which of these effects will dominate is ex ante unclear and could have differential spatial effects. I answer this question using the context of Trump's 2018 trade war. I utilize a shift-share methodology to exploit geographic variation in the incidence of domestic (placed by the US) and foreign (levied against the US by other countries) tariffs and assess their impact on air quality.

My research fits in with recent literature on the causes of local air quality as an effect of shocks to production. Some examples are mine closures or the shift to fracking in the US (Chu et al. 2023; Johnsen et al. 2019). Trade policies can also serve as a shock to production. Fowlie, Reguant, et al.

(2016) predict leakage in trade-exposed dirty industries if policy instruments do not address import competition. Leakage is a major concern for global pollutants such as carbon dioxide. I focus on the impact of trade barriers on local air pollutants, so whether leakage is a concern depends on the scope of the social planner's utility function and how they value air quality in foreign nations. Wu and Reimer (2016) demonstrate that the spatial distribution of polluting firms is not socially optimal in many cases, and shocks from trade exposure could exacerbate these inefficiencies. Post-NAFTA evaluations attribute nearly two-thirds of the reduction in US emissions of PM_{10} and SO_2 in the mid-1990s to trade liberalization offering greater access to dirty inputs (Cherniwchan 2017).

As the pendulum swings back towards protectionism, some of these environmental gains may be erased. The research most closely related to mine is Du and Li (2025). They find that Chinese cities exposed to US tariffs (analogous to foreign tariff exposure by my definition) see relative deterioration in air quality. The authors ascribe this result to relaxation of pollutant standards in an attempt to ease pressure on businesses who are hurt by the loss of access to markets in the United States. I find that export exposure results in cleaner air, but the difference in regulatory structure between the two countries could explain this difference.

My study also addresses the recent literature on the empirical evidence of the pollution haven effect. Prior to the 2018 trade war, most tariffs in developed nations focused on downstream, clean goods, resulting in an implicit subsidy towards pollution (Shapiro 2021). The 2018 trade war's increases to tariffs on upstream goods such as steel are a deviation from this trend. As the North American Free Trade Agreement (NAFTA) was set to be implemented, Grossman and Krueger (1991) established a framework to predict the resultant patterns in production and environmental quality across the United States, Canada, and Mexico. Those authors discuss various ways that absent a massive increase in capital, NAFTA might not bring about the negative environmental damages that others had projected.

The evidence of strategic policy with environmental goals in mind is limited (Duan et al. 2021), as is empirical evidence of pollution haven effects. Both Copeland et al. (2022) and Levinson (2023) document an increasing trend in the amount of pollutants emitted during the production of goods destined to be traded, but Levinson (2023) points out that developed and developing countries "offshore" their pollution to each other at similar rates. While developing countries' emissions have grown more quickly in recent years, pollution related to the production of exports is a small fraction of overall emissions.

An additional angle to the pollution haven hypothesis is that tightening restrictions in developed countries can result in displacement of industry and pollution to regions of the world with more lax environmental regulation. Evidence for this channel of the pollution haven effect is also sparse, but Tanaka et al. (2022) describes large increases in Mexican lead concentrations after the US tightened their standard on ambient lead in 2009. Henderson (1996) documents that polluting firms will relocate to areas that are in attainment under the Clean Air Act when pressured by more stringent regulation, but these are not firms moving across international borders. Two more notable studies show reasonably large improvements to air quality in China after the Chinese government's ban on importing waste (Shi and Zhang 2023; Unfried and Wang 2024).

I also contribute to the literature assessing the spatial impacts of the Trump tariffs. Several papers look at the effects of the tax hikes using shift-shares. While Fajgelbaum et al. (2020) documents an immediate decrease in import and export value and quantity, they model the regional effects of tariffs on real wages without demonstrating changes to output. Blanchard et al. (2024) uses a similar measure of spatial exposure to assess the impact of tariffs on voting patterns. I run a secondary shift share using a reduced form methodology similar to the papers above to assess the impacts of tariffs on upstream and downstream industries in the supply chain.

I use a shift-share specification to assess spatial effects of broad increases in barriers to trade. The shocks are predicted changes in industry output using the model developed by Jones (1975) and expanded by Kovak (2013). I run a difference in differences specification using the shift share exposure as a treatment variable to quantify relative effects of exposure to protection and retaliation. My preferred outcome variable is air quality as reported by the EPA with the county-level, daily AQI. I contribute to the literature by offering an estimation of the environmental impact of the Trump administration's tariff hikes. Other research in the past has used factory-level emissions data. However, since most health effects impact individuals outside of factory settings, the relationship between factory output and local air quality is important to know. Flaaen and Pierce (2024) present suggestive evidence that any effect of tariffs on produced output faces a noticeable lag. As such, whether I can detect effects on air quality in the short or medium run is unclear.

I find that areas of the country which are relatively more exposed to foreign countries' tariffs on US exports see modest improvements in air quality. Increased exposure to domestic tariffs yields results that are not statistically significant, but the point estimates are similar to those for domestic tariffs. These results are robust to different weighting schemes for the construction of the shift-share, choice of air pollution data, and placebo tests placing the treatment in 2015. I also use facility level emissions data to demonstrate that industry exposure to retaliatory tariffs causes small decreases in recorded emissions. My results show energy production decreasing near regions exposed to foreign tariffs and from power plants located near regions with high domestic tariff exposure. Due to the nature of the difference-in-differences methodology, my results should be interpreted as a relative effect, rather than an absolute effect.

2 The 2018 Trade War

In 2018, the United States raised tariffs on imports from trade partners across the globe in several waves. While the United States constitution places tariffs under the purview of the Legislative branch, the executive branch invoked sections of the Trade Act of 1974 and the Trade Expansion act of 1962 to levy their tariffs. These acts allow for tariffs in response to national security concerns or unfair trading practices by other countries. This rationale had not been formally challenged during President Trump's first term, and almost all tariffs remained in place during the Biden Administration.

The first hikes of tariffs were levied on solar panels and washing machines. China, the European Union, Turkey, and other countries responded by raising their tariffs in retaliation. Subsequent waves saw the United States increase tariffs against China in particular, to which China responded in similar fashion. When all was said and done, US tariffs were applied to 7.4% of all imported varieties (product-country pairs), which accounted for 12.1% of the market value of 2017 imports. Foreign nations placed tariffs on 6.1% of exported varieties, which comprised 11.2% of market value. Conditional on being increased, the average increase of domestic and foreign tariffs was 13.7 and 8 percentage points, respectively. While most tariff changes were increases, domestic tariffs decreased for some varieties, mainly those originating in South Korea. In total, these varieties accounted for less than half of a percent of the value of imports in 2017. Foreign tariffs were decreased on 2.6% of exports, mainly on varieties destined for the Philippines, Colombia, and South Korea.

Figure 1 displays a scatter plot of the tariff hikes and total sector emissions for manufacturing sectors (NAICS codes beginning with 3) in 2017. Many of the sectors hit by domestic tariffs are among the heaviest polluters. The bottom left quadrant of the figure is empty, indicating that none of the sectors upon which tariffs were levied were low emissions sectors.

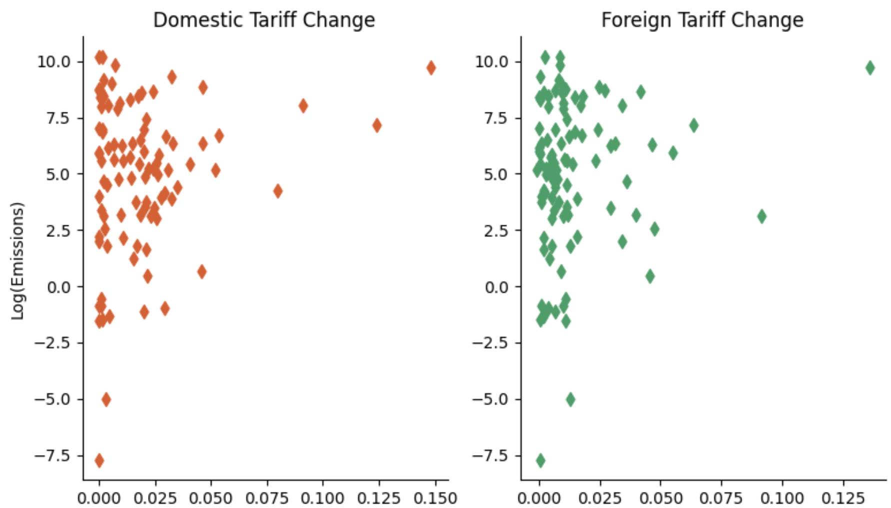

Figure 1: Baseline Emissions

Each data point represents a 4 digit NAICS sector. The y-axis shows the logarithm of total emissions in each sector during 2017. The x-axis includes the average sectoral tariff hike.

