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HOW THE US-CHINA TRADE WAR ACCELERATED URBAN ECONOMIC GROWTH AND ENVIRONMENTAL PROGRESS IN NORTHERN VIETNAM

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ABSTRACT

The Trump Administration's tariffs created a wedge between mutually beneficial trades between China's producers and U.S. consumers. Moving production to nearby Vietnam allows firms to jump the tariff wall. Within Vietnam, cities closer to China with respect to distance and industrial mix grow faster and attract more FDI. They are increasingly consuming renewable power to fuel their local economy. We study the local air quality gains and the carbon dioxide emissions reductions associated with the growth in regional trade. China's regional trade increases have important implications for the rise of the system of cities across Asia.

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1. Introduction

In March 2018, the Trump Administration introduced Section 301 China Tariffs and implemented them in phases on *all products* imported from China. The additional *ad valorem* duty on top of the normal rate was 25% on 6,874 goods and 10% on 3,771 items. The launch of the US-China Trade War created a wedge between mutually beneficial bilateral trade between China's producers and U.S. consumers.

Moving production to nearby countries allows firms to jump the tariff wall. Vietnam, a lower-middle-income country neighboring China, has gained more than any other nations from the trade war. Its physical proximity to China reduces transportation costs. Its cheaper labor facilitates export growth. (Grossman et al., 2006; Helpman, 2006). Vietnam's hydro, wind and solar potential offer it the opportunity to generate ample renewable power and thus avoid experiencing rising air pollution levels during a time of fast industrialization.

We study the differential economic and environmental gains for various cities in Vietnam due to the recent export boom. Across Vietnam's system of cities, a new geography of economic growth is taking place. Within Vietnam, those cities that are physically closer to China's border and those cities featuring better baseline transport infrastructure and those whose industrial base complements China's production all gain more from this China Shock. The Guangdong Province generates 26% of China's exports.[3] *Roadway* freight transportation takes *only six hours* to go from Guangdong to Vietnam.[4] If a six-hour drive can avoid 25% of the United States import duty, then many supply chains have strong incentives to outsource some production and assembly steps to the nearby Vietnam cities.

Our empirical analysis of Vietnam's urban economic growth dynamics uses a simple economic geography model focused on city "closeness" to China's manufacturers. Our closeness metric reflects both the physical distance based on the existing transport infrastructure connecting these two countries, and the "product space" distance between a Vietnamese city's industrial base with China's producers.

We find a border effect for Vietnam such that a one percentage point increase of a Vietnamese location's industrial-composition-weighted average of the *ad valorem* China tariff (defined as this location's tariff privilege relative to China) is associated with an increase in a location's enterprise output by 4.6% if the location is in the proximity of China. This location-

[3] This export figure for 2018 is from the Data and Profiles webpage of the Hong Kong Trade Development Council.
[4] While road transport only takes six hours, the same-origin-destination maritime trip takes four days excluding the travel time on the roads. The average turnaround days of ports in China and Vietnam were 1.1 and 0.9 days, respectively (2022 World Bank data). The average speed is around 12 knots per hour for container ships traveling from China to Vietnam, based on data from Ludwig (2024). At that speed, the sailing time is 2.2 days between the important Guangzhou and Hai Phong ports in Guangdong and Northern Vietnam. The 2.5-day sailing from Hai Phong's (North) to Ho Chi Ming City's (South) sea areas also far exceeds the 1.2-day road travel time.

specific output growth contracts by 0.2% for every 100 km increment up to the farthest province 2,000 km away from China as measured by roadway distance.

In the past the South Vietnam (farther from China) was more prosperous than the North – the metropolitan area around Ho Chi Minh City in the South was the main economic engine of the entire Vietnam. A nation with only one giant city always faces big challenges such as congestion and pollution, as well as low-quality governance (Ades and Glaeser 2015; Glaeser 2022). Competition between cities within the same nation leads to better local governance and helps people to adapt to negative shocks (Henderson and Kriticos, 2018). This US-China trade war accelerates economic growth in the North relative to the South. This constitutes a reversal of spatial growth pattern in Vietnam, and many cities in the North are now catching up fast. In this sense, this trade war will help build out Vietnam's system of cities. Firms and workers will have a much richer menu of cities to choose where to locate.

Vietnam and China are not playing a "zero-sum game." Facing the tariffs, China's producers gain from continuing to do the first several steps in the value chain and then jumping the tariff wall for the later steps and final assembly of creating the final export good. In this way, China is better off compared to losing production to Vietnam. Vietnam is better off by building up its production capacity as it relies on China's existing supply-chain components, infrastructure, and expertise rather than starting from scratch. China's wages and environmental regulations have significantly increased, amplifying Northern Vietnam's cost advantage for siting such production facilities. Vietnam gains in the medium term if there is a learning effect in producing manufacturing goods. This tariff shock acts as a demand shifter that stimulates Vietnam's infant industries.

Our empirical approach allows us to conduct several placebo tests. For industries whose goods the United States is not importing, we do not find evidence of a Vietnam border effect. We do not find evidence of a border effect for Vietnam with respect to its other neighbors (Laos and Cambodia), either. Vietnam's distinctive geographic shape helps us here with respect to identifying border effects.

Our within-nation analysis complements the recent macro/trade literature that has explored how offshoring affects upstream and downstream nations and industries. Influential papers in this literature include; Melitz (2003), Helpman et al. (2004), Helpman (2006), Rossi-Hansberg et al. (2009), Arkolakis (2010), Liao (2012), and Melitz and Redding (2015). The macro quantitative spatial model literature has estimated the overall impacts of the Trump Tariffs – Each 1% *ad valorem* tariff added in 2018 caused a 6% fall in US imports (Amiti et al., 2019). The US consumption-growth elasticity to S301 China tariffs (Lists 1-3) was about minus one (Waugh, 2019). The tariff pass-through to consumer prices was complete, and Americans bore considerable welfare or real-income loss (Amiti et al., 2019; Fajgelbaum et al., 2020; Fajgelbaum and Amit, 2022). American firms' stock prices also fell upon the tariff announcement (Huang et al., 2023). More recent studies examine impacts beyond the US. Besides Flaaen et al. (2020) and Fajgelbaum et al. (2023), Jiang et al. (2023) estimated a 16% decline in China's exports to the US and a modest sign of short-run export diversification to nearby countries by mid-2019. Alfaro and Chor (2023) found rising US import shares from Vietnam among products with declining import shares from China during 2017-2022. These results support our hypothesis of near-shoring from China to Vietnam.

After studying the urban growth effect, we move on to explore the environmental consequences of Vietnam’s manufacturing boom. As Vietnam’s border cities boom, the Environmental Kuznets Curve hypothesis posits that local air pollution levels will grow worse as the scale effects of industrialization increase (Grossman and Krueger, 1992, Dasgupta et al., 2002; Levinson et al., 2002). Below, we present evidence of the rising use of cleaner energy in Vietnam. If China’s manufacturing regions rely on coal fired power while Vietnam’s growing cities rely on cleaner power, then the transfer of economic activity from the richer nation to the poorer could actually improve environmental quality in both nations.

We reject the hypothesis that Vietnam is now following China’s past pollution-intensive trajectory. Using coal as the exceedingly dominating energy source in power generation, China once experienced unprecedented deterioration in air quality, and the journey to regain blue skies has been a long march (Kahn and Zheng, 2016). Vietnam, on the other hand, has ample renewable energy resources such as hydro, wind, solar, and biomass. As FDI flows into Vietnam, it is likely that this foreign capital and human capital with green production know-how is playing a role in facilitating pollution progress during a time of urban economic growth (Zheng, Kahn and Liu 2010).

The rest of the paper is organized as follows. Section 2 provides details about the US-China Trade War and Vietnam's natural and economic geography and energy policies. Section 3 introduces our methodology, and Section 4 discusses the data sources and compiled sample. Sections 5 and 6 present and analyze empirical results. Section 7 concludes.

2. Background and Data Construction

2.1. U.S. Trade Relations and the US-China Trade War

As a WTO member, the United States maintains the PNTR (Permanent Normal Trade Relations) with all other WTO member economies; it grants them the most favored NTR tariffs. Exceptions, however, can happen in circumstances that the WTO permits. One is the Section 301 retaliation against an economy pursuing unfair trade with the United States.

The Section 301 China tariffs were announced in early 2018 and implemented in phases. List 1 took effect on Jul. 6, 2018, which marked the start of the US-China trade war. By Feb.

14, 2020, 68% of US import volume from China was subject to the S301 *ad valorem* duty. Commodities (i.e., subheadings) in Lists 1, 2, and 3 were taxed an additional 25%, and those in List 4A were charged an extra 7.5%. Due to the Phase One agreement, the S301 tariffs have never applied to commodities in List 4B. Appendix Table A1 tabulates the duty, date of implementation, and coverage of each phase.

China's PNTR took effect upon its accession to WTO in 2001, and exports to the US had fuelled its growth for nearly two decades. While Americans benefited from cheaper manufactured goods in general, economic studies document that the import substitution from China constituted declines in industrial employment (e.g., Pierce and Schott, 2016) and manufacturing towns (e.g., Autor et al., 2013) in the US. The tension in the US-China trade relationship intensified during the Trump Administration and led to the trade war.

2.2. Vietnam's Natural and Economic Geography

As illustrated in Figure 1, Vietnam (8º10' to 23º24' N; 102º09' to 109º30' E) is a Southeast Asian country located at the eastern edge of the Indochinese peninsula, to the South of China and the east of Laos and Cambodia. Its territory exhibits a thin, long S-shape, occupying over 3,000 km of coastline. The longest north-south straight-line distance is around 1,600 km, but the east-west distance is as narrow as about 50 km. The country features rugged mountainous terrain between 11º and 23º N in the west. It has sixteen major drainage basins comprising more than 2,000 rivers that vastly flow from west to east. Most rivers are unnavigable for freight.

[Insert Figure 1 here]

The country has five cities under the central government and 58 provinces; we call all of them "cities" hereafter for brevity. These 63 provincial-level locations are appropriate for our research because they are generally have a greater population density than China's prefectural cities (See Appendix Figure A1). Moreover, unlike China and India, Vietnamese provinces are not big. Their average size is only 5,257 km^2 (2,030 mi^2), about 1.7 times the size of an average U.S. county.

Vietnam's freight transport mainly relies on roadways. The General Statistics Office's (GSO) 2015-2017 data show that railways and airways only carried 0.6% of domestic and international freight shipments. Maritime and inland waterways carried 20%. Roadways counted for as high as 79%. Roadways are most convenient for China-Vietnam freight transport as maritime transport is far longer. Our analysis focuses on roads and controls for other types of transport infrastructure.

Due to its physical geography, Vietnam has two economic cores. One is the North, led by the Ha Noi city in the Red River Delta, which is a plain of 15,000 km^2. The other is the South, led by Ho Chi Minh City (Saigon) in the Mekong River Delta, which comprises 40,000 km^2 of flat land and is one of the world's largest rice-growing regions. In the middle regions, economic activities are present along the coastline, where spurs and rivers divide lands into compartments. While Vietnam is a lower-middle-income country, it is the world's 35th-largest economy because it is the 16th most populated nation with more than 100 million people. The South is traditionally more prosperous than the North, but this spatial pattern of prosperity has been going through a reversion in recent years, as Figure 2 shows. This naturally raises the question of how the US-China trade war has reshaped Vietnam's economic geography.

[Insert Figure 2 here]

Vietnam's growth was already in motion before the trade war. Significant events, such as the commencement of the US-Vietnam Bilateral Trade Agreement in 2001 and the accession to WTO in 2007, fuelled the country's economy but have had differential effects across the nation's regions. Our analysis addresses those past events' influences by controlling the time trend of each location's annual economic growth rate averaged over a long period before the sample's initial year (McCaig et al., 2023).

2.3. Vietnam's Clean and Renewable Energy Investment

While all developing nations face social costs associated with relying on cheap and dirty fuels such as coal, Vietnam's geography and endowments increase the likelihood that it substitutes towards ramping up its green power generation as it industrializes. The country's rivers allow it to rely on hydropower, and with its mountainous natural geography, it can ramp up its wind and solar power generation.[5]

The country has committed to developing clean energy. Minh and Van (2023) report that the share of Vietnam's electricity from clean energy, including hydro, wind, solar, and biomass, was about 40% in 2019; since then, the share has grown significantly. The reported figure and pattern are close and similar to our source of energy data presented in Table 1, which tabulates the shares of clean vs. thermal power plants' electricity generation capacities. The clean energy capacity already exceeded 50% in 2021. The Power Development Plan VIII, approved by the central government in 2023, further sets an ambitious goal. By 2030, the new clean energy that excludes hydronic power will produce more than 32% of the nation's electricity. Indeed, clean energy accounts for 72% of the additional capacity that will be added by future power plants that have passed the impact assessment or are in construction.

[Insert Table 1 Here]

[5] See the McKinsey report by Deffarges et al. (2023).

This energy development trajectory of Vietnam is in sharp contrast to China (See Figure 3). Vietnam's growth has been supported by the rapid development of clean energy power plants—wind and solar in particular—since 2018, which marked the start of the trade war. The accessibility to clean energy is improving across the whole country, as Figure 4 shows. Vietnam's electricity grid creates less local air pollution and greenhouse gas emissions than China's current power grid. These facts imply that industrial growth in Vietnam is likely to have a smaller environmental impact than if the same growth occurred in China.

[Insert Figure 3 Here]

[Insert Figure 4 Here]

2.4. Data Construction

This section introduces our data sources and sample construction, and the Data Appendix covers full details, including the variables' formulas. Section 301 China tariffs are from the US Trade Representative Office's Federal Register Notices, which inform every affected commodity's *ad valorem* duty and effective date. Commodity and industry code concordance follows Pierce and Schott's (2012) algorithm and matches 10,586 HTSUS (8-digit) commodities with 102 NAICS (4-digit) industries.

Comprehensive establishment-level data of firms in Vietnam from 2015 to 2021 are from ORBIS. The shift δ_{it} and share s_{ij} of equation (1) are calculated by NAICS (4-digit) industry. Firms are also classified into two categories. Those in industries producing goods the US imports are in the "export sector." The rest belong to the "local sector."

The 63 provincial locations—cities—constitute the panel of analysis. Production-side variables are aggregated from ORBIS firm data or sourced from Viet Nam Statistical Yearbooks (VSYs). The VSYs tabulate various information by provincial locations, and the relevant data includes population, income, education, production, and FDI.

The cities' transport infrastructure and physical locations affect their domestic and international trade costs and growth potential. The geocoded data below control such influences. The border gates to China, Laos, and Cambodia were identified from the Foreign Affairs Ministry's official documents. Seaport and riverport data were from the Seaports Association and Inland Waterways Administration. Port data include economic capacity, besides locational information. Roadways were from the 2015 open street map. *China Dist.* is the city's average roadway distance to its three nearest China border gates. *Laos Dist.* and *Cambodia Dist.* are similarly defined. MA_{j0}, $SprtA_{j0}$, and $RprtA_{j0}$, respectively, are the city's access to domestic markets, seaports, and riverports via roadways in 2015. In the Data Appendix, we report our definitions of these variables.