3 Data

Throughout this paper I will use the terms imports and exports from the perspective of the United States. I refer to tariffs placed by the US on imports as domestic tariffs and tariffs placed by other governments on US exports as foreign tariffs. I have data on tariff levels and values of imports and exports compiled by Fajgelbaum et al. (2020). Trade flow data are derived from the US Census. Domestic tariffs come from baseline public schedules released by the US International Trade Commission and 14 schedule revisions released over the course of 2018. Data on foreign tariffs are derived from other governments' finance departments or the World Trade Organization. Goods are differentiated to the level of Armington varieties, or product-country pairs. For these data, import values are reported at the HS10-country level, while domestic and foreign tariffs vary at the HS8 and HS6 levels, respectively. For an example of the specificity of these classifications, HS code 7202.21 refers to "ferroalloys containing by weight more than 55% of silicon." The HS8 code 7202.21.10 further clarifies "containing by weight more than 3% calcium." Tariffs were increased in several waves throughout 2018, but for each product-country pair, each tariff was changed at most once. The dataset contains monthly observations for tariffs and trade flows from January 2013 to April 2019.

My measure of air quality is the EPA's county level daily AQI dataset. In some counties, air quality measures occur less frequently than daily. I aggregate to a county-month measure by taking the mean, median, and 75th percentile of available observations for each county with at least 8 observations per month, which is equivalent to at least one observation every three days. Results are not sensitive to this sample restriction. I also use measurements of ozone, particulate matter, sulfur dioxide, nitrogen dioxide, and carbon monoxide from the EPA Air Quality System, applying the same frequency restriction. These data are the inputs in the creation of the Air Quality Index (AQI). The reported AQI is the maximum index value of the five constituent pollutants, but PM2.5 is the determining pollutant for the majority of daily observations, despite having sparse monitors.

I use the National Bureau of Economic Research Manufacturing Industry Database to calculate the share of costs for labor and capital, and combine these data with county-industry-level payroll data from the 2016 County Business Patterns to construct a measure of each industry's importance in the county economy.

The 2017 and 2020 editions of the National Emissions Inventory provide measures of factory level emissions. The EPA publishes this dataset every three years and has not yet released data for 2023. I provide summary statistics of emissions in 2017 prior to the trade war. In Figure 2, I consolidate sectors into their two-digit NAICS code (for readability) and plot total emissions of PM2.5, SO_2, and NO_x. The majority of emissions from non-traded sectors come from electricity generation (22) with non-trivial emissions from transportation (48) and waste management (56) as well.

My data are somewhat limited by the availability of air quality monitors and emission sources to create the shift share. As such, my final sample covers only 258 commuting zones (with slight variation between the pollutant weighting schemes). While these represent just under half of US commuting zones, they contain 90% of the US population. An additional 97 counties have exposure measures and are included when using remotely sensed PM2.5 concentration data. This extends my coverage to 75% of counties in the US and 95% of the population. As demonstrated in Table 1, commuting zones without AQI data are less exposed to domestic tariffs and slightly more exposed to foreign tariffs, on average. These commuting zones are also less populated and have cleaner air, based on remote data. Thus, I believe my results capture a substantial portion of the pollution that affects national health. Figure 5 depicts the counties that are present in the dataset and the availability of data for each commuting zone. For those with sufficient data from the CBP, Figures 3 and 4 plot their exposure to the tariff shocks.

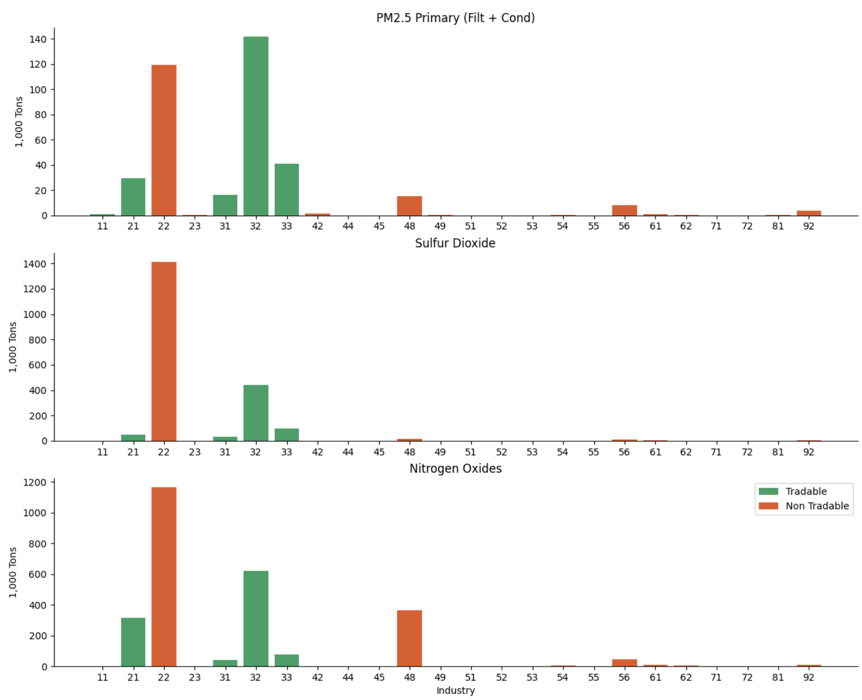

Figure 2: Baseline Emissions by Industry

Notes: Emissions are aggregated to 2 digit NAICS sectors for readability. Values depict tons of emissions and values are industry sums. Sectors beginning with 3 are manufacturing. Sector 21 is mining and sector 22 is power generation.

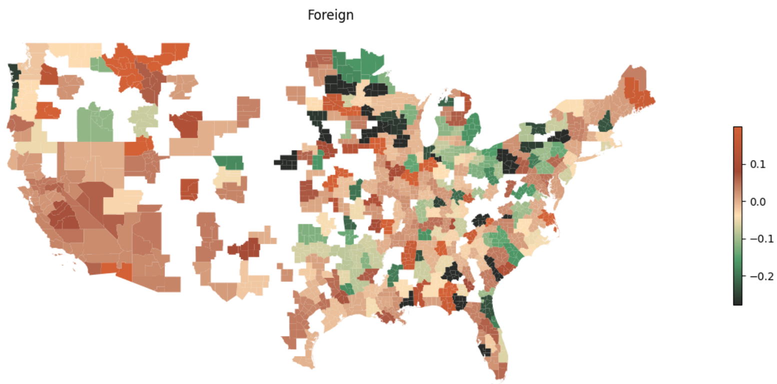

Figure 3: Commuting Zone Level Foreign Tariff Exposure

Figure depicts commuting zone level exposure to foreign tariff shocks.

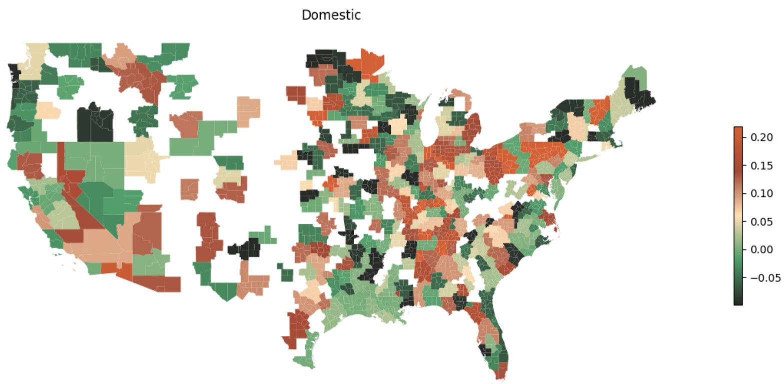

Figure 4: Commuting Zone Level Domestic Tariff Exposure

Figure depicts commuting zone level exposure to domestic tariff shocks.

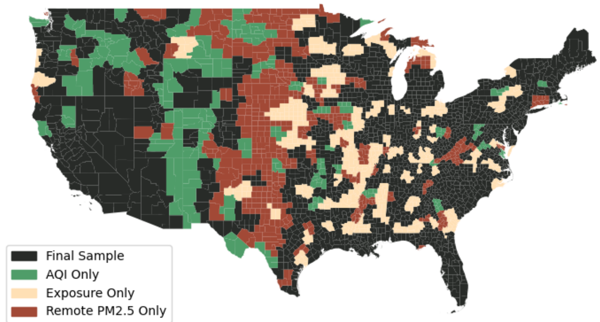

Figure 5: Availability of Data by County

	In Final Sample	No Exposure	No AQI	Remote PM2.5 Only
Count	258	70	97	156
Pop. (1000s) Mean	1124.529	104.418	179.482	46.592
Pop. (1000s) Median	514.91	57.931	147.408	30.853
Mean	42.821	38.203	-	-
Median	42.161	37.862	-	-
Mean	6.802	5.874	6.691	5.79
Median	6.488	5.276	6.451	5.414
Domestic Exposure (PM2.5)	0.068	-	0.048	-
Foreign Exposure (PM2.5)	-0.017	-	-0.031	-
Domestic Exposure (NO_x)	0.055	-	0.026	-
Foreign Exposure (NO_x)	-0.021	-	-0.046	-
Domestic Exposure (SO_2)	0.044	-	0.026	-
Foreign Exposure (SO_2)	-0.028	-	-0.041	-

Table 1: Commuting Zone Exposure Summary Statistics

Several interpolated or remotely sensed datasets exist to provide measures for counties that are not present in the EPA's air quality dataset. Several papers have studied how well remotely sensed data concord with monitor readings (Fowlie, Rubin, et al. 2019; Zou 2021). Fowlie, Rubin, et al. (2019) recommends the dataset compiled by Donkelaar et al. (2021). They compile a gridded monthly dataset of PM2.5 exposure at a scale of a one-hundredth of a degree latitude and longitude in a grid across the United States from 1998 to the present. I present estimates using this dataset and comparing pollution measures with the AQI. These data are a geophysical-hybrid combination of satellite retrievals and chemical transport modelings calibrated with ground monitors. The main sources of satellite data are from MODIS and AERONET satellites. Coverage by monitors can be sparse, even within the United States, so pollution estimates come from total column aerosol optical depth. While the reference for the dataset states that observations are calibrated with ground-based monitors, the supplemental material only describes the process of predicting values for unmonitored days, so how this calibration works is unclear.

4 Model

I utilize the model crafted by Jones (1975) and extended by Kovak (2013) to predict changes in industry output in each county. An economy is divided into industrial sectors and geographic regions. I model firms as possessing a constant returns to scale production function. Firms utilize labor and a type of capital that is specific to their sector. In the medium run, this specific factor is fixed within that sector. A high emitting steel mill cannot be repurposed as an low emitting apparel factory, nor vice versa. Labor can flow between sectors within a region, but is immobile between regions. This assumption is restrictive, but as far as it does not hold, my results are attenuated. In the most parsimonious form of my model, I consider local air pollution as the sum of pollution from all industries, which is proportional to their output Y_{sr} by a pollution intensity factor α_{sr}, with s and r indicating sectors and regions, respectively.

$$Pollution_r = \Sigma \alpha_{sr} Y_{sr} \tag{1}$$

I assume that all firms have the same technology within a sector and region, but α_{sr} can differ across counties. With hats representing proportional growth, the effect of a shock to output on pollution is a weighted average of all proportional changes in output.

$$Poll\hat{u}tion_{rt} = \Sigma_s \frac{\alpha_{sr} Y_{sr}}{\Sigma_{s'} \alpha_{s'r} Y_{s'r}} \hat{Y}_{srt} \tag{2}$$

This equation depicts the components of the shift-share methodology. The weights or shares are each industry's baseline emission shares, and that proportional changes in pollution are driven by a shock to the level of output of each industry. A shock to the price of a good (such as one resulting from an increase in tariffs) will increase the marginal product of labor in that industry, which will increase the demand of labor and result in an flow of labor from unshocked industries into shocked industries, until the marginal product of labor is equalized across all sectors in a region. This shock to price will also affect the profit maximizing output of each industry.

I can solve for $\hat{Y}_{sr}$ by rearranging the following market clearing conditions from the appendix of Kovak (2013). To simplify notation, I have dropped the subscript r from each of the following equations. θ_s is the cost share of capital. σ_s is the elasticity of substitution between capital and labor in sector s. a_{Ls} and a_{Ts} are the amount of labor and capital required to produce one unit of output. w is the wage level and R_s is the rental rate for capital of type s. P_s is the price for goods from sector s, and β_s measures the "importance" of industry s in region r's economy. L and L_s are total labor supply and the amount of labor consumed by sector. Equations 3-8 are market clearing conditions which I can use to solve for $\hat{Y}_{rs}$

$$\beta_s = \frac{\frac{L_s}{L}\frac{\sigma_s}{\theta_s}}{\Sigma\frac{L_{s'}}{L}\frac{\sigma_{s'}}{\theta_{s'}}} \tag{3}$$

$$(1-\theta_s)\hat{a}_{Ls} + \theta_s\hat{a}_{Ts} = 0 \tag{4}$$

$$\hat{Y}_s = -\hat{a}_{Ts} \tag{5}$$

$$\hat{a}_{Ts} - \hat{a}_{Ls} = \sigma_s(\hat{w} - \hat{R}_s) \tag{6}$$

$$\hat{w} = \Sigma\beta_s\hat{P}_s \tag{7}$$

$$\hat{R}_s = \frac{\hat{P}_s - (1-\theta_s)\hat{w}}{\theta_s} \tag{8}$$

Rearranging equation 4 I obtain an expression for $\hat{a}_{Ls}(\hat{a}_{Ts})$ which I can plug into equation 6.

$$-\hat{a}_{Ls} = \hat{a}_{Ts}\frac{\theta_s}{(1-\theta_s)} \tag{9}$$

$$\hat{a}_{Ts} + \hat{a}_{Ts}\frac{\theta_s}{(1-\theta_s)} = \sigma_s(\hat{w} - \hat{R}_s) \tag{10}$$

This expression reduces to equation 11 which is equivalent to equation 12 after applying equations 5, 7, and 8.

$$\hat{a}_{Ts} = (1 - \theta_s)\sigma_s(\hat{w} - \hat{R}_s) \tag{11}$$

$$\hat{Y}_{sr} = -(1 - \theta_s)\sigma_s(\Sigma\beta_s\hat{P}_s - \frac{\hat{P}_s - (1 - \theta_s)\Sigma\beta_s\hat{P}_s}{\theta_s}) \tag{12}$$

The expression for $\hat{Y}_{sr}$ is increasing in $\hat{P}$ and decreasing in θ_{sr} and $\frac{L_s}{L}$. This expression has $Y(\theta, \sigma, \beta, \hat{P})$.

In 2017, US imports of intermediate goods and raw materials comprised around 40% of the value of imports. As such, some protected industries might decrease their output as they see increases to the price of their inputs. Thus, their resultant output and pollution emissions depend on their effective protection. According to Jones (1975) , this effective production is given by

$$\hat{p}'_s = (\hat{p}_s - \sum_{s'}\omega_{s's}\hat{p}'_s)/(1 - \sum_{s'}\omega_{s's}) \tag{13}$$

where s' indexes across other industries in summations, and $\omega_{s's}$ represents industry s's share of revenue that is spent on inputs from industry s'. The change in the wages and the rental rates for each specific factor in industry s appear similar, but the changes in prices are now represented by changes in effective protection.

$$\hat{w} = \Sigma\beta_s\hat{p}'_s \tag{14}$$

$$\hat{R}_i = \frac{\hat{p}'_s - (1 - \theta_s)\hat{w}}{\theta_s} \tag{15}$$

Figure 6 plots the direct protection and effective protection for each 4-digit NAICS industry. Industries which rely on inputs subject to tariffs, such as 3312 - Steel Product Manufacturing from Purchased Steel, experience a lower level of effective protection than their direct exposure to tariffs would suggest. This measure of effective protection is my preferred specification of exposure to tariffs.

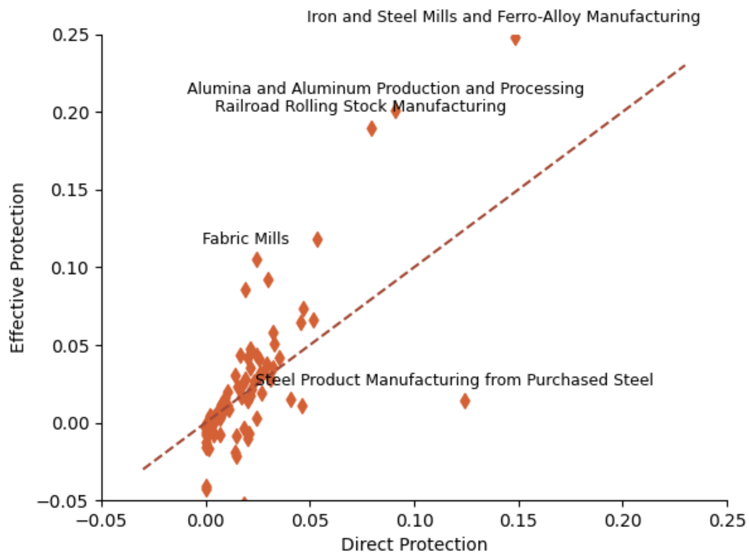

Figure 6: Effective Protection vs Direct Tariff Changes

Figure compares industry level direct protection to effective protection.

This specification includes the effect of upstream tariff shocks on downstream industries, but it does not capture the effect of downstream tariff exposure to upstream industries, thus omitting the effect of the tariffs on energy production. I address this with an alternative specification of the shift share described in Section 5.3 below.

I regress $\hat{AQI}$ on $\hat{Pollution}$ using $\frac{\alpha_{sr} Y_{sr}}{\Sigma \alpha_{s'r} \hat{Y}_{s'r}}$ as the shares and $\hat{Y}_{sr}$ as the shifts. Due to the methodology used to construct the AQI, pollutants do not have a 1-to-1 correspondence with the value of the index, so I do not expect the coefficients to be 1. Also, direct emissions of PM2.5 are only responsible for just under 50% of the PM2.5 in the ambient air, with chemical reactions (including those involving SO_2 and NO_x) also being largely responsible. As such, I use emissions of PM2.5, SO_2 and NO_x in separate specifications, and transform tariff exposure and AQI into z-scores to aid with interpretation of coefficients. The map of commuting zone exposure to foreign tariffs is displayed in Figure 3 and 4:

5 Methods

5.1 Shift-Share Methodology

Shift-share methodology allows a researcher to construct instruments of regional exposure to shocks based on local features. Borusyak, Hull, and Jaravel (2022) and (2025) describe how exogenous variation in shocks can be exploited even when shares are endogenous. Shift-share instrumental variables are consistent if two sufficient conditions are met: shocks are as good as random, and a shock-level law of large numbers applies, in other words, if sufficiently many independent shocks occur with sufficiently small average exposure. An instrument can be exogenous as long as the shifts are not concentrated in regions which experience higher shocks to the outcome variable. I implement the shift-share methodology in a "reduced form" approach, which treats the shift-share exposure as an explanatory variable without instrumenting for treatment directly.