The annual average data for *PM2.5* and *PM10* from 2015 to 2021 are derived from M2TMNXAER and M2I3NVAER of MERRA-2 of NASA Earth Data (See Figure 5). Energy data are from the Global Energy Monitor, which has every Vietnamese power plant's geocoordinates, energy type, power capacity, opening date, and operation status. We use these data to construct measures at the city/year level. A city's accessible electricity is the total electricity generated by itself or in other cities within a threshold distance, for which the baseline is 200 km. The *clean energy share*, which varies by city and year, is the share of accessible electricity produced by solar, wind, hydro, or biomass power plants.

The climate and geography data are from three sources. The 2015 VSY documents 15 provincial locations' *total sunlight duration*, *total rainfall*, *mean humidity*, and *mean air temperature*. The remaining 48 locations' variable values can be spatially interpolated because climate features exhibit spatial autocorrelation. The *wind speed* and *wind direction* are derived from the Global Wind Atlas. The t*errain ruggedness* index is the city average of granular land pixels' index values, which are calculated using the elevation data from GTOPO30 of NASA Earth Data.

The above data construction leads to a balanced panel of annual data covering all 63 cities from 2015 to 2021. Table 2 provides the names, definitions, and summary statistics for all variables used in regression analysis except for the fixed effects. The table arranges these city-level variables into three groups: the outcome variables, key covariates, and the year-2015 initial conditions.

[Insert Table 2 Here]

3. Testing for Asymmetric Urban Growth Within Vietnam

Macroeconomic trade shocks can affect a domestic economy's regions differently in the and reshape a nation’s economic geography, as demonstrated by Krugman and Elizondo (1996) and Autor et al. (2013). We test whether the US-China trade war has introduced a fundamental asymmetry in Vietnam’s urban growth as cities closer to China gain more from this opportunity.

3.1. Measuring Urban Economic Growth Dynamics as a Function of the Trade War

We hypothesize that the S301 tariffs increased export demand from Vietnamese cities that are “close” to the Chinese industries in the “product space”. The analysis requires us to approximate the increased demand for output by city, industry, and year. Since the shocks are specific to industries but not to locations, we use the Bartik shift-share design to specify a time-varying treatment variable:

$$TRF_{jt} = \sum_{i \in I} s_{ij} \delta_{it} \quad (1)$$

The variable measures Vietnamese producers' *tariff privilege* in city j in year t. The shift is δ_{it}—the mean S301 tariff rate of the goods made by industry i in year t. The share is s_{ij}—the industry i's share of city j's output in 2015, the sample's initial year.

To interpret TRF_{jt}, note that there were no industrial tariff differentials ($\delta_{it} = 0, \forall i, t < 2018$) between Vietnam and China before 2018, although the NTR tariffs varied by industry. When the trade war began, positive industrial tariff differentials ($\delta_{it} \geq 0, \forall i, t \geq 2018$) presented and equalled the S301 *ad valorem* duty. The δ_{it} differentials reflect the premiums needed by Chinese exporters due to the added tariffs, and the premiums can result in substitution. Thus, a higher δ_{it} implies a greater opportunity for Vietnamese firms in industry i to export to the US in year t. Due to different initial industrial compositions, locations may not benefit equally. A marginal increase of δ_{it} may cause greater gain in city j if industry i has a larger s_{ij} (weighs more) there. To Vietnam, TRF_{jt} is city j's industrial-composition-weighted average S301 China tariffs—the city's tariff *privilege* in US-export production relative to China. We refer to TRF_{jt} as tariff privilege hereafter for brevity.

The S301 tariffs were exogenous shocks to Vietnamese cities. Table 3 tabulates the results of a battery of bivariate regressions on every city's initial condition (and pandemic situation) in the sample. None of these variables exhibits a worrying pairwise correlation with the TRF_{jt} (see the table's note). TRF_{jt} was also uncorrelated with local infection dynamics during the COVID-19 pandemic, as Appendix Figure A2 shows. Thus, we can infer that the tariff privilege was unlikely to be correlated with local unobservables. Appendix Figure A3, in more detail, shows scatter plots between the tariff privilege and the key variable, the distance to China's borders. The TRF_{jt} spreads of the Northern and Southern locations were remarkably similar, and the tariff shocks were not more favorable for the North or for the South.

[Insert Table 3 Here]

In estimating the effects of the Trump Tariffs on economic output across Vietnam's system of cities, we adopt a standard difference in difference framework.[6] TRF_{jt} in equation (1) is a continuous treatment variable, and the regression specification is:

[6] Our empirical approach has been widely used in empirical trade research including studies that examine the China shocks (Autor et al., 2013), Trump Tariffs (Flaaen et al., 2020; Fajgelbaum et al., 2020), and the US-China trade war (e.g., Waugh, 2019), for which Caliendo and Parro (2023) provided an excellent review. In this important literature, trade shocks or market penetration are often the treatment presenting in the form of a continuous variable, either in a time-varying (e.g., Autor et al., 2016; Amiti et al., 2019; Waugh 2019) or static setting (e.g., Pierce and Schott, 2020; Handley et al., 2023) depending on contexts. The research on intra-country locations widely adopts the Bartik shift-share, applicable to DID (Goldsmith-Pinkham et al., 2020), to specify the continuous treatment variable, which allows the shock intensity to depend on industrial composition (e.g., Pierce and Schott, 2020) or market penetration (e.g., Autor et al., 2013; 2016).

$$lnY_{jt} = \beta_0 + \beta_1 TRF_{jt} + lnX_j \cdot T_t \alpha + \lambda_j + \tau_t + \varepsilon_{jt} \quad (2)$$

where lnY_{jt} is an economic outcome of city j in year t, like output or Foreign Direct Investment (FDI), and λ_j and τ_t are city and year fixed effects (FEs). Output data is aggregated from ORBIS firm dataset; and FDI data is from Viet Nam Statistical Yearbooks. FDI is measured by FDI_j^{LQ}, a location quotient (LQ) about the pre-existing foreign investment in the initial year. It is the city j's share of the country's accumulated FDI capital divided by the city's share of the country's aggregate capital. A larger FDI LQ indicates a higher geographic concentration of FDI in the city. Based on this LQ's value, a $Low\ FDI_j^{LQ}$ dummy variable is defined. In all of our regressions, the error term are clustered at the city level and we report Conley standard errors to account for spatial correlations (Conley, 1999; Colella et al., 2023), for instance, due to spatial spillovers.

The vector $lnX_j \cdot T_t$ consists of interaction terms. X_j represents the city's pre-existing conditions in the initial year. T_t indicates time and is either an integer variable marking the year or a dummy variable that equals one in the trade war period. In the urban and development economics literature, researchers have examined growth as a function of base-year attributes and identified correlates, such as base-year demographic metrics, human capital, industrial compositions, and public infrastructure, as important determinants of long-run growth (e.g., Glaeser et al., 1995). The estimators of $lnX_j \cdot T_t$ account for the persistent influences from the aforesaid determinants and from the past long-term economic growth rate before the initial year[7].

It is important to note that the time period of our study overlaps with the COVID-19 Pandemic. Vietnam's containment strategy did not obstruct economic activities nationwide nor cause prolonged disruption to individual cities.[8] Although one might suspect the trade and pandemic shocks were interwoven, the tests in Appendix Figure A3 show that the cities' pandemic dynamics were orthogonal to their tariff privilege, distance to China's borders, and presence of FDI. Thus, we can proceed under the assumption that the pandemic's city level

[7] Adding interaction terms of the cities' initial conditions with the year integer or trade-war indicator variable can help address two issues. One is to distinguish the portion of the trade-war gain owing to the tariff privilege—the driver of near-shoring for the tariff wall jumping—from the portion attributable to favorable local conditions, such as better human capital endowments and pro-business environment, that are orthogonal to the tariff privilege but can attract multinational enterprises. Secondly, those interaction terms can control for possible spatial pre-trends in cities' economic growth that already existed before the trade war, for instance, the 2001 US-Vietnam Bilateral Trade Agreement. Controlling the time trends of long-term city economic growth predictors (Glaeser et al., 1995) absorbs spatially heterogeneous pre-trends. We also control the 2010-2015 average annual growth rate's 2015-2021 time trend. See Appendix Table A2 and its table notes.

[8] Targeted and short-lived, Vietnam's lockdowns were generally mandated at 15 days and confined to locations that exhibited spikes in infection cases.

effects is an orthogonal unobservable and use Conley standard errors to capture the pandemic effects flexibly.

3.2. Testing for a China Border Effect in Production, FDI and Employment

The distance to the China border can affect a city's gains from the tariff shock. Firms' incentive to offshore their downstream production arises when applicable tariff rates change (Pierce and Schott, 2016). Tariff barriers motivate affected producers to pursue downstream value-chain reallocations for tariff avoidance (Flaaen et al., 2020). China has diversified exports to nearby countries (Jiang et al., 2023; Alfaro and Chor, 2023). These findings indicate that affected Chinese exporters may have offshored downstream production to Vietnam. The concern is inland freight costs. Vietnam's natural geography impedes transport infrastructure development, making cities closer to China more favorable offshoring destinations. To evaluate this border effect, we add an interaction of $China\ Dist_j$—the average distance to the three nearest border gates to China—with TRF_{jt} into equation (2).

Output Growth

The TRF_{jt} tariff privilege has stimulated more growth in cities closer to China, all else equal. We quantify this effect by estimating equation (2) and report the results in Table 4. The regressand is local aggregate output, and primary regressors concern individual and interaction terms of the tariff privilege (TRF_{jt}), distance to China ($CN\ Dist._{(100km)}$), and initial FDI concentration ($\ln FDI^{LQ}$ or $Low\ FDI^{LQ}$). TRF_{jt}—the industrial weighted average of tariff differential that advantages exporters in Vietnam over China—may lift regional economic growth. The baseline equation (2) of Column (1) suggests that the production was 2.8% more when TRF_{jt} was one percentage point (p.p.) higher.

[Insert Table 4 Here]

The preferred specifications of Columns (5) and (6), consistently applied in subsequent tables, show that for locations near China, the output gain from a one p.p. higher TRF_{jt} was up to 3.9%. However, the output gain depended on two factors. Firstly and strikingly, spatial proximity to China was decisive, leading to a tariff-privileged *China border effect*. The gain from a one-p.p. increase in TRF_{jt} dropped by 0.2% for every 100km increment in road distance to China. Vietnam's furthest South is about 2,000km away from the China border. The disadvantage added up to a 4.0% discount and eliminated the tariff-privileged impact completely at the furthest south location. Also, the initial FDI's presence mattered. The output gain of an extra p.p. of TRF_{jt} was about 3.7% less in low FDI locations than in high FDI areas, where the initial FDI LQ was above the median in 2015.

The -0.2% distance gradient toward China's border is stable and robust across all specifications, including Columns (4)-(6), which control various time-varying locational features. As the places that grasped the new export opportunity could be those with favorable human capital, industrial composition, agglomeration economies, transport infrastructure, and geographic and business environment, we control the evolving impacts of locational initial conditions. Adding these controls cannot dismiss the significant border effect; they only slightly lower $\hat{\beta}_{TRF}$ (intercept) and make no influence on $\hat{\beta}_{TRF\times CN\ Dist.}$ (gradient).[9] Our finding on this China border effect is robust against spatial growth pre-trends, because the regressions also control cities' 2010-2015 average annual growth rates.[10]

Table 5 distinguishes production sectors. The output gain of *TRF* came from the export sector. As Columns (1) and (2) show, the China border effect magnifies when focusing on industries with the potential of exporting to the US. The distance gradient, $\hat{\beta}_{TRF\times CN\ Dist}$, is steepened to -0.3%. In contrast, this coefficient fades to insignificance in Columns (3) and (4). The local sector, whose goods and services are irrelevant to US import tariffs, did not experience such a border effect.

[Insert Table 5 Here]

As a type of placebo test, we examine whether a border effect existed at the boundary close to Vietnam's other neighbors, namely Laos and Cambodia. These results are in Table 6. Laos or Cambodia border effect may also exist if Vietnam's gain is not tied to developing a China-Vietnam upstream-downstream relationship for the tariff-wall jumping.

[Insert Table 6 Here]

We modify the regression to overcome the challenge of testing the three neighboring countries' border effects together. The distances to China and Laos exhibit an extremely high correlation, as do those to China and Cambodia. The reason is that Vietnam's territory is long and thin. Thus, Table 6's regressions alternatively use the nearest-border-nation dummy variables. For clarity, the regressions adopt separate regressors for high and low FDI locations' tariff-privileged border effects. A valid tariff-privileged border effect requires the corresponding coefficient to be significantly positive. Neither Laos nor Cambodia has any significant positive coefficient. On the other hand, the estimated China border effects remain robust, and the significant coefficient (0.039) is identical to that in Table 4.

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[9] We have also tested for the border effect using night lights using the NASA VIIRS data. The results are available upon request.

[10] One might worry about a "North-Vietnam pre-trend" that the growth in the North already picked up relative to the South even before the trade war. The 2010-2015 average annual growth rates of cities can flexibly control the path dependence and city growth pre-trends. In regressions that are available upon request, we found that the 2010-2015 growth can explain the 2015-2017 growth, but neither the 2010-2015 growth nor the 2015-2017 growth can explain the growth in the trade war period. When the 2010-2015 growth is controlled, the distance to China has no correlation with the 2015-2017 growth, but it has a significant correlation with the trade-war period growth.

FDI Growth

The presence of FDI may also affect the gains to trade. Global value chain research highlights the role of platform FDI (Antras and Chor 2022). Large multinational corporations commonly invest in developing countries to create export platforms catering to international markets (Helpman, 2006). The incentive arises from saving the unit cost of output that leads to a sizable gain conditional on high production and export volumes (Grossman et al., 2006)—FDI and exports are complementary. The FDI to Vietnam is primarily to create export platforms and is a major factor driving the country's export growth (Xuan & Xing, 2008). Besides creating export-oriented foreign firms, it also stimulates local enterprises with horizontal or forward linkages with these foreign firms at the FDI locations to export (Anwar & Nguyen, 2011). FDI capital, therefore, can approximate local export orientation.

Urban economics growth models predict that capital should flow to cities where demand for the city's core industries is rising. Measures of Foreign Direct Investment allow us to test this hypothesis. In Table 7, we documented that FDI inflows exhibited a remarkable China border effect. Vietnam is an export-oriented country attracting platform FDI. The US-China trade war has directed more FDI to Vietnam, but there has been spatial heterogeneity. The tariff privilege helped the North to attract more FDI capital and projects. Cities could attract 27% more FDI capital and 18% more projects annually if their tariff privilege increased by one p.p. and they were near China. Every 100km increment of their roadway distance to China significantly lowered this gain by 2.8% for capital and 1.6% for projects.