Borusyak et al. (2025) provide a checklist for using a shift-based approach which shapes the discussion of the validity of my methodology. In my case, idealized shifts would be randomized tariffs placed on industries at the sector level. While tariff changes were not randomly assigned, I can proxy randomized shocks by calculating the weighted average of all country-product level tariff shocks within an industry. These shocks are exogenous if they are not correlated (or were not targeted to counties) with unobservable shocks or trends in air quality. I use complete shares, so my weights sum to one. My shares are calculated using 2017, which is the year immediately prior to the beginning of the sample period. I account for the tariff increases unfolding over time by dropping the months in between these shifts, so each observation is either before any shocks or after all shocks have taken effect. Each shift carries an importance weight proportional to the average exposure share for an observation. The effective number of shifts is the inverse of the Herfindahl-Hirschman index of these importance weights.

$$\text{Effective Shifts } = \frac{1}{\underset{s}{\Sigma} share_s^2} \quad \text{where} \quad share_k = \frac{1}{N_r} \underset{r}{\Sigma} share_{sr} \tag{16}$$

The effective number of shifts is 2.16 for PM2.5, 2.05 for SO_2, and 2.06 for NO_x. A low number of effective shifts increases the risk that a few dominant shocks disproportionately influence the estimates.

With a few more assumptions, Equation 2 is estimable with available data. First, I assume that

$\hat{Y}_{sr}$ is small enough that α_{sr} remains constant. I assume $\theta_{ri} = \theta_s \forall r$, so that the cost share of capital for an industry is constant across the country. Due to limited data on the elasticity of substitution between labor and capital, I assume a Cobb-Douglas production function, which implies $\sigma_{ri} = 1 \forall r, i$. This model restricts pollution to just direct industry emissions, and temporarily ignores emissions from energy production and the emissions generated by transportation when workers commute. I restrict my analysis to medium-run outcomes wherein prices and quantities can adjust, but do not model firm entry, exit, or relocation, which can have environmental consequences (Wu, Segerson, et al. 2023; Wu and Reimer 2016).

Figure **??** displays the shift-share measures of county exposure for all counties for which I have AQI data. Counties with high exposure to domestic tariffs are common in the Northeast and Rust Belt. Counties with high exposure to foreign tariffs are located farther into the Midwest and California's central valley.

5.2 Tariff Exposure

The main specification examines the association of each region's exposure to protective and retaliatory tariffs and their trends in air pollution. For my empirical analysis, I use commuting zones to represent each region and sectors are represented by industries at the 4 digit NAICS level. One example is code 3112 for grain and oilseed milling. Commuting zone exposure ($\Delta\tau_r^j$) in country r for direction j is calculated as defined previously:

$$\Delta\tau_r^j = \Sigma_{s\in S} \frac{\alpha_s Y_{sr}}{\Sigma \alpha_{s'} Y_{s'r}} \hat{Y}_{sr}^j \tag{17}$$

Direction, j, can be either domestic or foreign. Shares are defined as each sector's share of the commuting zone's total emissions for tradable sectors. I present results using emissions of PM2.5, NO_x, and SO_2 to construct county weights. In accordance with Kovak (2013), only traded sectors are included when calculating weights, because price and output shocks from tariffs can be transferred through to non-traded sectors. As such, including such industries with a shock of 0 would introduce bias. I limit my analysis to manufacturing NAICS codes due to the lack of availability for data on emissions generated by agricultural sectors.

I assume full passthrough of tariffs, or that $\hat{P}_s = \Delta\tau_s$. This assumption is reasonable, as estimates of the average passthrough of the 2018 tariff hikes are close to 1 (Cavallo et al. 2021). Output changes are calculated at the industry level, so individual variety tariff changes are averaged to create an industry tariff shock. Tariff exposure is defined as the average change in tariff for all varieties weighted by 2013-2016 market value for each sector, as shown in the expression below:

$$\Delta\tau_s^j = \frac{\Sigma_{g\in G_s}\Sigma_{k\in\mathcal{K}} p^*_{kg} m_{kg}}{\Sigma_{g'\in G_s}\Sigma_{k'\in\mathcal{K}} p^*_{k'g'} m_{k'g'}} \Delta\tau_{kg} \tag{18}$$

The subscripts g and k correspond to goods, and origin or destination countries, respectively. The set G_s is all goods corresponding to sector s. p^* is the tariff inclusive price of a good, and m is the quantity of goods traded, so $p^*_{kg} m_{kg}$ is the market value of good g from (or to) country k.

I transform the outcome and exposure variables into z-scores and estimate the following equation at the commuting zone-month level.

$$\begin{aligned} aqi_{rt} = \beta_0 + \beta_1 \Delta\tau_r^{protect} \times \mathbf{1}(year > 2018) + \beta_2 \Delta\tau_r^{retaliate} \times \mathbf{1}(year > 2018) \\ + \Gamma X_{rt} + \delta_r + \gamma_t + \epsilon_{it} \end{aligned} \tag{19}$$

Months are indexed by t and fixed effects are included for each time period to capture nationwide shocks, trends, and seasonality. As controls, I include the share of energy production by coal and by gas at the state level, Clean Air Act attainment status in the previous year, temperature, pressure, and average wind speed. aqi_{rt} is monthly air quality in a commuting zone, aggregated from the daily level by taking the mean, median, and 75th percentile. These three different metrics produce qualitatively similar results. Results are presented in Figure **??**.

5.3 Reduced-Form Inclusion of Downstream Shocks

While my model includes the effective protection, which takes into account cost increases to inputs from protection to upstream industries, it does not account for downstream effects. Although energy production was not directly impacted by tariffs, the sector is responsible for a sizable proportion of emissions. As such, it would be remiss to exclude energy production entirely from my analysis. On the national level, manufacture of tradable goods consumes around a quarter of electrical output.

From the detailed use table provided by the Bureau of Economic Analysis' input-output tables, I calculate tariff shocks as the average shock to downstream industries, weighted by output value.

$$\Delta\tau_s^{j,downstream} = \sum_{s'} \frac{c_{ss'}}{P_s Y_s} \Delta\tau_{s'}^{j} \tag{20}$$

The denominator includes all output, so industries that mainly produce final goods will have lower levels of exposure to downstream tariff shocks. Upstream tariff exposure is calculated similarly, including all variable input costs for each industry. Thus, an industry that has high labor costs (row V00100 in the use table) will appear to have lower exposure (the tariff shock on employee compensation is 0). Each industry's total use is given by the values in the columns. The model does not make predictions about the change in output due to downstream effects, so I use a reduced form shift share specification for these channels, in a manner similar to Flaaen and Pierce (2024). This exposure measure used the change in price as the shock, rather than predicted change in output.

$$\Delta\tau_r^j = \sum_s \phi_{sr} \Delta\tau_s^j \text{ where } \phi_{sr} = \frac{pollution_{sr}}{\sum_{s'} pollution_{s'r}} \tag{21}$$

The estimation equation is similar to Equation 19, except j now encompasses the Cartesian product of {upstream, downstream, direct} and {domestic, foreign}. Results for this estimation are presented in Figure 11.

5.4 Robustness Checks

I regress equation 19 using the pollution data assembled by Donkelaar et al. (2021). These data provide monthly particulate matter measurement on a .01 degree spatial grid. As such, the aggregation of this data occurs spatially, rather than temporally. For this regression, the outcome variable is either the mean or the median of all data points in the commuting zone.

I also run a placebo test on the county air quality data from 2013 to 2017. The shocks to tariffs are the same but my placebo tariffs are assumed to go into effect in July 2015. As such, this regression is the same as equation 19 but treatment is defined as $\Delta\tau_r^j \times \mathbf{1}(year > 2015.5)$ The results of this estimation are presented in Figure 12.

With dynamic effects, the coefficients returned from a two-way fixed effects specification can be dependent on the length of the sample window. I estimate the model in Equation 19 but with a restricted sample of years. The results are presented in Figure 13.

5.5 Factory Level Emissions

Using data from the 2017 and 2020 versions of the National Emissions Inventory (NEI), I assess the effect of industry-level tariff shocks on factory emissions. This estimation follows a two-period difference-in-differences methodology. Unfortunately, values for the 2020 year are impacted by the COVID-19 pandemic and its related supply and demand shocks. As such, to interpret these results as causal, I must assume that COVID-19 related shocks are not correlated with industry level tariff exposure. At the time of writing, the 2023 version of the NEI has not yet been released. Table **??** details the results of estimating Equation 22 for emissions as a z-score and a logarithmic transformation of emissions. I run this regression at both the factory level and at the industry level, the latter by summing emissions across all facilities within an industry nationwide.

$$y_{it} = \beta_0 + \beta_1 \Delta\tau_s^{protect} \times Post + \beta_2 \Delta\tau^{retaliate} \times Post + \delta_i + \gamma_t + \epsilon_{it} \tag{22}$$

Only 50% of facilities in the dataset have observable emissions in both 2017 and 2020. Of the remaining facilities, 29% emit in 2017 but not 2020, and 21% emit in 2020 but not in 2017. Firms that enter or exit the dataset are much smaller on average than firms that are present both years (Table 2). I limit my analysis to the facilities that are present in both years of data. Due to a lack of a suitable instrument, I do not perform any Heckman-style correction for censored data. However, for censoring to be an issue, firm exit or entry must somehow additionally violate the parallel trends assumption for continuing emitters.

	2017 Emissions		2020 Emissions	
	Both	Exit	Both	Enter
Count	40924	24020	40924	17489
Mean	8.763	0.899	7.842	0.679
Protective Exposure	0.0048	0.0028	0.0046	0.0025
Retaliatory Exposure	0.0046	0.0022	0.0036	0.0046

Table 2: Summary Statistics for Emitting Facilities

5.6 Trade Flows

Tariff shocks will impact pollution as far as they increase (or decrease) production in the United States. The effect on pollution can occur through a variety of channels, including direct emissions from production of each good, emissions from the production of energy used to produce goods, and other emissions related to increased economic activity (such as the emissions generated by commuting workers). In order to assess the effect of tariffs on output—measured by trade values—I calculate the elasticity of import value using the method set forth in Fajgelbaum et al. (2020). As before, goods are categorized into sectors, which correspond to 4 digit NAICS codes. Sectors are indexed by s and contained in set $\mathcal{S}$. Within each sector, aggregate demand is a three-tier CES demand system. In the upper nest, consumers differentiate between domestic and imported goods. Within each nest, there are products indexed by g and contained in $\mathcal{G}_s$. These products correspond to the HS10 level of aggregation. In the nest for imported products, varieties are differentiated by country of origin, which are contained in set $\mathcal{K}$ and indexed by k. This structure causes the value of a country k's imports to the US to be given by

$$m_{kg} = m_g a_{kg} (\frac{p_{kg}}{p_{Mg}})^{-\sigma}$$

a is a demand shock, m_g is the value spent on varieties of type g, p_{ig} is the price of good g from country i and P_{Mg} is a price index for all countries who produce good g. As the US uses ad valorem tariffs, $p^*_{kg} = (1 + \tau_{kg})p_{kg}$, where τ_{kg} is the tariff on country k for good g. Demand depends on the elasticity σ. Taking logs and differencing across time yields the equation

$$\Delta \ln\, m_{kgt} = \eta_{gt} + \eta_{kt} + \eta_{ks} - \sigma \Delta \ln\, p_{kgt} + \epsilon_{kgt} \tag{23}$$

which is useful for estimation. Supposing that tariffs are uncorrelated with unobserved import demand and export supply shocks, I estimate the demand elasticity by instrumenting the duty inclusive price with changes to the tariffs. Using the code package provided with Fajgelbaum et al. (2020), I recreate their Table IV. These results are presented in Table 4. The estimation equation is depicted below.

$$\Delta \ln\, m_{kgt} = \eta_{gt} + \eta_{kt} + \eta_{ik} - \sigma \Delta \ln\, (1 + \tau_{kgt}) + \epsilon_{kgt} \tag{24}$$

My data for employment and emissions in the United States are at the four digit NAICS level. As such, I need to ascertain how tariffs affect the total value of imports within an industry. I create an industry level tariff as a weighted average of all country-product pairs in an industry. The weights are determined by a country-product combination's share of total import value during 2017. Let $s \in \mathcal{J}$ represent each four digit NAICS industry, then

$$\tau_{ist} = \sum_{g \in s} \frac{m_{ig,2017}}{\sum_{g \in s} m_{ig,2017}} \tau_{igt}$$

The outcome variable is the value of imports. I sum the import value during each month for all products in an industry for each country, so that

$$m_{kst} = \sum_{g \in s} m_{kgt}$$

My estimation equation is similar to (24), but at the NAICS 4 level rather than HS10. Results of this estimation are presented in Table 5.

$$\Delta \ln\, m_{kst} = \eta_{st} + \eta_{kt} + \eta_{ks} - \sigma \Delta \ln\, (1 + \tau^*_{kst}) + \epsilon_{kst} \tag{25}$$

While I have 28 monthly observations for most country-HS10 pairs, the tariff on a good changes at most once for any variety in my data set. As such, more than 99% of observations of $\Delta \ln\, \tau_{igt}$ are 0. I present the event study from Fajgelbaum et al. (2020) as Figure 15 to demonstrate that the noted effects on import values and quantities are sudden and permanent.

5.7 Energy Generation

The energy grid in the United States is a wide interconnected network. While the power plants located near a city will likely produce much of the electricity consumed in that city, local consumption is not guaranteed. Some energy produced by a plant will be consumed many kilometers away. As such, difference in differences estimates of electricity generation that use spatial variation in treatment are subject to SUTVA violations. However, since transporting energy along power lines is costly, reason exists to believe that energy generation exhibits some local effects. Long distance power lines are more efficient than local connections, so the losses from long distance transmission are small. With this caveat in mind, I present evidence of the effect of tariff exposure on three outcomes: energy generation at the "commuting zone" level, energy generation at the facility level, and energy sales to industrial customers at the utility level.

For each commuting zone, I sum up total generation from facilities within 100 miles of the county population centroid. The estimation equation is similar to the estimation equation for my main specification, using a difference in differences methodology to compare highly treated and less treated counties.

$$y_{rt} = \beta_0 + \beta_1 \Delta\tau_r^{domestic} \times Post + \beta_2 \Delta\tau_r^{foreign} \times Post + \delta_r + \gamma_t + \epsilon_{rt} \tag{26}$$

I also estimate a similar specification at the facility level, and construct the mean exposure of all counties within 100 miles of the plant. However, for such commuting zones as are missing exposure data this plant level exposure is incomplete. I limit my sample to facilities with no more than 20% of nearby commuting zones lacking an exposure measure. The commuting zone-level and facility-level results are presented in Figure 16 and 17, respectively.

Using the data from EIS-861, I run a similar specification on sales of energy to industrial customers by utilities. The data are at the utility-state level, so I have separate observations if a utility crosses state lines. I have a list of all counties in which a utility operates, but not county level sales so I cannot observe more detail if a utility covers a large swath of any state. I limit the dataset to utilities with for which at least 50% of their counties are in a commuting zone for which I have a measure of exposure to tariffs. This is 78% of state-utility pairs and 66% of total commercial electricity sales. I lack data on what percentage of each utility's sales are in a certain county, so I take the simple average of commuting zone exposure to create a measure of utility tariff exposure. I also compute an exposure score using population weighted averages. However, there is no reason to believe this measure is better. Suppose Utility C serves counties A and B. County A has a population of 20,000 and all utility needs are serviced by Utility C. County B has a population of 500,000 of whom 1,000 are served by Utility C. As I can only observe that Utility C operates in both counties, I cannot create a better measure of exposure metrics. The estimation equation for this specification is similar to Equation 26, where i denotes electric utility.

6 Results

6.1 Pollution

The coefficients of the regression from Equation 19 are displayed graphically in Figure 7. All variables are standardized into Z-scores, so the coefficients represent the response, in standard deviation terms, to a one-standard-deviation increase in the right-hand side variables. The outcome variable is either the mean, median, or 75th percentile of daily AQI observations. A higher value of AQI indicates a more polluted area, so a negative coefficient reflects an air quality improvement. I present results using weights of baseline emissions of PM2.5, SO_2, and NO_x. A one-standard deviation increase in foreign exposure leads to a 0.01 standard deviation improvement in air quality. The coefficients for foreign tariff exposure are negative and statistically significant for the PM2.5 weighting scheme, with qualitatively similar results for SO_2 and NO_x. The coefficients on domestic tariff exposure are not statistically significant, but are not statistically different from the coefficients on foreign tariff exposure.

The difference-in-differences methodology means that my results represent the relative effect of a commuting zone being more exposed to domestic or foreign tariffs than other commuting zones. The results do not speak to overall trends in the level of air pollution across the nation, only to how this trends differs across counties based on exposure

This regression includes direct tariff exposure and the exposure scores are adjusted for effective protection, but any downstream effects are not included. This restriction excludes energy generation emissions, which are a larger share of county emissions for NO_x and SO_2, which could explain why the results are different for these alternate weighting schemes.

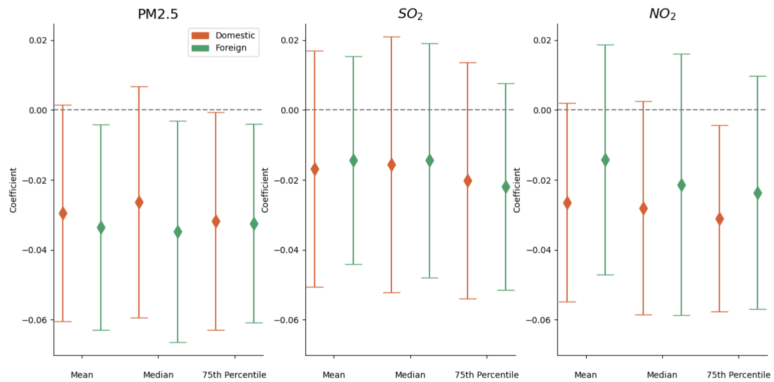

Figure 7: AQI on Shift Share Exposure - Commuting Zone Level

Figure depicts coefficients and 95% confidence intervals of Tariff Exposure (Z-score) on PM2.5 concentration (Z-score). Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Standard errors are clustered at the commuting zone level, and controls include temperature, precipitation, wind speed, barometric pressure, state share of energy production from coal and gas, exposure of other nearby regions, and county and year fixed effects.