[Insert Table 7 Here]

Because $\hat{\beta}_{TRF}$ is larger and $\hat{\beta}_{TRF\times\,CN\,Dist}$ is smaller in Column (1) than in Column (2), the FDI projects made in the North would be larger than those in the South. The attractiveness of Northern Vietnam to foreign investment may be particularly pronounced for large multinational companies (MNCs). The result of Column (3) does support such a China border effect on FDI project sizes. An extra p.p. of *TRF* increased the average project size by 27% in cities near China. This figure is realistic, given that Northern Vietnam has attracted many large MNCs' FDI during the trade war, including Fortune Global 500 companies such as Samsung, Foxconn, and Wistron. The increase in the average size was 1.5% lower for every 100km increment of the city's road distance to China.

Employment and Population Growth

The tariff privilege in Vietnam has led to more production and new FDI happened in cities closer to China. Those emerging economic activities there should also stimulate employment and population growth in North Vietnam. We find such evidence and present it in Table 8.

[Insert Table 8 there]

Column (1) concerns the employment. For cities with above-median pre-existing FDI, a one p.p. increase in the tariff privilege could increase local employment by 2.7% if the city is close to China, but the strength of this employment stimulus would be 0.1% weaker for each 100 km increment in the China border distance. For other cities with below-median pre-existing FDI, the tariff privilege's stimulus to employment was insignificant.

Increased employment opportunities would enhance the city's appeal, thereby having an impact on urban population growth. Indeed, after controlling the time trend of the initial income level, we confirm the border effects on the city population in Column (2) and the city net migration rate in Column (3). The effects depended on the FDI and distance to China in the same way as the effect on local employment. As the tariff privilege in border cities was as high as 10 p.p. and each p.p. increased the net migration by 0.67%, there would be notable population influxes to cities in the North. The increased employment and population would be able to stimulate local consumption. Therefore, we also find a modest yet significant border effect on retail sales.

Given that Vietnam does not feature major cities just over the Vietnam/China border, in this sense, our study does not represent a sharp border discontinuity design. Instead, we embrace a type of trade cost framework such that, all else equal, a city that is closer to China gains more from the Trade War. We recognize that the relationship between distance and such gains does not have to be linear and we now provide some evidence of this "decay function". In Figure A4, we performed regressions that carry the flavor of a "spatial event study" to gain a more comprehensive picture of the China border effect. The cities are grouped into ten bands sorted by roadway distance to China. Each band covers 200 km. The border effect on outputs is pronounced, and the negative gradient is largely shaped by industries that can export to the US. Each extra p.p. of the *TRF* tariff privilege raised export sector outputs by 8% in cities, including Ha Noi and Hai Phong, that were less than 200 km by road to China. The positive effect was persistent within 800 km, beyond which the gain was gradually lower and eventually insignificant.[11] There was a positive spillover effect. In cities where the export sector rallied strongly, local sector outputs, including retail sales, also tended to increase. The border effect on new FDI was sizable; the North gained substantially more foreign capital and projects than the South.

3.3.The North-South Reversal of Vietnam's Urban Economic Growth

[11] The 400-600 and 600-800 km bands have only one city and three smaller cities, respectively. Thus, these two bands' coefficient estimates should be interpreted with caution.

The US-China trade war accelerates economic growth in the North relative to the South. This constitutes a reversal of spatial growth pattern in Vietnam. Figure 6 highlights this reversal. Year dummy variables are interacted with distance to China, with 2017 being the base year. The regressions here do not include TRF_{jt}, as the purpose is to exhibit the North-South spatial disparity.

[Insert Figure 6 Here]

The figure shows that the South (farther from China) used to be more prosperous than the North before the trade war, all else equal. Most of the distance gradients $\hat{\beta}_\tau$ of the earlier years were positive, and the one for export output was significant. However, these gradients consistently turn positive to negative after the trade war's occurrence. In 2021, the negative gradients of the distance to China were pronounced and significant across the base sector production, retail, and FDI. The gradient changes imply that the North has been growing relatively faster than the South in the trade war and reversing the North-South spatial disparity.

4. Is the Trade-War Good for the Environment?

We posit that Vietnam's cities that gain the most from trading with China experience scale, composition and technique effects that together shape local environmental quality. Scale effects refer to increases in economic output. All else equal, this will increase local air pollution levels. Composition refers to the city's industrial composition. Industries that complement China's export sector are more likely to grow. Finally, technique refers to pollution per unit of output. This can decline if a city attracts Foreign Direct Investment that leads to new, cleaner factories being built or if the region relies more on cleaner power to fuel the local economy, such as using renewable power.

We test if cities in Vietnam experience rising pollution levels as cities experience industrial growth. The classic Environmental Kuznets Curve hypothesis posits that this relationship features an inverted "U" shape such that as poor nations grow richer, they become more polluted. A second hypothesis posits that over time, due to technological progress, this inverted "U" shifts down and in over time so that economic development causes less environmental damage (Dasgupta et. al. 2002). In this section, we present our framework for testing both of these hypotheses.

4.1. Testing the Environmental Kuznets Curve Hypothesis

We start with a simple descriptive analysis by estimating the Environmental Kuznets Curve (EKC) for Vietnamese cities, by estimating equation (3):

$$lnPM_{jt} = \beta_0 + \beta_1 \ln Inc_{jt} + \beta_2 \left(\ln Inc_{jt}\right)^2 + lnX_j \cdot T_t \alpha + \lambda_j + \tau_t + \varepsilon_{jt} \qquad (3)$$

PM_{jt} is the mean PM2.5 or PM10 (μg/m^3) of city j in year t. Inc_{jt} is the city's average annual family income per capita in that year. The $lnX_j{\cdot}T_t$ vector is the same as equation (2), except X_j now also includes climate and geography variables. The two ways of standard errors introduced earlier are applied. This reduced-form quadratic regression of air pollution on per capita income is expected to depict an inversed-U-shaped EKC. We posit that the shape of the Environmental Kuznets Curve depends on the adoption of clean energy. Consider an extreme case where a nation switches from using coal to using renewables to generate electricity. In this case, the pollution impact of economic growth would sharply decrease.

Table 9 presents the results. The environmental outcome is air quality, represented by the PM2.5 or PM10 concentration, and the economic development level is the provincial annual income per capita. Columns (1) and (2) examine the whole sample period, 2015-2021. Each regression's coefficient estimates of income can yield an estimate of the EKC turning point—the income level at the peak of the hump. Above this threshold level, environmental quality improves with further economic development. The estimated turning points of Columns (1) and (2) on PM2.5 and PM10 are close and approximately equal to 49 million Vietnam Dong (≈US$2,000).

[Insert Table 9 Here]

Columns (3) and (4) of Table 9 focus on the trade-war period, 2018-2021. The regressions add variables relating to FDI, as this period featured an inrush of foreign investment. These variables include the number of FDI projects and the two income variables' interaction terms with the average FDI capital per project. The regressions highlight two effects on the environment. One is a scale effect. The concentration of PM2.5 and PM10 increased with the increase of FDI projects. The influx of FDI can cause surging local production that may increase pollution (He, 2006, 2009).

The other is a more important technique effect. The EKC estimated function is significantly affected by the average size of the local FDI projects. We calculate the EKC turning points of two scenarios. The first assumes no new FDI accrued between 2018 and 2021; the second assumes a one million USD increment in the average size of the accrued FDI projects. Again, the estimated turning points on PM2.5 and PM10 are close. The turning-point income levels are consistently smaller in the scenario with the increased FDI project size than in the other—indicating the technique effect. When multinational corporations, especially large ones, invest in FDI in Vietnam, they may implement cleaner technologies and standards in production (Wang and Jin, 2007). The locations receiving the FDI may also experience diffusion of more environmentally friendly practices (Zheng, et al., 2010). In addition, the turning-point income levels are notably smaller in the trade-war period than in the whole sample period. Appendix Figure A5 also shows that the turning-point income level and the entire EKC can fall, owing to the technique effect. These results of Vietnam's provincial EKC are in line with with

Dasgupta et al. (2002) and Zheng and Kahn (2017), which argue that improved receptiveness and accessibility to cleaner technology and standards may curb the negative environmental consequences associated with economic development.

4.2. The Role of Clean Energy Adoption in Improving Urban Environmental Quality

To better understand the underlying mechanisms behind the above EKC patterns, here we estimate a pollution production function. Equation (4) presents our main regression specifying air pollution as a function of industrial output:

$$lnPM_{jt} = \beta_0 + \beta_1 \ln\hat{Y}_{jt} + \beta_2 \ln\hat{Y}_{jt} \times \widehat{CES}_{jt} + lnX_j \cdot T_t\alpha + \lambda_j + \tau_t + \varepsilon_{jt} \quad (4)$$

Y_{jt} is city j's output in year t as in equation (2). PM_{jt} is the air particulate-matter concentration as in equation (6). CES_{jt} is the clean energy share, which is the share of electricity generated by hydronic, wind, solar, and biomass power plants in the year and accessible to the city.[12] The two ways of standard errors apply[13].

Output Y_{jt} is clearly endogenous. However, the TRF_{jt}—Bartik Instrument—of equation (1) is exogenous because (1) the S301 China tariffs surprised the international community, and (2) the tariffs are against China rather than Vietnam and target industries but not locations. The exogenous TRF_{jt} tariff privilege is orthogonal to local unobservables (exclusion restriction) (See Table 3 and Figure A2). Also, TRF_{jt} can relate to air quality but only by affecting the city's production (inclusion restriction). Thus, TRF_{jt} can instrument Y_{jt} in a 2SLS, with equation (2) being a first-stage regression.

The clean energy share CES_{jt} is also endogenous. Reverse causality may arise. For instance, the government may be more determined to build clean power plants in regions with severe air pollution, resulting in a higher clean energy share. Also, omitted variable bias may exist. For example, not only production causes pollution. Growing locations may show surging demand for commuting, transportation, and other activities. Unobserved activities may increase energy demand, leading to new power plant openings in these bustling locations and their vicinity. Since new power plants' likelihood of using clean energy generally correlates with time, these bustling locations may also have a higher clean energy share.

[12] Power from biomass plants is also counted, but that amount is negligible. There is no nuclear or geothermal power plant in the country.

[13] A point that is worth noting is about the drifting of air pollution from China. Air pollution may drift and impact downwind locations. If the drift toward downwind is a static relationship, the impact can be absorbed by the city fixed effects. One might worry that the trade war shock that shrunk production in China caused a treatment effect of less air pollution drifting to Vietnam, and the treatment intensity correlated with the distance to China. If this spillover effect is of primary importance, Vietnam's Northern border cities would exhibit the strongest air pollution in 2015 or the greatest air quality improvement in the trade war. However, Figure 5 implies that the importance of this spillover effect may be secondary because the severity of air pollution in the North is strongly correlated with the geographic concentration of production but not the distance to China.

To address this clean energy endogeneity, we estimate equation (5) as the first stage of 2SLS using the Clean Energy Share (CES_{jt}) as the outcome variable.

$$CES_{jt} = \beta_0 + \beta_1 Z_{jt} + lnX_j \cdot T_t \alpha + \lambda_j + \tau_t + \varepsilon_{jt} \quad (5)$$

The Z_{jt} is a vector of instrumental variables relating to city-level climate conditions, including sunlight, wind speed, wind directions, temperature, humidity, and precipitation. These characteristics affect the efficiency and impact the adoption of renewable clean energy, as established in science and engineering.[14] Since climate conditions typically change little within a decade, we use their initial year values. The instruments are the interaction terms of these initial values with the year integer variable and the square terms of these interactions. They shape nonlinear time trends that reflect how technology and policy may leverage favorable climate conditions and allow green power to grow over time. These climate time trends are different from the climate conditions, which are relatable to pollution and absorbable by city fixed effects.

As discussed above, the scale of economic activity has increased in Vietnam's cities near China. The increased scale could worsen local air pollution, but two offsetting trends are emerging at the same time. First, more FDI is flowing in. Second, the greening of the electricity grid is taking place. This section quantifies these offsetting effects.

4.3. Clean Energy Adoption Safeguards Blue Skies in Vietnam

The manufacturing reallocation due to the trade war increases the demand for electricity in Vietnam. In response, the average annual growth rate in the aggregate capacity of electricity generation increased from 4.9% in 2015-2017 to 13.3% in 2017-2021 (see Table 1). The growth rate has tripled. The dramatically fastened pace of energy development can cause worry over environmental sustainability, as the standard view about such a situation in a developing country is that the added energy capacity will be dirty (e.g., Managi et al., 2009). However, public policy can affect the emission intensity of production (Shapiro and Walker, 2018). There are reasons to believe that the fast-growing North Vietnam may go green as it industrializes. As we discussed in Section 2, Vietnam has rich endowments in renewable energy sources, leading to a promising green power potential. Furthermore, the new wave of FDI to the North tended to be large and likely investments made by multinational enterprises, and such FDI inflows may be greener than those flowing into China 20 years ago. The recent surge in ESG

[14] Besides sunlight and winds, other factors also affect renewable energy efficiency. For example, For example, humidity reduces solar cells' and wind turbines' power generation efficiency (Danook et al., 2019), and so are higher temperatures (Jehad et al., 2019). Rainfalls lower wind turbines' efficiency by eroding the blades (Chen et al., 2018), but the impact on solar panels is ambiguous. Besides, rugged terrains make solar panels and wind turbines less efficient.

push may also make these multinational large corporations more cautious about their environmental responsibility in global operations.

We now study whether the recent industrial growth in areas close to China has been associated with an increased rate of clean energy use. A "greening" of the composition and technique in the power sector would shift the EKC relationship such that less pollution (both PM2.5 and carbon dioxide) would be produced as a byproduct of production.

The regressions in Table 10 focus on the 2018-2021 trade war period. The logarithmic dependent variables from Panels (1)-(3) are about PM2.5, PM10, and CO2, respectively. The OLS of Column (1) is a biased estimator, because the output is endogenous. A stronger production sector implies urban vibrancy, so the agglomeration is associated with congestion, which also causes air pollution; the estimate can be biased upward. On the other hand, suppose the production sector tends to be weaker in locations with more blissful ignorance of pollution and more unruly activities (e.g., illegal incineration) causing pollution. Then, the estimate can be biased downward. As a result, Column (1) fails to depict output and pollution's apparent relationship.

We apply the Bartik Instrument in 2SLS to address this issue and report the result in Column (2). An enrichment of equation (2), the first-stage regression is Table 4's Column (6), having four excluded instruments, including *TRF*, *TRF* × *CN Dist.*, *TRF* × *Low FDI*^{LQ}, and *TRF* × *CN Dist.* × *Low FDI*^{LQ}. The predicted output is fed into the pollution regression. The positive relationships of output with PM2.5, PM10, and CO2 then stand out. The output coefficients are statistically identical for the two particulate matters, while the one for CO2 is smaller.

[Insert Table 10 Here]

We estimate equation (4) to test for a heterogeneous effect: Adoption of clean energy can mitigate the production's negative effect on air equality. An interaction term between the output and clean energy share is added. Column (3) indicates that a 1% increase in a location's output would cause less deterioration in its air quality and less emissions of greenhouse gas if clean energy constitutes a greater proportion of electricity accessible to the location. However, the regressions here neglect the clean energy share's endogeneity. For example, air pollution may motivate green energy development, leading to a greater clean energy share. Thus, we incorporate the additional first-stage regression of equation (5), which uses the exogenous initial year climatic conditions' quadratic time trends ($Z_{j0} \cdot T_t$ and $\left(Z_{j0} \cdot T_t\right)^2$) as the instruments. These time trends mean to capture the quadratic shape of the clean energy development trajectory revealed in Figure 3. The time trends reflect how technology and policy may leverage favorable climate conditions, and allow green power to grow over time. The time trends are different from the static spatial variation of climate (Z_{j0}), which is relatable to pollution and absorbable by city fixed effects. The regression of equation (5) predicts a clean energy share used in the equation (4) estimation. The result is reported in Column (4), and the clean energy's air-pollution mitigation effect remains robust.[15]

Overall, Table 10 shows that clean energy can mitigate economic development's negative environmental impact on blue skies and greenhouse gas emissions. Using our preferred estimates in Column (4), we may infer that a 1% growth in output increased the concentration of PM2.5 by 0.25%, PM10 by 0.18%, and CO2 by 0.01‰. Note that output increased by 3.9% in response to a one-p.p. increase in *TRF* (Table 4, Column 6), all else equal. We can infer that an extra p.p. of *TRF* would increase the PM2.5 and PM10 concentration in the air by as much as 1% and the CO2 concentration by about 0.04‰. The elasticity of CO2 is smaller because the variable's minimum is large and its support (408, 417 ppm) is narrow. The lower elasticity, however, does not imply a lesser worry for greenhouse gas emissions, as the magnitude of TRF is non-trivial; the mean *TRF* is 2.71% (Table 3), and the maximum exceeds 10%.

Table 10 shows that a 1% increase in a city's output would cause less deterioration in its air quality and less emissions of greenhouse gas if clean energy constitutes a greater proportion of electricity accessible to the city. Specifically, one standard deviation (0.35) increase in the accessible clean energy share was able to ease up the negative impact of output growth by 6.4% on PM2.5 (0.046×0.35/0.250), by 9.4% on PM10, and by 2.8% on CO2.

Infrastructure development of high-voltage electricity transmission lines can make electricity more transmissible, and new technology can reduce energy lost in transmission distance. As the segmentation within the existing transmission network is unclear, we have alternatively used a low-resolution approach, which sets a limiting distance for transmission. Here, we alternate this cutoff distance of accessible electricity to examine the robustness of the results. Table 11 presents this sensitivity analysis by repeating Table 10's Column (4) regressions. In Table 11, The cutoff distance is extended from 400 km to 500 km for Columns (1)-(3) and to 600 km for Columns (4)-(6). The significant pattern of β_{ouput} and $\beta_{ouput \times CES}$ estimates are robust against the cutoff distance adjustment.

[Insert Table 11 Here]

Nevertheless, a closer examination of β_{ouput} and $\beta_{ouput \times CES}$ estimates' changes reveals a spatial decay pattern. The pattern of changes has an important implication: If a city can access electricity generated by more distant locations, the impact of the city's output growth on its local air quality will be less negative. If the powerplants are generally greener in the city's surrounding areas (as defined by the cutoff distance of transmissible electricity), then the

[15] For robustness, we conduct the regressions of Column (5) that do not use any of the climate time trends as IVs. The alternative IVs are the quadratic time trends of latitude and longitude of the city centroid point. As revealed in Figure 5, the geo-coordinates are also good instrument sources for Vietnam's clean energy development trend. Again, the results remain robust.

amount of air pollutants that drift from the powerplants to the city will be lesser, thereby reducing the city's eventual air pollution attributable to its own production.

5. Conclusion

In this paper, we have used Vietnam city-level panel data to study how this nation's system of cities is affected by the China Shock. Our empirical work focuses on the hypothesis that cities in Vietnam that are "closer" to China both in distance and in characteristics space can gain more from the Tariff War. Using data on output, foreign direct investment, and pollution dynamics, we document significant beneficial impacts for these cities. This cross-elasticity is large enough to affect Vietnam's North/South regional divide. The South was the more prosperous region in the recent past, as the North had its communist past. However, the Northern areas have been disproportionately gaining through rising trade with China and openness with the rest of the world.

Our findings are likely to have broader implications for other pairs of nations. Around the world, many small nations are adjacent to larger nations. This asymmetry in size raises important issues of cross-elasticities such that a shock to the large nation can have significant consequences for the smaller nation. In the case of the U.S. and China Trade War, macroeconomists have recognized that the shock has important implications for nearby nations such as Vietnam.

Our findings on Vietnam in the US-China trade war is similar to, and yet different from the dynamics that unfolded after NAFTA was formed in the early 1990s. Krugman and Elizondo (1996) document the migration of economic activity in Mexico out of Mexico City as manufacturing moved closer to the U.S border. Our Vietnam findings are similar because we also show that international trade reduces the heavy concentration of economic activities in a core megacity as producers' cost-saving priority is not domestic but international transportation costs. It is different because, in Vietnam's case, the shifting geographic concentration of economic activities toward the border is for the efficiency of trading with the upstream suppliers rather than the downstream consumers.

While the Biden Administration has continued the Trump Tariffs, it is certainly possible that the United States may reverse this policy in the future. An open question is whether the expectation that this may only be a short run policy slows down the investment in the North Vietnam cities. We recognize that our empirical strategy does not recover estimates of the casual effects of an expected permanent U.S tariffs. It is possible that the short run effects of the trade diversion set in motion a dynamic process such that even if the tariff policy is reversed that enough capital investment momentum is now taking place such that the Northern Vietnam cities are on a new urban growth path.

In studying economic progress in Vietnam's northern cities, we have also made a contribution to the city-level Environmental Kuznets Curve literature. We have documented an optimistic result that Vietnam's Northern Cities have enjoyed pollution progress during a time of growth because of the inflow of FDI and the increased reliance on green power to fuel the local economy. We believe that there are general lessons here for decoupling greenhouse gas emissions and PM2.5 production during a time of growth. If older, dirtier factories in China operate less as newer, cleaner Vietnam factories operate more, then this mutually beneficial trade induced by the Tariffs contributes to improving environmental performance in both nations.

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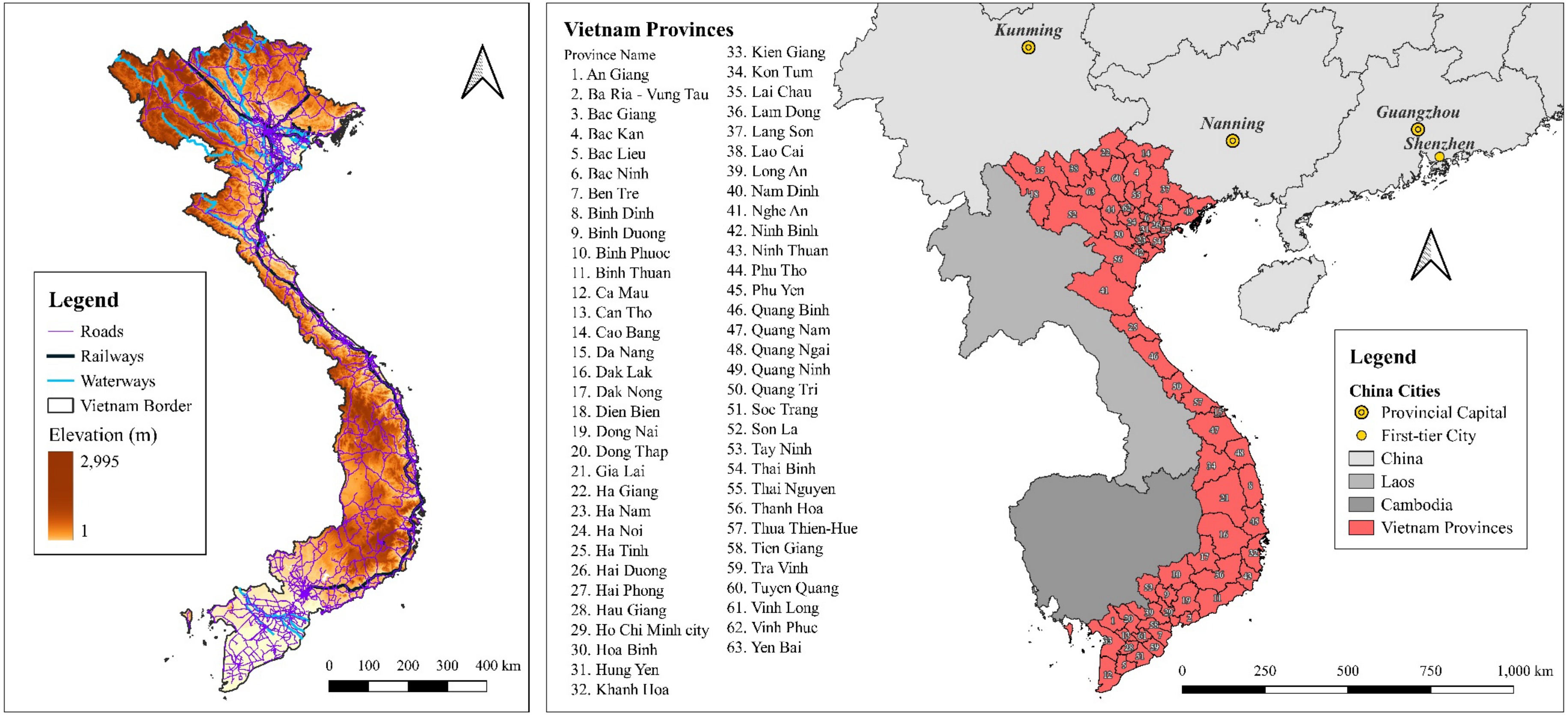
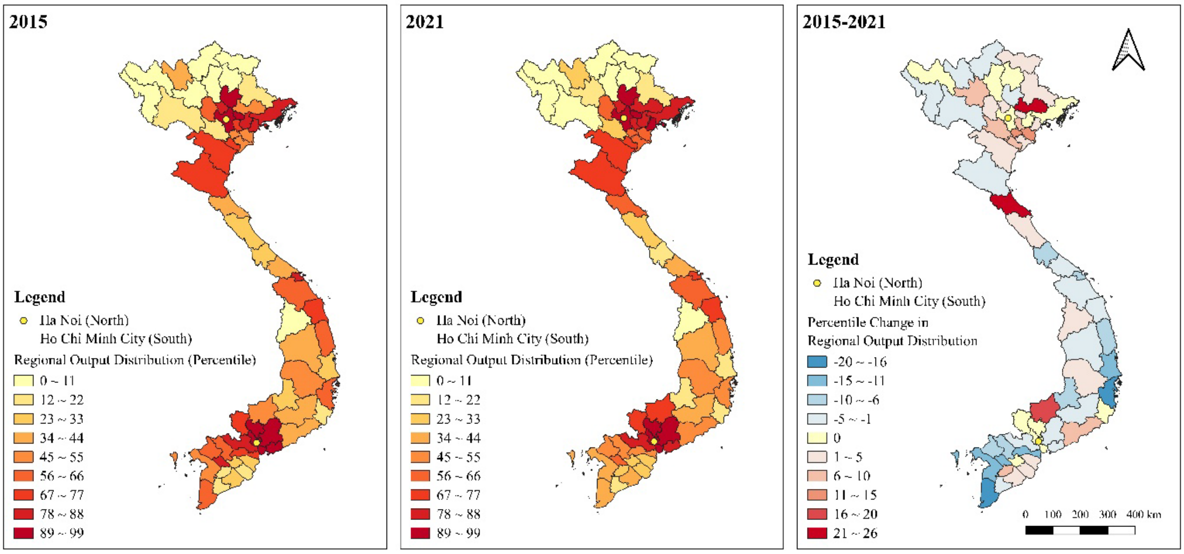
Figures and Tables

Figure 1: Vietnam's Geography and Administrative Divisions



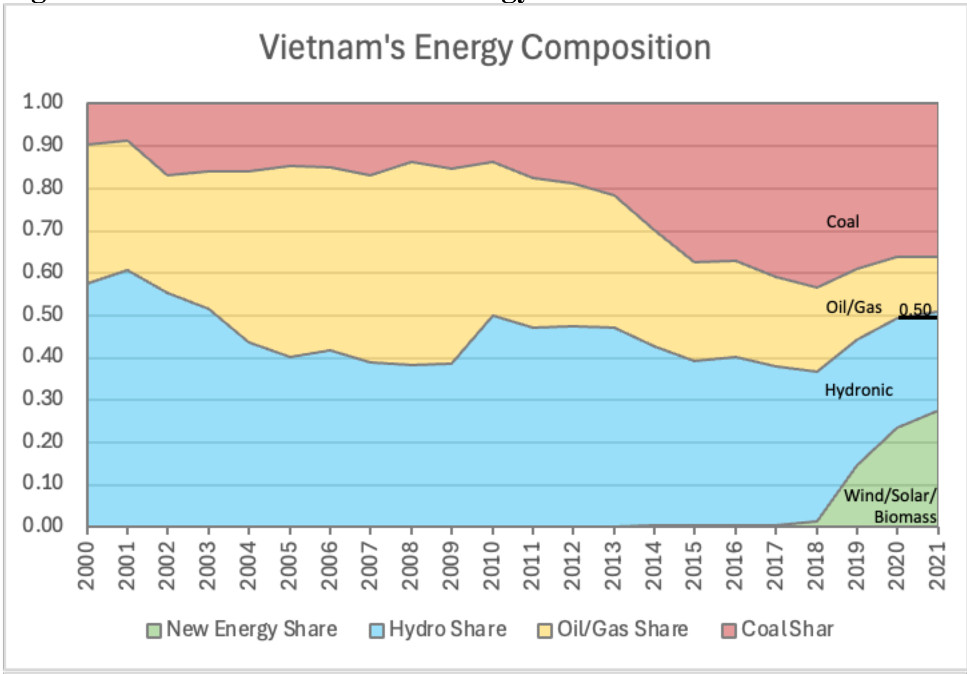
Note: The left map illustrates Vietnam's natural geography and domestic transport infrastructure. Much land is mountainous, with the highest peak of about 3,000 meters. Flat land is concentrated in the Red River Delta in the North and Mekong River Delta in the South. Despite many rivers in the West-East direction, cross-border navigation is mainly through the plotted waterways. A north-south railway serves the country, but its importance to freight transport is minimal. Roads carry the large majority of freight, and the map plots secondary roads and above; the total length of highways was merely 300 km during the paper's study period. The right map delineates Vietnam's provincial-level administrative divisions, comprising 58 provinces and 5 municipalities, including (24) Ha Noi City, (27) Hai Phong City, (15) Da Nang City, (29) Ho Chi Minh City, and (13) Can Tho City, from North to South. Neighboring countries are China, Laos, and Cambodia. Northern Vietnam adjoins China's Yunnan province to the northwest and Guangxi province to the northeast. It is also near the Guangdong province, where a quarter of China's exports are produced, and Shenzhen and Guangzhou cities are situated.