I run a similar regression at the county level. The results are displayed in Figure 8. The point estimates are qualitatively similar, but are no longer statistically significant.

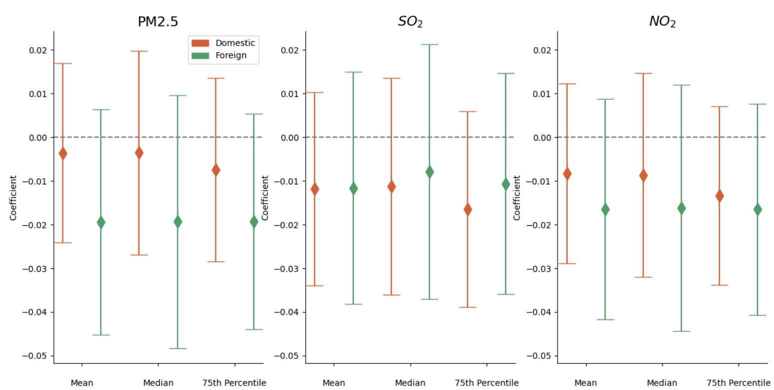

Figure 8: AQI on Shift Share Exposure - County Level

Figure depicts coefficients and 95% confidence intervals of Tariff Exposure (Z-score) on AQI (Z-score). The three panels represent alternate weighting schemes. Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Standard errors are clustered at the county level, and controls include temperature, precipitation, wind speed, barometric pressure, state share of energy production from coal and gas, exposure of other nearby regions, and county and year fixed effects.

6.2 Remotely Sensed Pollution Data

I also run the main specification using the remotely sensed PM2.5 concentration compiled by Donkelaar et al. (2021). These results are displayed in Figure 9. Including the additional 148 commuting zones attenuated my results for the PM2.5 specification, but the results remain the same for the NO_2 weighing scheme.

For both commuting zones and counties and both monitored and remote data, there is no statistically significant difference between foreign and domestic tariff exposure. However, this is not due to regions receiving similar measures of domestic and foreign exposure. Figure 10 displays a scatterplot of commuting zone's domestic and foreign exposure. More commuting zones lie in the off-diagonal quadrants, indicating a higher than median exposure to one direction and a lower than median exposure to the other. Table 3 contains correlation coefficients for tariff exposures and average scores for nearby commuting zones. These metrics are not strongly correlated.

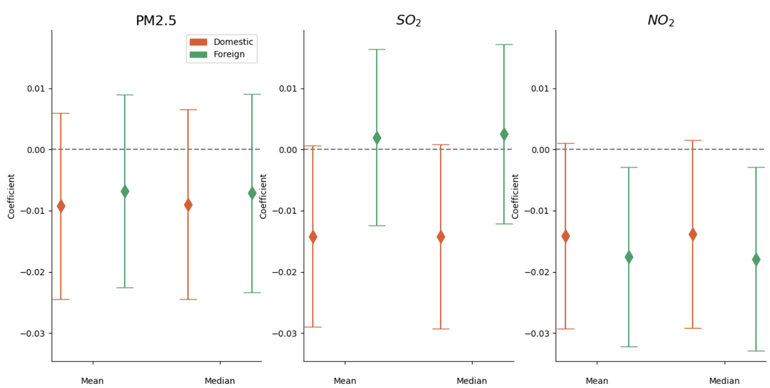

Figure 9: Regression Results with Remotely Sensed Pollution Data

Figure depicts coefficients and 95% confidence intervals of Tariff Exposure (Z-score) on PM2.5 concentration (Z-score). Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Standard errors are clustered at the commuting zone level, and controls include temperature, precipitation, wind speed, barometric pressure, state share of energy production from coal and gas, and county and year fixed effects.

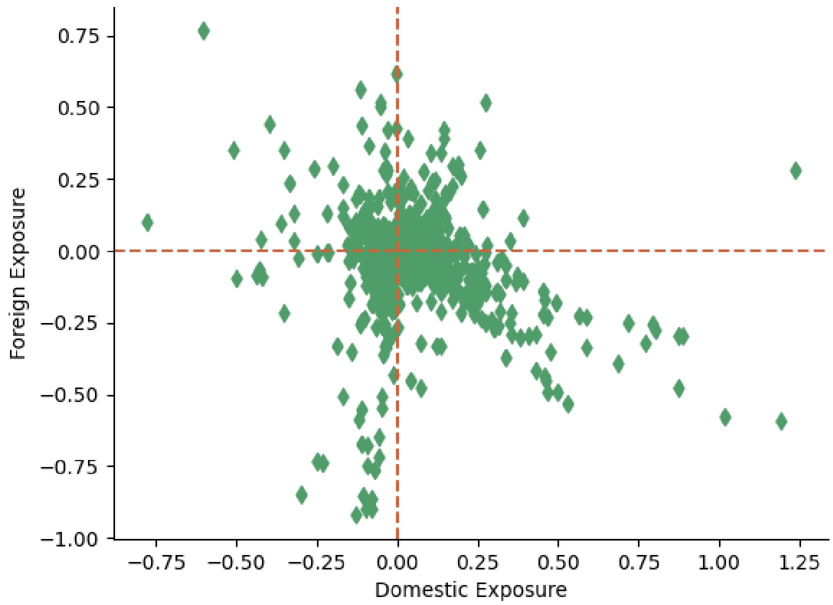

Figure 10: Comparison of Foreign and Domestic Tariff Exposure

Figure depicts foreign and domestic tariff exposure for all commuting zones. The dashed lines represent the median of each sample.

	Domestic Exposure	Nearby Domestic Exposure	Foreign Exposure	Nearby Foreign Exposure
Domestic Exposure	1.0	0.06	-0.22	-0.07
Nearby Domestic Exposure	0.06	1.0	-0.09	-0.3
Foreign Exposure	-0.22	-0.09	1.0	0.11
Nearby Foreign Exposure	-0.07	-0.3	0.11	1.0

Table 3: Correlation Coefficients for Tariff Exposure

Table has correlation coefficients for each commuting zone's domestic tariff exposure, foreign tariff exposure, and average measures of nearby tariff exposure.

The results including upstream and downstream channels in a reduced form shift share as described in Equation 21 are presented in Figure 11. The estimates are noisy and only upstream domestic protection has a statistically significant coefficient under one weighting scheme.

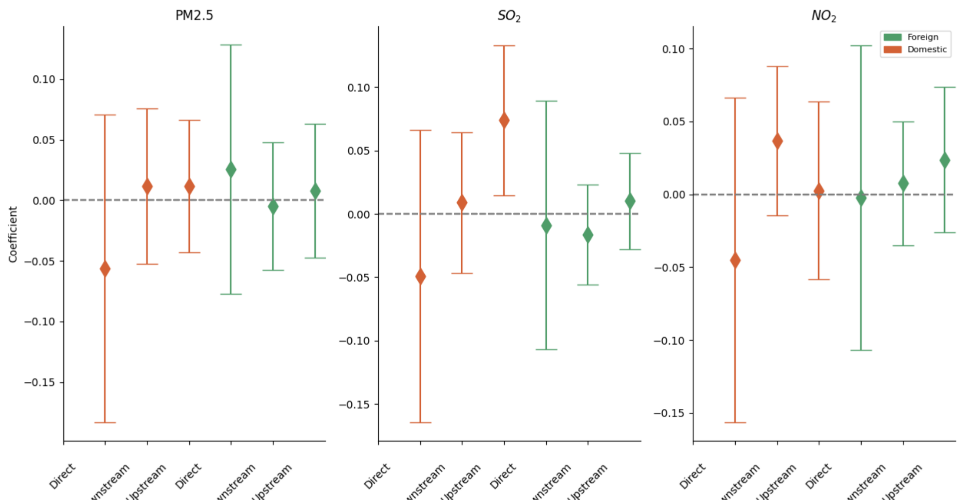

Figure 11: AQI on Reduced Form Upstream, Downstream, and Direct Exposure

Figure depicts coefficients and 95% confidence intervals of Tariff Exposure (Z-score) on PM2.5 concentration (Z-score). Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Standard errors are clustered at the county level, and controls include temperature, precipitation, wind speed, barometric pressure, state share of energy production from coal and gas, exposure of other nearby regions, exposure of other nearby regions, and county and year fixed effects.

6.3 Robustness Checks

Results from a placebo test placing treatment in July 2015 are displayed in Figure 12. All other definitions and calculations are otherwise the same. There are no statistically significant results for any of the weighting specifications. These results suggest that parallel trends hold in pre-period.

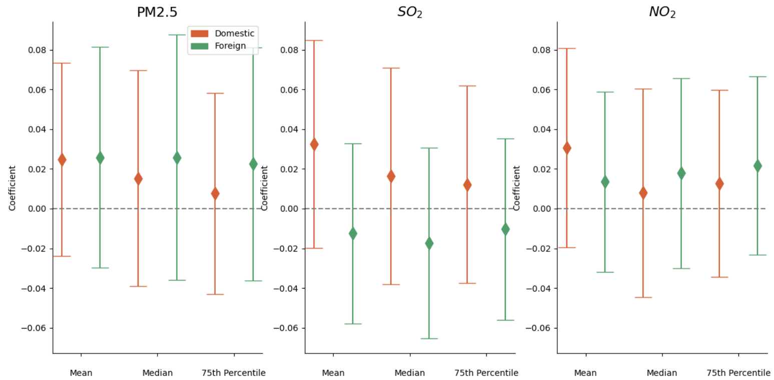

Figure 12: Placebo Test - Treatment in July 2015

Figure depicts coefficients and 95% confidence intervals of Tariff Exposure (Z-score) on PM2.5 concentration (Z-score) with placebo treatment in July 2025. Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Standard errors are clustered at the commuting zone level, and controls include temperature, precipitation, wind speed, barometric pressure, state share of energy production from coal and gas, and county and year fixed effects.