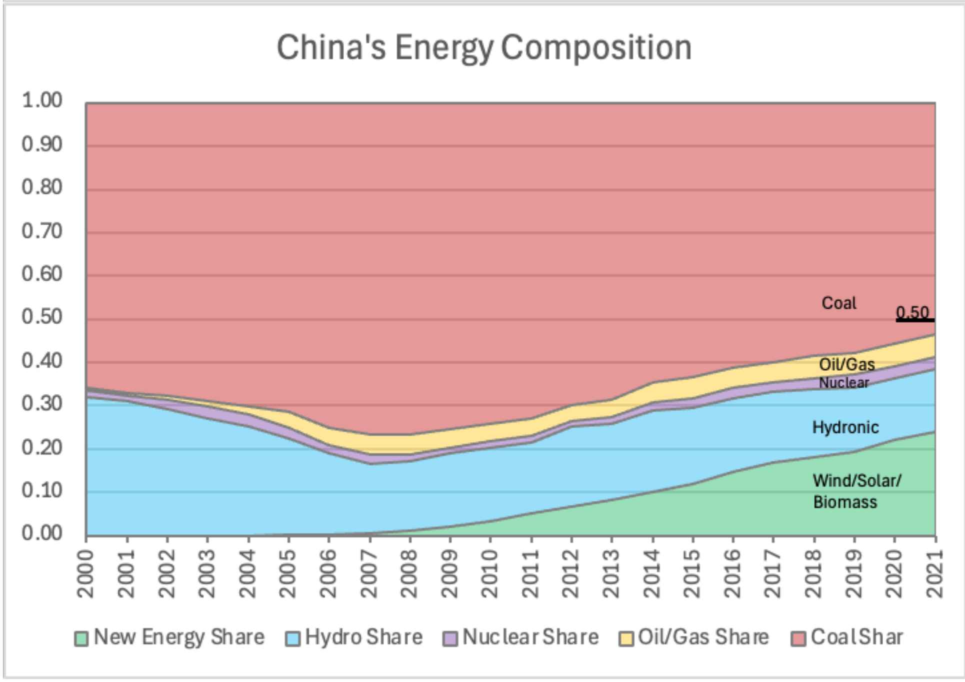
Figure 2: Vietnam's Regional Output Growth over the Years, 2015-2021



Note: Cities are ranked by their aggregate outputs for 2015 and 2021. The cities' percentile standings in aggregate outputs are plotted in the corresponding years of maps. The last map plots the changes in the cities' percentile standings from 2015 to 2021. The majority of cities in Northern Vietnam have been improving their rankings in output relative to other regions. The North has grown more strongly than the South.

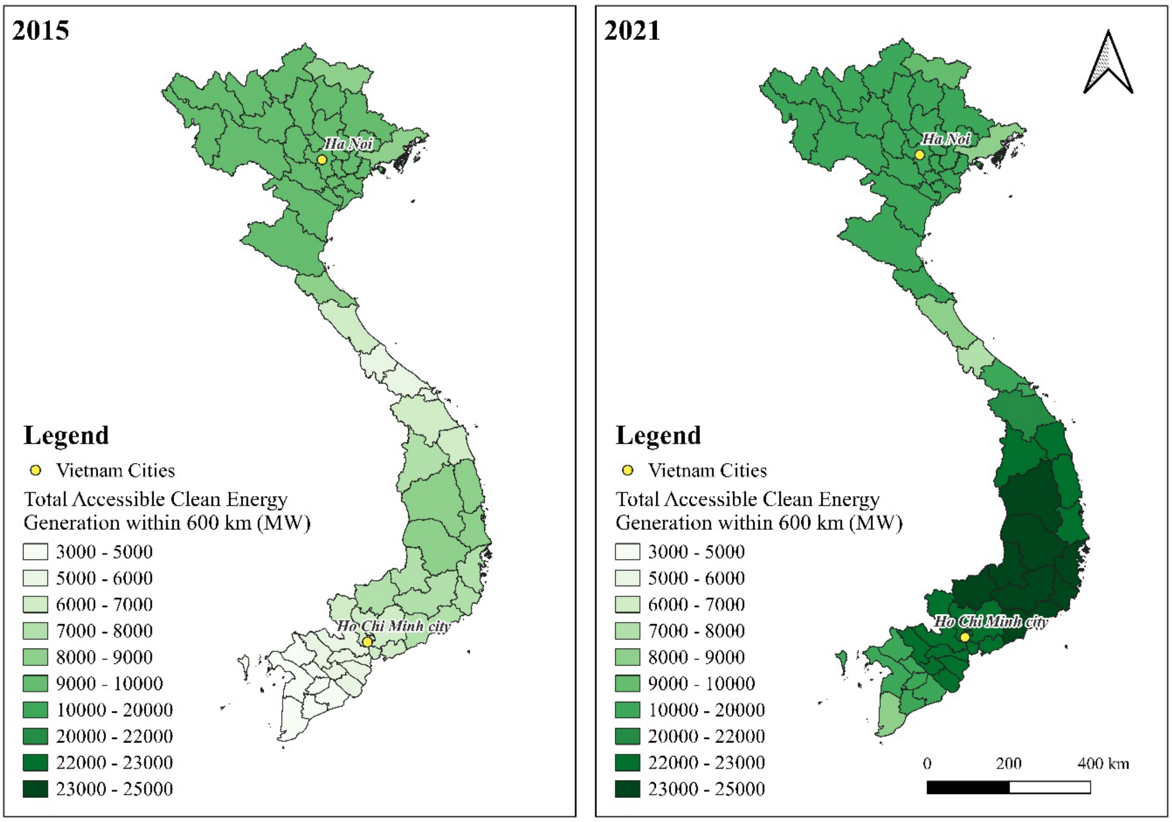
Figure 3: Vietnam and China's Energy Source Trends from 2000 to 2021





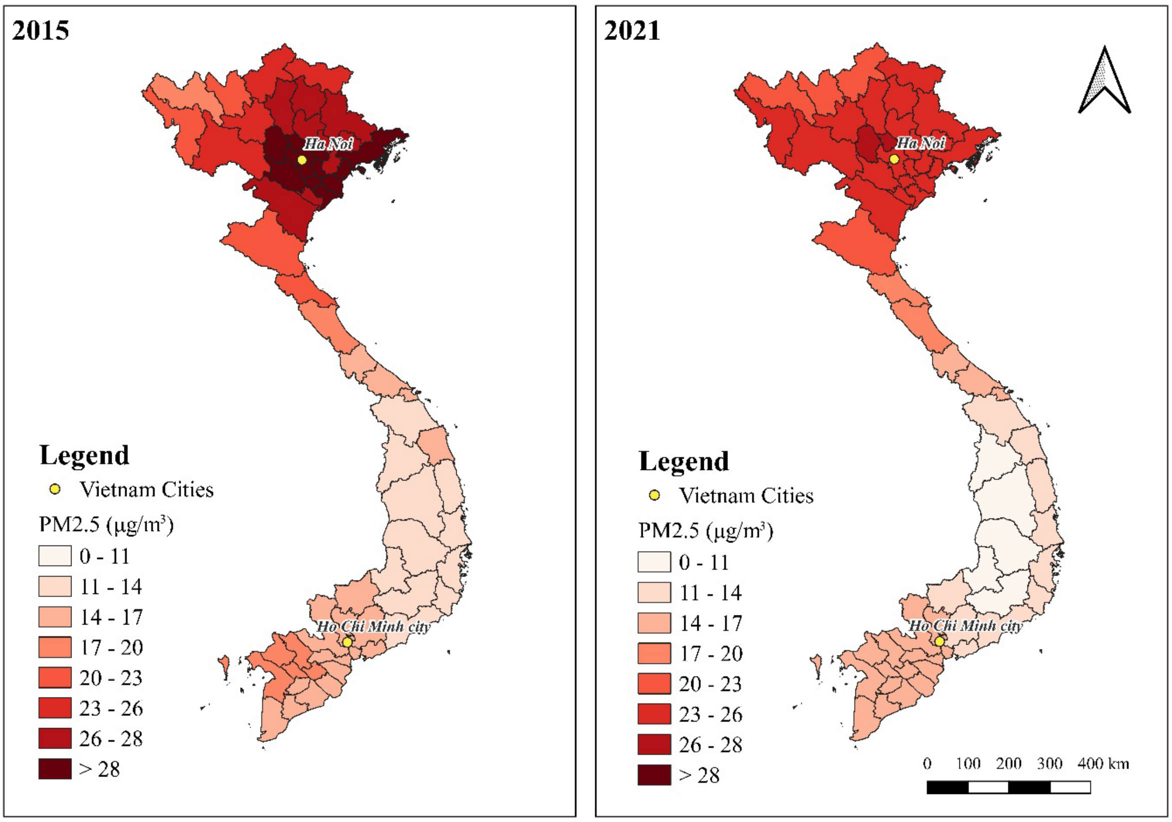
Note: New energy sources include solar, wind, and biomass. Vietnam has no nuclear power plant. We use the Global Energy Monitor data to derive Vietnam and China's energy compositions over time.

Figure 4: The Geographic Distribution of Vietnam's Clean Energy Growth



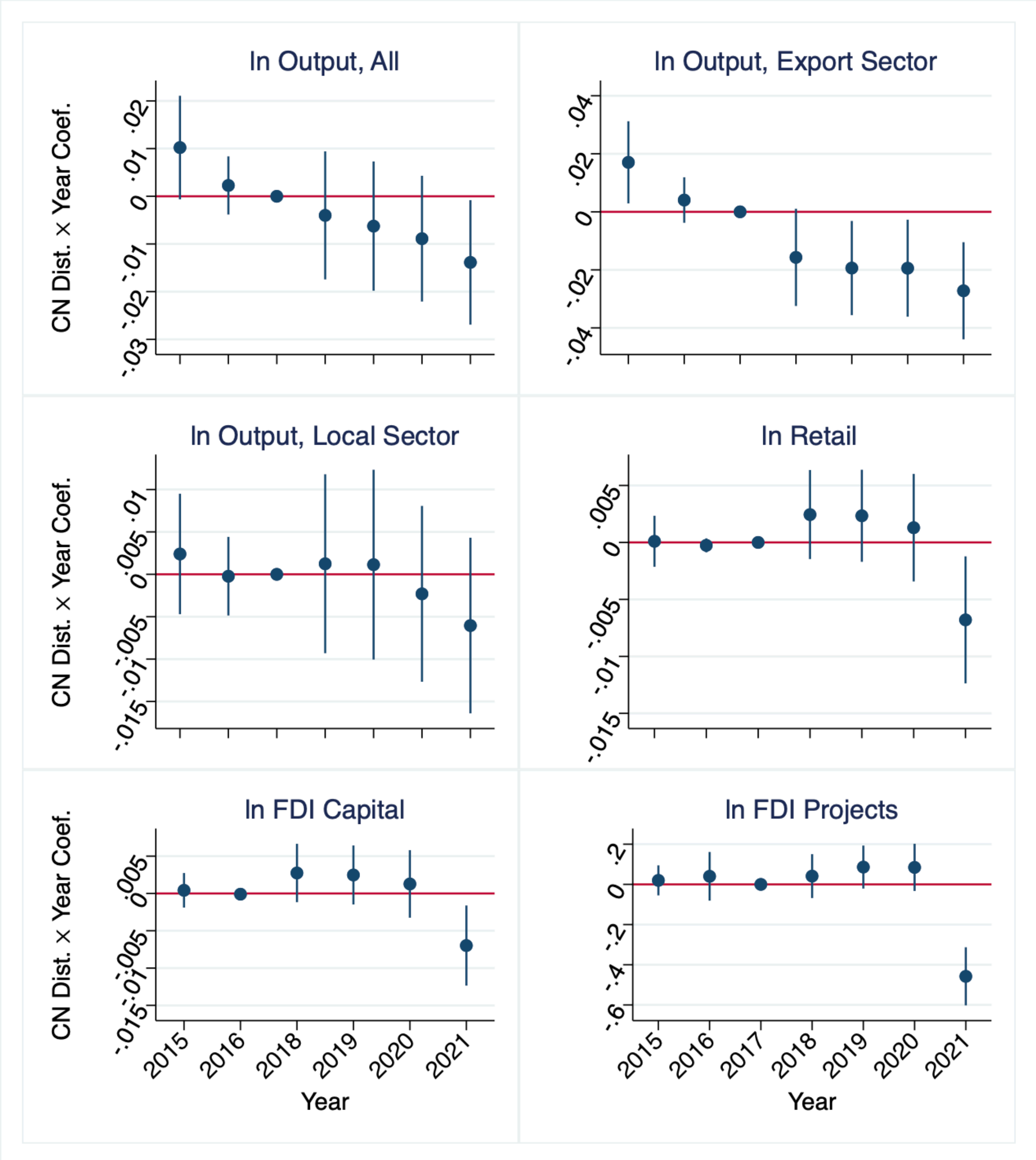
Note: As showed in Figure 3, Vietnam has demonstrated rapid development in clean energy, particularly in wind and solar power. The maps here show where the clean electricity capacity has grown. From 2015 to 2021, cities' accessibility clean energy commonly grew, especially in the South Central Coast and Central Highlands.

Figure 5: Improving Air Quality Within Vietnam



Note: Cities in Northern Vietnam have showed much improvement in air quality, although the region has grown relatively faster than others (Figure 4) during the period. Skies at the Red River Delta used to be more polluted, but the PM2.5 concentration has dropped notably. The annual average PM2.5 concentration at the Delta in 2021 was commonly around 24.5, which is equivalent to an AQI value of 76 in the moderate range (50-100).

Figure 6: The Trade War and The North-South Reversal of Economic Development



Note: The regressions here do not include TRF_{jt}, because the purpose is to show that Northern Vietnam has been growing relatively faster than the South and has been closing the gap. The specification is: $lnY_{jt} = \beta_0 + \sum_{\tau \in T} \beta_\tau Dist_j^{China} \times I_t^\tau + \sum_{\tau \in T} \lambda_\tau LowFDI_j^{LQ} \times I_t^\tau + lnX_j \cdot T_t \alpha + \lambda_j + \tau_t + \varepsilon_{jt}$ where $I_t^\tau, \forall T$ are the year indicator variables. The estimations on output and retail apply Conley AR1 S.E, and those on FDI adopt Tobit regression and city-clustered S.E. This set of event studies reveals a reversal of Vietnam's spatial economic pattern. The figure shows that the South (farther from China) used to be more prosperous than the North before the trade war, all else equal. Most of the distance gradients $\hat{\beta}_\tau$ of the earlier years were positive, and the one for export output was significant. However, these gradients consistently turn positive to negative after the trade war's occurrence. In 2021, the negative gradients of the distance to China were pronounced and significant across the base sector production, retail, and FDI. The changes of these gradients also suggest that the North has been growing faster than the South in the trade war.

Table 1: Vietnam's Energy Sources by Type and Year

Power plants in operation

		Clean Energy			Thermal Energy		
Year	Capacity MW	New Energy Share	Hydronic Share	**Total Share**	Coal Share	Oil/Gas Share	**Total Share**
2015	34,691	0.003	0.388	**0.39**	0.374	0.235	**0.61**
2016	35,879	0.003	0.399	**0.40**	0.370	0.227	**0.60**
2017	38,174	0.003	0.375	**0.38**	0.408	0.213	**0.62**
2018	41,006	0.015	0.352	**0.37**	0.434	0.199	**0.63**
2019	48,638	0.145	0.297	**0.44**	0.391	0.167	**0.56**
2020	56,023	0.235	0.258	**0.49**	0.362	0.145	**0.51**
2021	62,822	0.274	0.235	**0.51**	0.361	0.130	**0.49**

Note: New energy sources include solar, wind, and biomass. Vietnam has no nuclear power plant.

Future power plants that passed the impact assessment or are in construction

		Clean Energy			Thermal Energy		
Year	Capacity MW	New Energy Share	Hydronic Share	**Total Share**	Coal Share	Oil/Gas Share	**Total Share**
	81,548	0.707	0.016	**0.72**	0.073	0.204	**0.28**

Table 2: Summary Statistics

Variable	Definition	Mean	S.D.
Outcome Variables:			
ln Output (ORBIS)	Output, aggregate of ORBIS firm data	15.30	1.36
ln Output (VSY)	Output, provincial data of the Vietnam statistics bureau	11.64	1.37
ln Lights (VIIRS)	Avg. night light intensity, NASA VIIRS data	-1.52	1.22
ln New FDI	New FDI capital in the year	2.74	4.80
ln FDI Projects	Number of new FDI projects in the year	0.30	4.15
ln FDI Project Size	Avg. amount of capital of the new FDI projects in the year	0.42	4.17
ln Retail	Retail sales	10.57	0.93
ln PM2.5	PM2.5 ($\mu g/m^3$)	2.90	0.33
ln PM10	PM10 ($\mu g/m^3$)	3.61	0.24
ln CO2	CO2 (ppm)	6.02	0.01
Key Covariates:			
TRF	Tariff privilege as defined by equation (1)	2.71	3.12
ln FDI^{LQ}	Initial FDI location quotient as defined by equation (6). The median defines the *Low* FDI^{LQ} variable.	-0.31	1.60
CN $Dist._{(100km)}$	Avg. Dist. to the three nearest border gates to China (100 km)	9.51	7.22
Nearest to China	Equals 1 if the city is nearest to China; 0 otherwise.	0.28	0.45
Nearest to Laos	Equals 1 if the city is nearest to Laos; 0 otherwise.	0.25	0.44
Nearest to Cambodia	Equals 1 if the city is nearest to Cambodia; 0 otherwise.	0.46	0.50
Income	Real income per capita (all sources; million VND; 2018 $)	41.65	14.22
Clean Energy Share	Share of electricity from hydronic, solar, wind, and biomass power plants in all locations within 400 km to the city	0.42	0.08
City Initial Conditions in 2015:			
ln Population	Population (1,000)	7.09	0.57
ln Density	Population density	5.68	0.99
ln Uni. Teachers	Number of university teachers	2.52	6.05
2nd Sector Share	Share of employment in the secondary sector	0.61	0.14
3rd Sector Share	Share of employment in the tertiary sector	0.33	0.11
Business Environment	Business competitiveness index value	58.07	3.22
ln Avg. Growth, 2010-2015	Real average annual output growth between 2010 and 2015	9.17	7.82
Terrain Ruggedness	Terrain ruggedness index value	1.48	1.43
ln MA^{Roads}	Roadway market access as defined in Section 4	9.39	0.57
ln $MA^{Seaports}$	Seaport access as defined in Section 4	10.96	1.36
ln $MA^{Riverports}$	Riverport access as defined in Section 4	6.22	1.65
Railway Access	Equals 1 if the city has rail services; 0 otherwise.	0.54	0.50
Intl. Airport Access	Equals 1 if the city has an intl. airport; 0 otherwise.	0.05	0.21
City Climate Conditions in 2015:			
Sunlight	Total sunlight duration in the year	2138	514
Humidity	Avg. humidity in the year	80.27	1.49
ln Precipitation	Total rainfall in the year	7.45	0.14
Temperature	Avg. temperature in the year	25.21	1.69
Wind speed	Wind speed (50th percentile & 100 meters above the ground)	5.56	0.74
Wind direction	Dominant wind direction dummy variables. (East: 0.16; North: 0.13; Northeast: 0.13; Northwest: 0.02; South: 0.03; Southwest: 0.24; West: 0.24)		

Note: The variable names indicate whether a natural logarithm is applied. The sample is a balanced panel comprising 441 observations and covering 63 cities (provincial-level divisions) from 2015 to 2021. The abbreviations avg., dist., and intl. stand for average, distance, and international, respectively. *Avg. Growth, 2010-2015*, is winsorized at the 95th percentile to mitigate the influence of lumpiness from two city outliers. Regressions apply interaction terms between the city's initial conditions in 2015 and the year-time integer variable or the trade war indicator variable to control possible pre-trends that already existed before the trade war or possible factors that affect the gains from the trade war but are orthogonal to the tariff privilege.

Table 3: The Correlates of the Baseline City Level Tariff Rate

Explanatory variable	$\hat{\beta}$	S.E.	R^2	Obs.
Demographic, economic, and geographic conditions				
ln Population	-0.051*	(0.030)	0.05	63
ln Density	-0.056	(0.052)	0.02	63
ln Uni. Teachers	-0.511	(0.316)	0.04	63
Business Environment	-0.056	(0.171)	0.00	63
2nd Sector Share	0.004	(0.008)	0.01	63
3rd Sector Share	-0.001	(0.006)	0.00	63
Avg. Growth, 2010-2015	0.560	(0.407)	0.03	63
Terrain Ruggedness	-0.022	(0.076)	0.00	63
Latitude	-0.122	(0.260)	0.00	63
Longitude	-0.096	(0.071)	0.03	63
Transport infrastructure conditions				
ln MA^{Roads}	-0.023	(0.030)	0.01	63
ln $MA^{Seaports}$	-0.078	(0.072)	0.02	63
ln $MA^{Riverports}$	-0.038	(0.088)	0.00	63
Railway Access	-0.006	(0.820)	0.00	63
Intl. Airport Access	-0.014	(0.205)	0.03	63

Note: The listed variables depict the cities' initial conditions in 2015. The definitions of these variables are provided in Table 3, except for the conventional latitude and longitude. Each row concerns a bivariate regression whose regressor is the listed variable in the first column. The subsequent columns report the regressor's coefficient estimate and standard errors, and the regression's R^2 and sample size. The regressand is a *TRF* (equation 1); the shifts are the applicable S301 China tariff rates (Table A1) upon the full implementation in 2020, and the calculation of the shares considers export industries only. The asterisk mark * indicates the 10% significance level. The results evidence the exogeneity of Vietnam's tariff privilege, as all regressors have no or minimal statistical significance in their pairwise correlation coefficients with the *TRF*. Also see Appendix Figure A3 that the tariff privilege is orthogonal to COVID-19 situations.

Table 4: The Correlates of Urban Economic Growth in Vietnam

Variables	(1) ln *Output*	(2) ln *Output*	(3) ln *Output*	(4) ln *Output*	(5) ln *Output*	(6) ln *Output*
TRF	0.028**	0.053***	0.061***	0.045**	0.039**	0.039**
	(0.011)	(0.013)	(0.013)	(0.017)	(0.018)	(0.018)
TRF × CN Dist.$_{(100km)}$		-0.002***	-0.002***	-0.002**	-0.002**	-0.002**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TRF × Low FDI^{LQ}			-0.032*	-0.031*	-0.037**	-0.037*
			(0.016)	(0.017)	(0.016)	(0.019)
TRF × CN Dist.$_{(100km)}$ × Low FDI^{LQ}			0.000	0.001	0.001	0.001
			(0.001)	(0.001)	(0.001)	(0.001)
ln MA ^{Roads} × TW					0.208**	0.208**
					(0.103)	(0.098)
ln MA ^{Seaports} × TW					-0.008	-0.008
					(0.015)	(0.011)
ln MA ^{Riverports} × TW					-0.024	-0.024
					(0.016)	(0.018)
Railway × TW					-0.017	-0.017
					(0.051)	(0.039)
Intl. Airport × TW					-0.134	-0.134*
					(0.088)	(0.073)
Observations	441	441	441	441	441	441
Detrended/Centered R^2	0.25	0.40	0.43	0.48	0.98	0.24
Constant	YES	YES	YES	YES	YES	YES
City characters × Trend/TW	NO	NO	NO	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
S.E.	Clustered	Clustered	Clustered	Clustered	Clustered	Conley

Notes: Balanced Panel with 441 obs. The asterisk marks ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively. Clustered standard errors are at the city level. Conley standard errors correct both spatial correlation and 1-period lagged (AR1) temporal correlation of the errors. TW stands for "after the trade war's occurrence." The preferred baseline results are Columns (5) and (6), as city-clustered S.E. is conventional, and Conley S.E. flexibly accounts for the subtle spatial-temporal correlations of COVID-19's impacts across locations. When clustered S.E. is used, the R^2 numbers are detrended and orthogonal to location and time-fixed effects, following Wooldridge (1991). When Conley S.E. is applied, the reported R^2 is the Centered R^2.

Table 5: Testing for Heterogeneous Treatment Effects in Explaining Urban Economic Growth

Variables	(1) ln *Output* Export Sector	(2) ln *Output* Export Sector	(3) ln *Output* Local Sector	(4) ln *Output* Local Sector
TRF	0.033	0.033	0.012	0.012
	(0.026)	(0.024)	(0.014)	(0.011)
TRF × CN $Dist._{(100km)}$	-0.003***	-0.003**	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
TRF × Low FDI^{LQ}	-0.066***	-0.066**	-0.002	-0.002
	(0.023)	(0.029)	(0.013)	(0.009)
TRF × CN $Dist._{(100km)}$	0.003	0.003	-0.001	-0.001
× Low FDI^{LQ}	(0.002)	(0.002)	(0.001)	(0.001)
Observations	441	441	441	441
Detrended/Centered R^2	0.99	0.25	0.93	0.12
Constant	YES	YES	YES	YES
City characters × Trend/TW	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
S.E.	Clustered	Conley	Clustered	Conley

Notes: Firms are sorted into either the export or local sector. The former produces goods that the US has imports from overseas. The latter does not make such goods. The results show that the tariff-privilege impacts were concentrated in export industries. The sample is a balanced panel and *TW* = 1 in the trade war period. Detrended R^2 (Wooldridge, 1991) is used for city-clustered S.E. Centered R^2 is reported for Conley S.E., which corrects the errors' spatial and temporal (AR1) correlations. The asterisk marks ***, **, and * indicate 1%, 5%, and 10% significance.

Table 6: Testing for Placebo Effects at Other National Borders

Variables	(1) ln *Output* All Ind.	(2) ln *Output* All Ind	(3) ln *Output* Export Sector	(4) ln *Output* Export Sector	(5) ln *Output* Local Sector	(6) ln *Output* Local Sector
TRF × Nearest to China ×	0.039**	0.039*	0.029	0.029	0.015	0.015
High FDI^{LQ}	(0.019)	(0.021)	(0.028)	(0.027)	(0.015)	(0.011)
TRF × Nearest to Laos ×	0.019	0.019	0.017	0.017	0.001	0.001
High FDI^{LQ}	(0.021)	(0.014)	(0.034)	(0.022)	(0.012)	(0.009)
TRF × Nearest to Cambodia ×	0.007	0.007	-0.027	-0.027	0.011	0.011
High FDI^{LQ}	(0.017)	(0.011)	(0.024)	(0.018)	(0.012)	(0.008)
TRF × Nearest to China ×	-0.004	-0.004	-0.037	-0.037	0.005	0.005
Low FDI^{LQ}	(0.024)	(0.017)	(0.031)	(0.025)	(0.020)	(0.013)
TRF × Nearest to Laos ×	0.005	0.005	-0.026	-0.026	0.011	0.011
Low FDI^{LQ}	(0.019)	(0.015)	(0.028)	(0.022)	(0.015)	(0.011)
TRF × Nearest to Cambodia ×	-0.018	-0.018**	-0.049***	-0.049***	-0.010	-0.010
Low FDI^{LQ}	(0.012)	(0.008)	(0.018)	(0.015)	(0.011)	(0.007)
Observations	441	441	441	441	441	441
Detrended/Centered R^2	0.98	0.24	0.99	0.26	0.93	0.13
Constant	YES	YES	YES	YES	YES	YES
City characters × Trend/TW	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
S.E.	Clustered	Conley	Clustered	Conley	Clustered	Conley

Notes: The tariff privilege had no positive effect near the borders of Laos and Cambodia. This finding is substantiated by the regressions using the three dummy variables to distinguish the cities by the nearest neighboring country. Cities' distances to the three countries are not used because these distance variables are highly correlated given these countries' relative locations with respect to Vietnam (see Figure 1). Both city-clustered S.E. and Conley AR1 S.E. are examined. The asterisk marks ***, **, and * indicate 1%, 5%, and 10% significance.

Table 7: The Correlates of FDI Investment at the City Level and the China Border Effect

Variables	(1) ln *FDI* $_t$ (volume)	(2) ln *FDI Projects* $_t$ (number)	(3) ln *Avg. FDI Project Size* $_t$
TRF	0.272**	0.181**	0.269**
	(0.122)	(0.089)	(0.109)
TRF × CN Dist.$_{(100km)}$	-0.028***	-0.016***	-0.015***
	(0.007)	(0.004)	(0.005)
TRF × Low FDI^{LQ}	-0.023	-0.017	0.093
	(0.131)	(0.092)	(0.085)
TRF × CN Dist.$_{(100km)}$	0.016*	0.007	0.003
× Low FDI^{LQ}	(0.009)	(0.007)	(0.007)
Observations	441	441	441
Pseudo R^2	0.21	0.30	0.17
Constant	YES	YES	YES
City characters × Trend/TW	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
S.E.	Clustered	Clustered	Clustered

Notes: FDI activities also exhibited the China border effect. Because the new FDI occurring in a year can exhibit zeros (about 20% of the observations), Tobit regression is applied and city-clustered S.E. is used. Controlling parametric COVID-19 variables makes negligible changes to the TRF coefficients and their significance levels. The tariff privilege helped the North to attract more FDI capital and projects. Because the β_{TRF} ($\beta_{TRF} \times CN\ Dist.$) estimate is larger (smaller) in Column (1) than in Column (2), the indication is that the FDI projects made in the North tended to be larger than those in the South. This indication is supported by the result of Column (3). The ***, **, and * marks indicate 1%, 5%, and 10% significance.