Research about the credibility of difference in differences specifications has shown that some estimates can be dependent on sample length. I restrict the data to shorter post-periods to assess the sensitivity of my results to the length of the sample period. Figure 13 contains the results of these sensitivity checks. In this case, the sample restrictions do not impact the results of the regression.

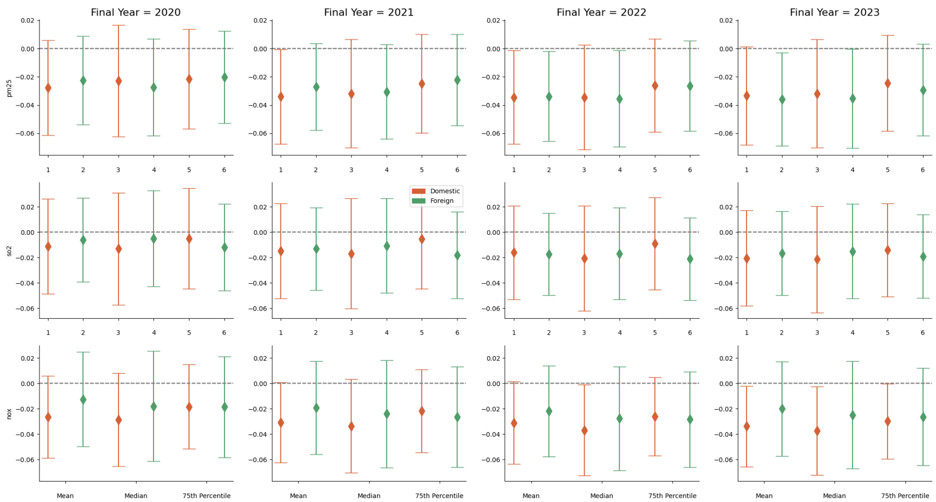

Figure 13: Sensitivity of Results to Sample Period Length

Figure depicts coefficients and 95% confidence intervals of Tariff Exposure (Z-score) on PM2.5 concentration (Z-score). Each column represents a different ending year for the sample, while each row represents different weighting schemes. Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Standard errors are clustered at the commuting zone level, and controls include temperature, precipitation, wind speed, barometric pressure, state share of energy production from coal and gas, exposure of other nearby regions, and county and year fixed effects.

6.4 Factory Level Emissions

Results for the regression of factory-level emissions on industry exposure are contained in Figure 14. On the left of each panel, emissions and exposures are computed as z-scores, so coefficients are interpreted as standard deviation increases in emissions associated with a one unit increase in exposure. Exposure is the weighted average of all variety-level tariff changes, which are much smaller than 1. On the right, I take the logarithm of emissions, so the coefficient represents the percent change associated with a one unit increase. These results come from a two-period difference-in-differences framework with 2020 emissions as the "post" period. At the industry level, none of the coefficients are statistically significant, but at the facility level, an increase in tariff exposure is associated with a small decrease in emissions. These results are in line with the downstream effect, where retaliatory exposure leads to a moderate improvement in air quality. However, any contemporaneous shocks to industries as a result of the global response to the pandemic will also be reflected in these results.

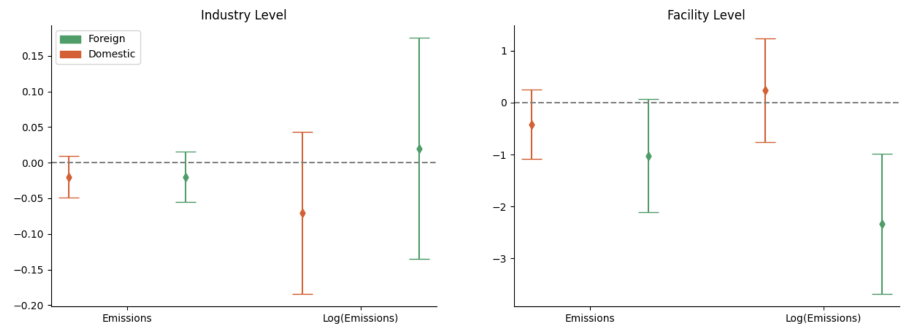

Figure 14: Emissions Regression

Figure depicts coefficients and 95% confidence intervals of emissions of PM2.5 (Z-score) on industry tariff exposure (Z-score). The left panel is a national aggregation of industry emissions (N=588), while the right panel is at the facility level (N=77957). Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Reported standard errors are robust to heteroskedasticity.

6.5 Trade Flows

Results for the tariff effects on trade flows are presented below. At both the variety and country-sector level, increasing a tariff has a negative effect on the market value of imports and on the quantity imported. A couple caveats shape how I think about these results.

First, these results demonstrate that raising a tariff on one country decreases imports from that country. If tariffs merely change the source of US imports, it is possible that US production will not be impacted, and therefore the first stage of my causal chain does not hold. Second, it is not clear that the coefficient on $\Delta \ln p^*_{kgt} m_{kgt}$ should be negative. A tariff is expected to have counteracting effects on the final price and the quantity traded, so a tariff should increase p^*_{kgt} and decrease m_{kgt}.

At both the HS10-country level and NAICS4 - country level implementing a tariff decreases the value of imports. Event study coefficients at the product level demonstrate that these changes are immediate and persistent. The coefficient on quantity is no longer significant for the sector-country level regression, but this can be an artifact of aggregating different products into one value.

Table 4: HS10 - Monthly

	$\Delta \ln p^*_{igt} m_{igt}$	$\Delta \ln m_{igt}$	$\Delta \ln p^*_{igt}$	$\Delta \ln p_{igt}$	$\Delta \ln p^*_{igt}$	$\Delta \ln m_{igt}$
$\Delta \ln(1+\tau_{igt})$	-1.52	-1.47***	0.00	0.58***		
	.	0.24	0.08	0.13		
$\Delta \ln m_{igt}$					-0.00	
					0.05	
$\Delta \ln p_{igt}$						-2.53***
						0.26
Product X Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
1st-Stage F					36.5	21.2
R2	0.13	0.13	0.11	0.11	0.00	.
N	2,993,288	2,454,023	2,454,023	2,454,023	2,454,023	2,454,023

Notes: Coefficients from the estimation of Equation 23. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Naics 4 - Monthly

	$\Delta \ln p^*_{igt} m_{igt}$	$\Delta \ln m_{igt}$	$\Delta \ln p^*_{igt}$	$\Delta \ln p_{igt}$	$\Delta \ln p^*_{igt}$	$\Delta \ln m_{igt}$
$\Delta \ln(1+\tau_{igt})$	-1.65**	-1.11	-0.36	-0.28		
	0.66	1.05	0.80	0.83		
$\Delta \ln m_{igt}$					26.20	
					481.35	
$\Delta \ln p_{igt}$						0.05
						3.13
Product X Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
1st-Stage F					0.0	0.3
R2	0.10	0.09	0.07	0.07	.	.
N	187,888	169,572	162,247	162,247	163,615	163,615

Notes: Coefficients from the estimation of Equation 25. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

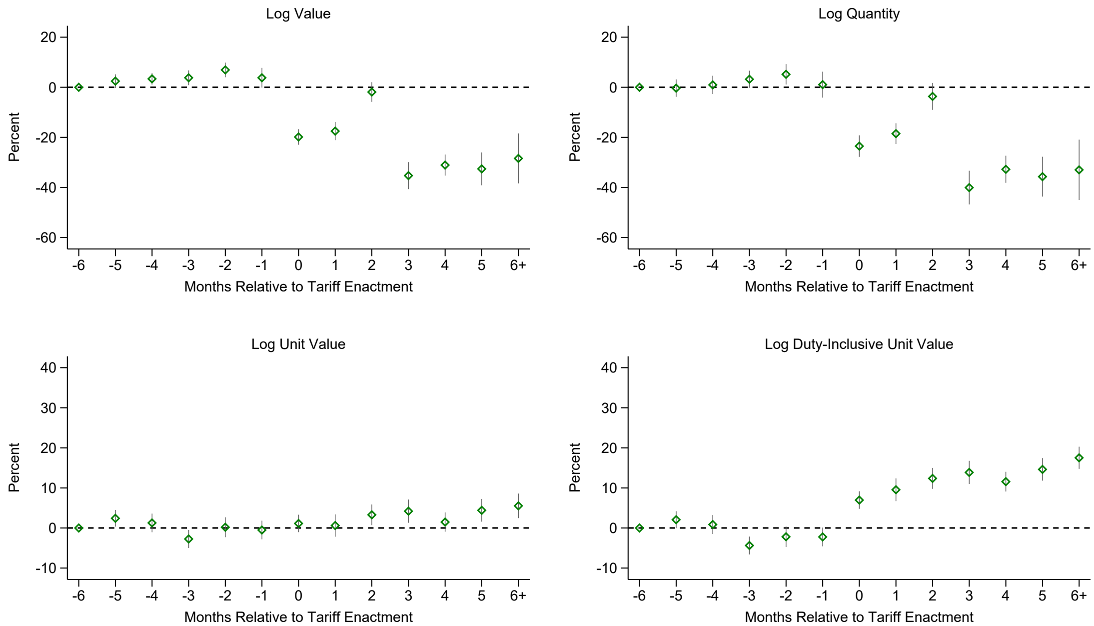

Figure 15: Event Study Estimates

Notes: Event study coefficients from Figure II of Fajgelbaum et al. (2020)