Table 8: The Correlates of Urban Growth

Variables	(1) ln *Employment*	(2) ln *Population*	(3) ln *Net-migration Rate*	(4) ln *Retail*
TRF	0.027***	0.009***	0.670***	-0.001
	(0.009)	(0.002)	(0.211)	(0.006)
TRF × CN $Dist._{(100km)}$	-0.001**	-0.0004**	-0.034*	-0.001**
	(0.000)	(0.0002)	(0.020)	(0.000)
TRF × Low FDI^{LQ}	-0.015*	-0.003**	-0.806***	-0.001
	(0.008)	(0.002)	(0.175)	(0.005)
TRF × CN $Dist._{(100km)}$	0.001**	-0.0001	0.022	0.001
× Low FDI^{LQ}	(0.001)	(0.0002)	(0.020)	(0.000)
Observations	441	441	441	441
Centered R^2	0.38	0.46	0.30	0.15
Constant	YES	YES	YES	YES
City characters × Trend/TW	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
S.E.	Conley	Conley	Conley	Conley

Notes: The tariff privilege benefited urban growth not only in terms of output, and the benefits exhibited the China border effect. The regressions of city population, net migration rate, and retail sales additionally control the city's initial income-per-capita time trend. Conley AR1 S.E. is applied. The asterisk marks ***, **, and * indicate 1%, 5%, and 10% significance.

Table 9: City-Level Environmental Kuznets Curve Estimates

Sample Period	2015-2021		2018-2021	
	(1)	(2)	(3)	(4)
Variables	ln *PM2.5*	ln *PM10*	ln *PM2.5*	ln *PM10*
ln *Income*	1.760***	1.909***	3.086***	2.502**
	(0.346)	(0.435)	(0.859)	(1.270)
$(\ln Income)^2$	-0.229***	-0.249***	-0.417***	-0.332**
	(0.045)	(0.059)	(0.113)	(0.168)
ln *Income* × FDI Avg. Size			-0.142***	-0.150**
			(0.048)	(0.065)
$(\ln Income)^2$ × FDI Avg. Size			0.017***	0.019**
			(0.006)	(0.008)
ln FDI Projects			0.004***	0.003***
			(0.001)	(0.001)
Observations	441	441	244	244
CenteredR^2	0.15	0.12	0.39	0.51
Constant	YES	YES	YES	YES
City characters × Trend/Post	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
SE	Conley	Conley	Conley	Conley
EKC Turning Point Estimate	2015-2021 (million VND)		2018-2021 (million VND)	
	49.8	46.5		
No FDI			39.2	41.6
FDI Avg. Size = 1 million USD			38.6	40.7

Notes: The measurement unit is μg/m^3 for both *PM2.5* and *PM10*, which are the annual average figures. The variable *income* is the annual income per capita (million VND) from all sources. *FDI Avg. Size* (million USD) is the average FDI capital per project. It is the total new FDI capital relative to the total new *FDI Projects* accrued by the city between 2018 and 2021. The exchange rate between USD and VND was about 1: 24,000 in 2018. The *Turning Point* is the income at which the estimated strictly concave EKC function reaches the maximum value of air pollution. The turning point estimates of Columns (3) to (4) consider two scenarios. The first assumes no new FDI accrued between 2018 and 2021 (the case of Cao Bang, Lai Chau, and Son La). The second assumes a 1 million USD increment in the average size of the accrued FDI projects during the period. Conley AR1 S.E. is used. The asterisk marks ***, **, and * indicate 1%, 5%, and 10% significance. The suppressed covariates include the total sunlight duration, total precipitation, average humidity, average temperature, average wind speed (at the 50th percentile and at 100 meters above the ground), and the dominant wind direction (eight categories) in 2015, besides all the control variables used in the earlier tables' regressions.

Table 10: Clean Energy Development Dynamics

Model	(1) OLS	(2) 2SLS ln *Output*	(3) 2SLS ln *Output*	(4) 2SLS ln *Output* *CES*, climate	(5) 2SLS ln *Output* *CES*, lat.-lon.
Panel 1: D.V.: ln *PM2.5*					
ln *Output*	-0.018	0.273***	0.285***	0.250***	0.216***
	(0.019)	(0.099)	(0.083)	(0.096)	(0.081)
ln *Output* ⨉ Clean Energy Share (CES)			-0.042***	-0.046***	-0.055***
			(0.005)	(0.007)	(0.008)
Centered R^2	0.30	0.31	0.46	0.44	0.49
Panel 2: D.V.: ln *PM10*					
ln *Output*	0.010	0.211***	0.223***	0.178***	0.148**
	(0.030)	(0.080)	(0.058)	(0.063)	(0.070)
ln *Output* ⨉ CES			-0.040***	-0.048***	-0.045***
			(0.007)	(0.007)	(0.009)
Centered R^2	0.38	0.39	0.49	0.50	0.47
Panel 3: D.V.: 100 ⨉ ln *CO2*					
ln *Output*	-0.003	0.083**	0.084*	0.086*	0.080**
	(0.006)	(0.041)	(0.047)	(0.046)	(0.037)
ln *Output* ⨉ CES			-0.005*	-0.007**	-0.011***
			(0.003)	(0.003)	(0.004)
Centered R^2	0.27	0.29	0.31	0.32	0.37
Observations	252	252	252	252	252
Constant	YES	YES	YES	YES	YES
City characters ⨉ Trend	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
SE	Conley	Conley	Conley	Conley	Conley

Notes: The header row states each column's regression model and instrumented endogenous variable(s). CES is the acronym for Clean Energy Share. The dependent variables (D.V.) are annual average figures, and their measurement units are μg/m^3 for *PM2.5* and *PM10* and ppm for *CO2*. Because the CO2 variable's minimum is large and its support (408, 417) is narrow, we multiply ln *CO2* by 100. The city sample is a balanced panel, 2018-2021. The ***, **, and * marks indicate 1%, 5%, and 10% significance. Columns (2) to (5) apply 2SLS, for which Table 4's Column (6) serves as the first-stage regression where *TRF*, $TRF \times CN\ Dist._{(100km)}$, $TRF \times Low\ FDI^{LQ}$, and $TRF \times CN\ Dist._{(100km)} \times Low\ FDI^{LQ}$ are the excluded instruments predicting the output. Columns (4) and (5) involve an additional first-stage regression that instruments the clean energy share, which is the city's share of accessible electricity generated by hydronic, wind, solar, or biomass power plants. The accessible electricity is the total electricity generated in the city itself and in other cities within 400 km. The IVs are the interaction terms of the city's exogenous conditions with the time integer variable and the square terms of these interactions. Column (4) applies Table 2's climatic variables as the exogenous conditions. Column (5) uses the city centroid point's latitude and longitude. Figure 5 reveals that the geo-coordinates are also good instrument sources for Vietnam's clean energy development trend.

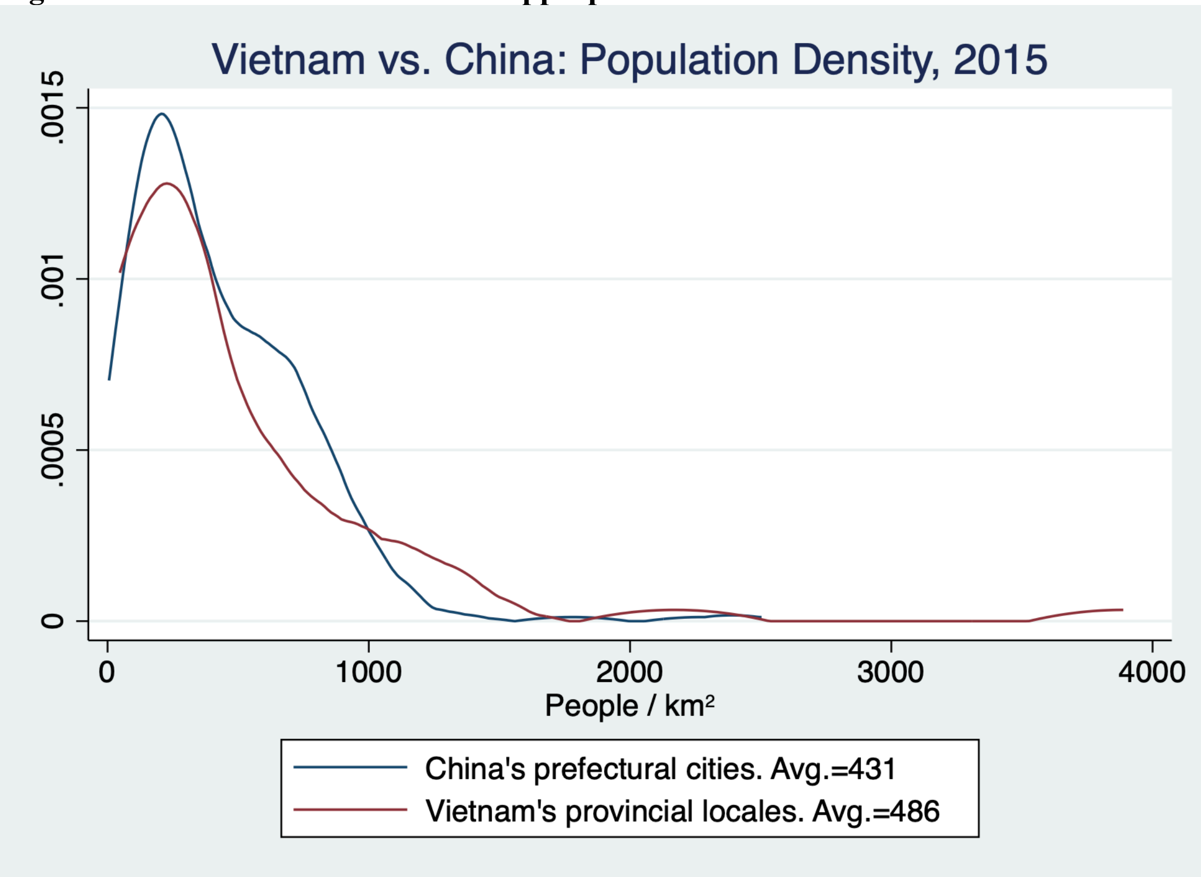
Table 11: 2SLS Sensitivity Analysis of Electricity Accessibility

Variables	(1) ln *PM2.5* 500 km	(2) ln *PM10* 500 km	(3) 100×ln *CO2* 500 km	(4) ln *PM10* 600 km	(5) ln *PM2.5* 600 km	(6) 100×ln *CO2* 600 km
ln *Output*	0.205**	0.134**	0.078*	0.171**	0.106*	0.069*
	(0.089)	(0.058)	(0.043)	(0.084)	(0.058)	(0.041)
ln *Output* × Clean Energy Share (CES)	-0.048***	-0.046***	-0.009***	-0.048***	-0.043***	-0.011***
	(0.007)	(0.008)	(0.003)	(0.009)	(0.010)	(0.004)
Predicted variable(s)	ln *Output* & *CES*	ln *Output* & *CES*	ln *Output* & *CES*	ln *Output* & *CES*	ln *Output* & *CES*	ln *Output* & *CES*
CES IVs	Climate	Climate	Climate	Climate	Climate	Climate
Observations	252	252	252	252	252	252
Centered R^2	0.44	0.48	0.34	0.43	0.46	0.36
Constant	YES	YES	YES	YES	YES	YES
City characters × Trend/Post	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
S.E.	Conley	Conley	Conley	Conley	Conley	Conley

Notes: Balanced Panels with observations from 2018-2021. The ***, **, and * marks indicate 1%, 5%, and 10% significance. The dependent variables are annual average figures, and their measurement units are μg/m^3 for *PM2.5* and *PM10* and ppm for *CO2*. A city's accessible electricity is the total electricity generated in the city itself and in other cities within the defined cutoff distance. The cutoffs are 500 km for Columns (1)-(3) and 600 km for Columns (4)-(6). These columns of results should be compared with Table 10's Column 4, which sets 400 km as the cutoff. These results together reveal a decay pattern in the cutoff distance.