6.6 Electricity Generation

The results of estimating Equation 26 are shown in Figure 16. The coefficient for foreign tariff exposure is negative and statistically significant, suggesting that energy generation decreases around areas that are exposed to foreign tariffs shocks. Results from a similar specification are presented in Figure 17. This specification looks at energy generation at the facility level. I calculate an exposure score by taking the average foreign and domestic tariff exposure of nearby commuting zones. In this specification, the coefficient for domestic exposure is negative and statistically significant, suggesting that facilities surrounded by regions exposed to the domestic tariffs decreased their production. Finally, results for the energy sales specification presented in Figure 18 are not statistically significant at the $p < .05$ level in either levels or logs, but the log specification is significant at the $p < .1$ level. This result could be in line with the commuting zone level exposure in Figure 16.

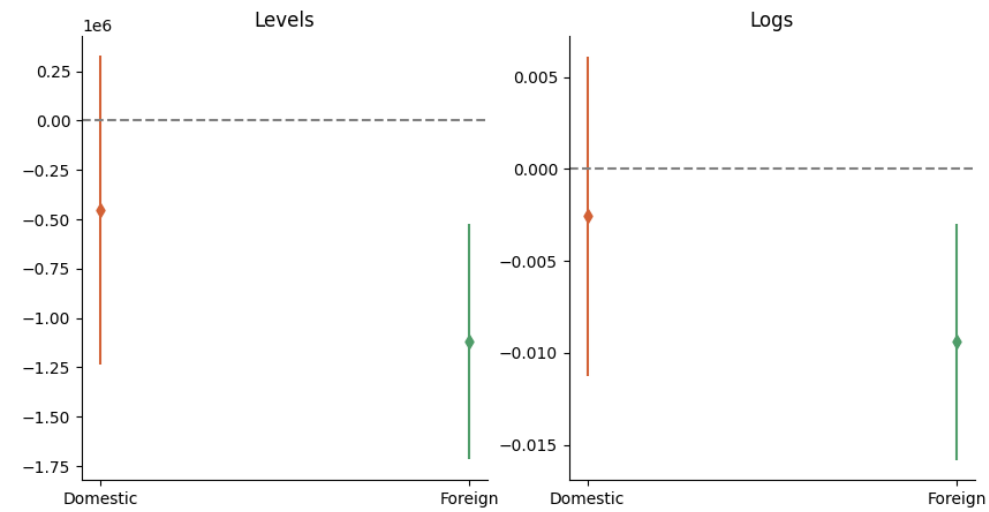

Figure 16: Commuting Zone - Energy Generation

Figure depicts coefficients and 95% confidence intervals for a regression of total energy generation (Thousand Mwh) on commuting zone tariff exposure (Z-score). Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. I control for the exposure level of nearby commuting zones. Reported standard errors are robust to heteroskedasticity.

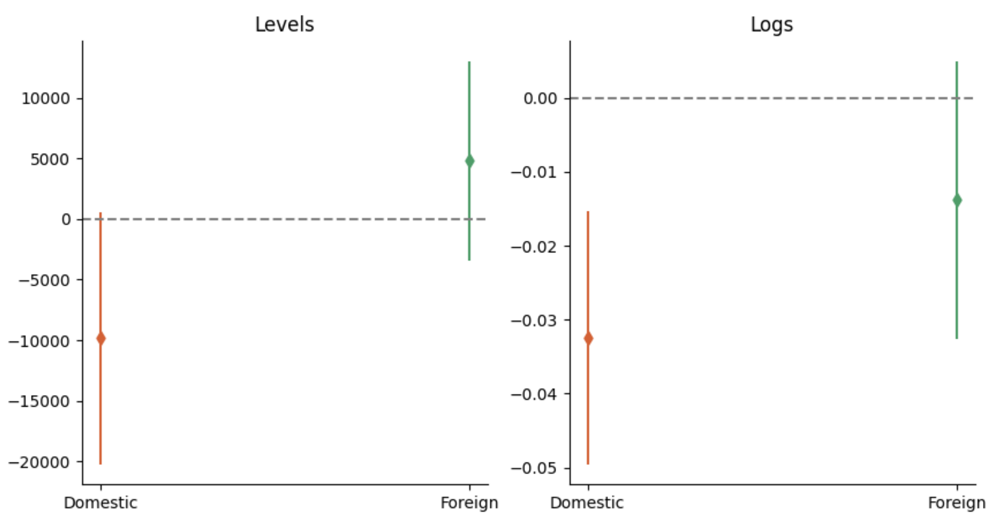

Figure 17: Facility Level Generation - Commuting Zone Level

Figure depicts coefficients and 95% confidence intervals for a regression of facility level energy generation (Thousand Mwh) on average tariff exposure of nearby commuting zones (Z-score). Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Reported standard errors are robust to heteroskedasticity.

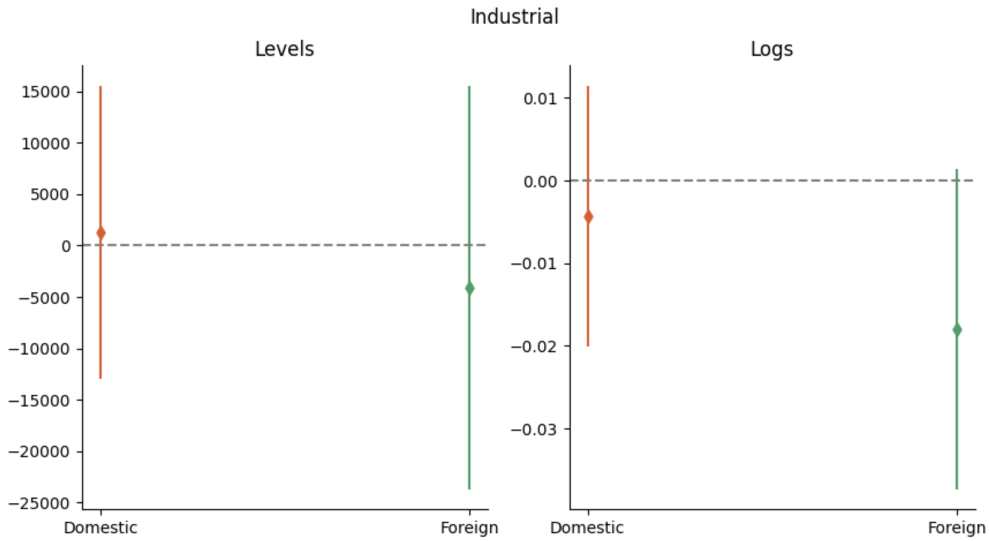

Figure 18: Utility Level Industrial Sales of Electricity

Figure depicts coefficients and 95% confidence intervals for a regression of utility level industrial energy sales (Thousand Mwh, log(Thousand Mwh) on average tariff exposure of the utility's coverage zone (Z-score). Left (brown) coefficients are for domestic tariff exposure, while right (green) coefficients represent foreign tariffs. Reported standard errors are robust to heteroskedasticity.

7 Conclusion

Trade wars appear likely to play a large part in the near future of the US. I examine the impact of tariff shocks on ambient air quality via a shift-share framework. I apply the Jones (1975) model to map tariff shocks and "effective protection" to changes in industry output. I also use the methodology established in Fajgelbaum et al. (2020) to estimate the elasticity of imports to tariff changes and assess how these shocks affect pollution at the commuting zone level.

I find that increasing tariffs reduces market value and quantity of imports at the good-country and sector-country level. This aligns with theoretical predictions. I also find that commuting zone-level exposure to foreign tariffs is associated with modest improvements in average air quality of 0.015 of a standard deviation in response to a standard deviation increase in tariff exposure. However, I do not find a statistically different effect of domestic tariff exposure. These findings suggest that tariff-induced shifts in economic activity can have tangible environmental consequences. I present suggestive evidence that these changes to air quality are driven by factory emissions. However, interpretation of the factory-level regression is hindered by the coincidence of the COVID-

19 pandemic. I also present some evidence that energy generation decreased near exposed regions, although I do not find a statistically significant similar decrease in industrial electricity sales.

Data availability limits my ability to examine effects for the entire United States, but my dataset covers close to two-thirds of the national population. The commuting zones covered by the air quality data also experience larger trade shocks, so I capture the majority of the effects I seek to measure. I assess the robustness of my results to the choice of pollution data. The nature of difference-in-differences causes my results to describe the relative effect of tariff exposure between highly exposed and less exposed counties. My sample period covers the first 5 years after the tariffs go into effect. As such, I may miss long run effects that arise as a result of new factory construction. The long run effects could cause larger changes to air pollution concentrations in the future.

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