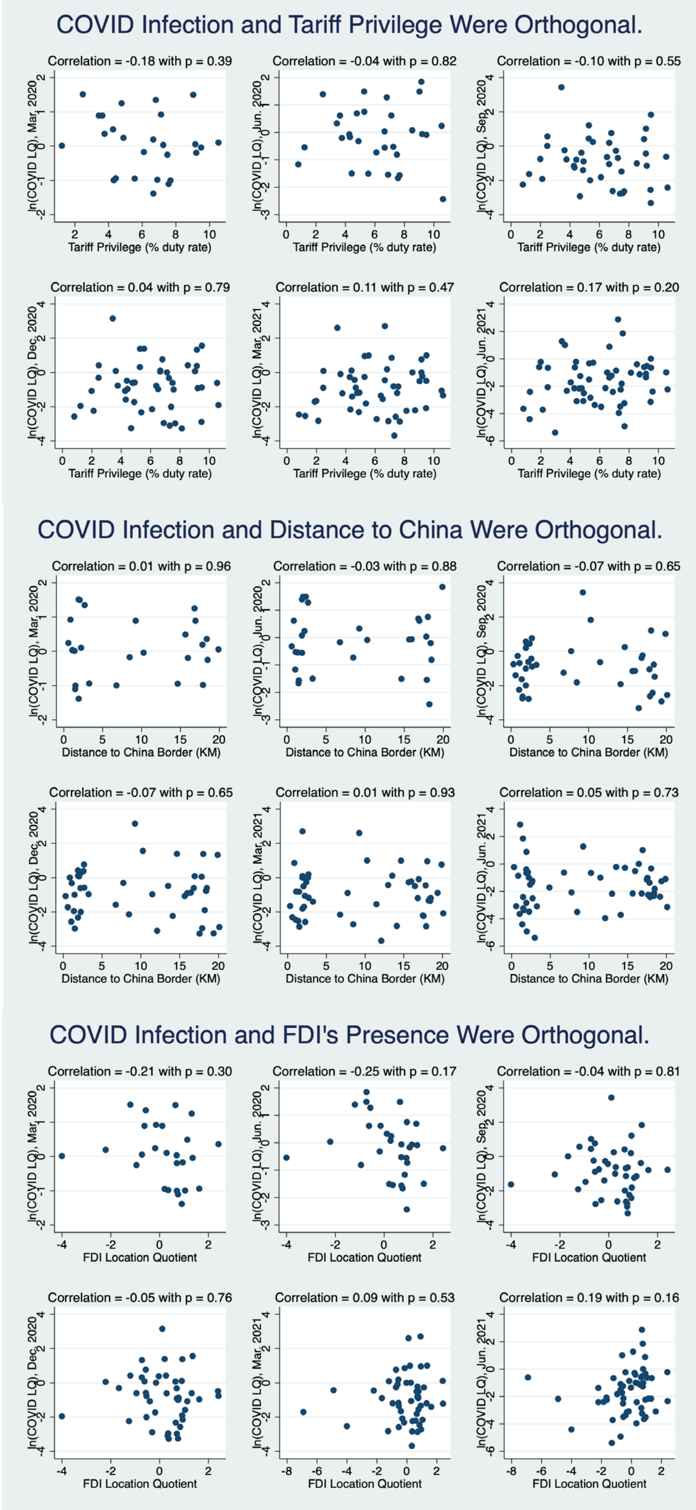
Appendix Figures and Tables

Figure A1: Vietnam’s Provinces are Appropriate Units for Urban Economic Research



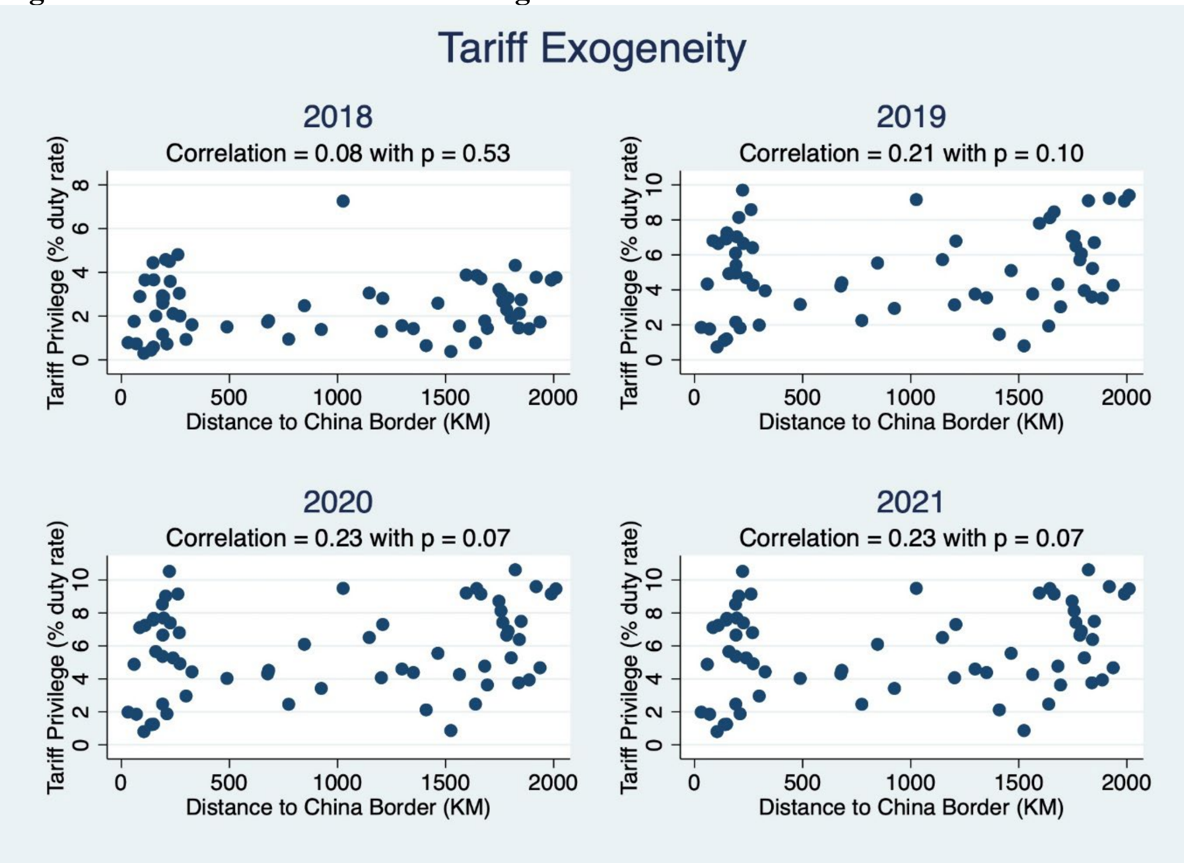
Note: The figure applies the year 2015 data and contrasts two kernel density functions of population density, one for Vietnam's 63 provincial-level locations and the other for China’s 291 prefectural cities. The Vietnamese provincial locations are generally denser than the Chinese cities. A simple comparison between the averages also concurs. The Chinese cities’ average population density is 431 people per km^2, but the Vietnamese provincial locations’ average is a larger figure of 486. Thus, Vietnam’s provincial-level locations are appropriate for urban economic research and we refer to them as cities.

Figure A2: Why Conley Standard Errors but not COVID-19 Variables



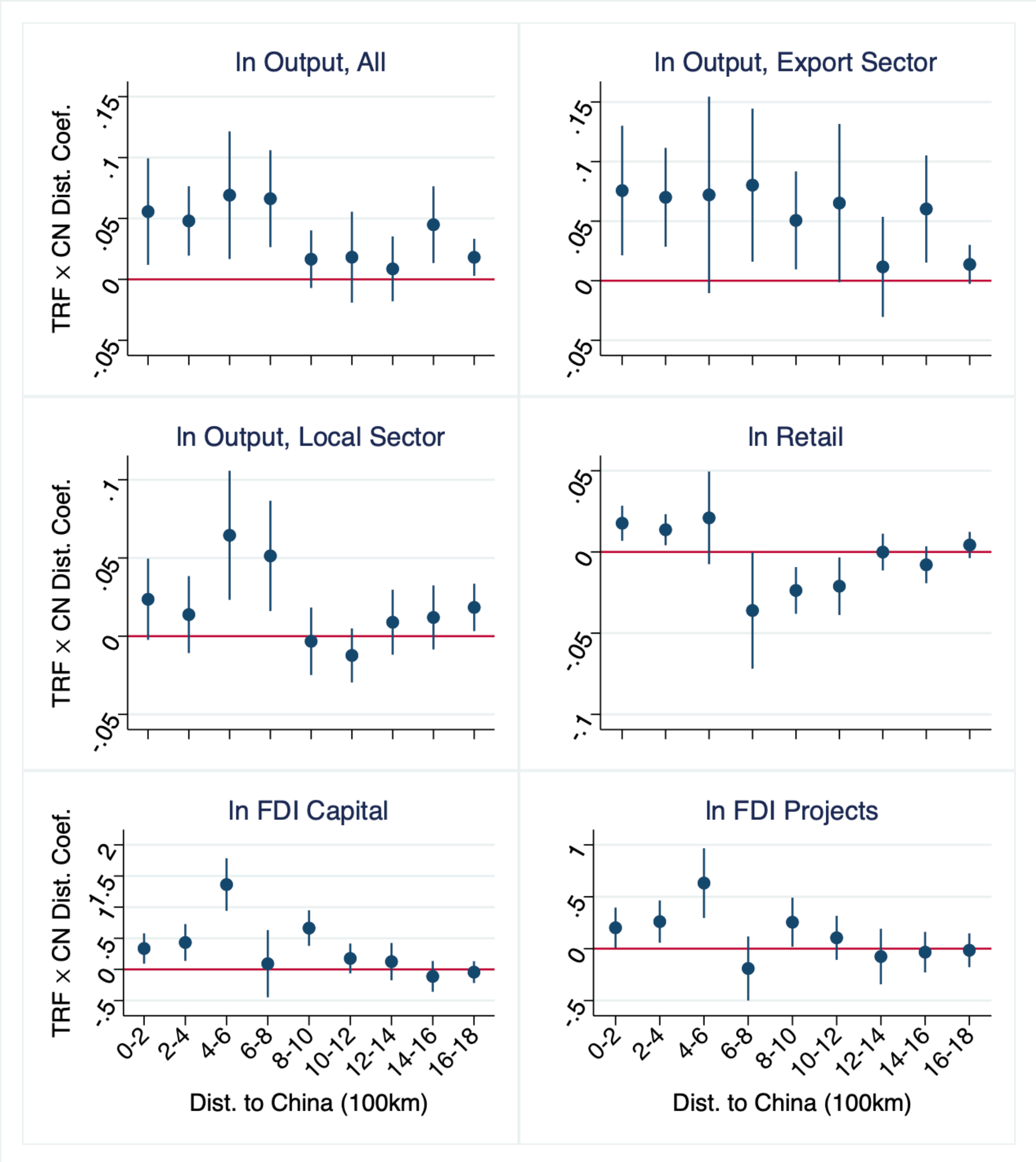
Note: The COVID LQ variable measures the city infection density. It is the city's share of the country's accumulated confirmed cases at the considered time divided by the city's share of the country's total population. A bigger LQ indicates a higher infection density and a more severe pandemic situation, which could affect the city more strongly. The scatter plots consider six different times, and the pairwise correlation coefficient estimation focuses on cities that already had confirmed cases at the time of concern. According to the results, the cities' COVID-19 dynamics were orthogonal to their tariff privilege, border distance, and FDI presence, which are the key variables of analysis. Thus, the regressions need not control any parametric explanatory variable about COVID-19. We can apply Conley standard errors and flexibly account for the pandemic's spatially and temporarily correlated impacts.

Figure A3: S301 China Tariffs as Exogenous Shocks to Vietnam



Note: The spreads of the tariff privilege are both wide in the North and the South. The correlation between the tariff and distance variables is somewhat positive but generally low. The US tariff dynamics were not more favorable for the North than for the South.

Figure A4: Estimating the China Border Effect by Distance Band



Note: Cities are grouped into ten bands sorted by the distance to China borders. Each band covers 200 km of distance. The base group is the furthest south ring for locations between 1,800 and 2,010 km to China. The regression specification is: $lnY_{jt} = \beta_0 + \beta_1 TRF_{jt} + \beta_2 TRF_{jt} \times LowFDI_j^{LQ} + \beta_3 TRF_{jt} \times Dist_j^{China} \times LowFDI_j^{LQ} + \sum_{d \in D} \beta_d TRF_{jt} \times I_j^d + lnX_j \cdot T_t \alpha + \lambda_j + \tau_t + \varepsilon_{jt}$ where D is the set of the nine distance bands and $I_j^d, \forall D$ are the distance band indicator variables. The estimations on output and retail apply Conley AR1 S.E, and those on FDI adopt Tobit regression and city-clustered S.E. The figure plots $\hat{\beta}_d, \forall D$ together with the 95% confidence interval. The border effect on outputs is pronounced, and the negative gradient is largely shaped by industries that can export to the US. Each extra p.p. of the *TRF* tariff privilege raised export sector outputs by 8% in cities, including Ha Noi and Hai Phong, that were less than 200 km by road to China. The positive effect was persistent within 800 km, beyond which the gain was gradually lower and eventually insignificant. There was a positive spillover effect. In cities where the export sector rallied strongly, local sector outputs, including retail sales, also tended to increase. The border effect on new FDI was sizable; the North gained substantially more foreign capital and projects than the South. The estimates for the 400-600 and 600-800 km bands should be interpreted with caution, as the 400-600 km band has only one city, and the other has only three smaller cities.

Figure A5: Environnemental Kuznets Curve Dynamics

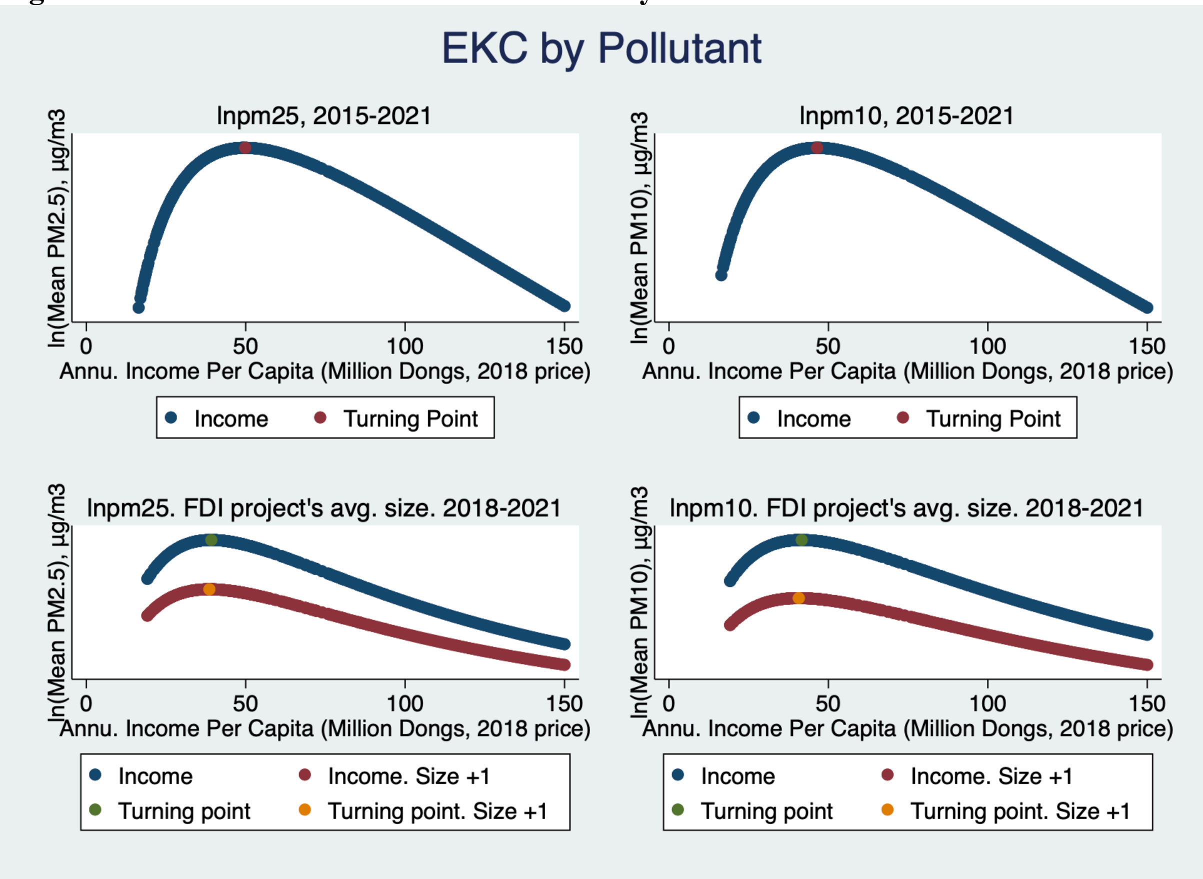


Table A1: Section 301 China Tariffs

List	# of tariff HTSUS subheadings	Extra duty	Value of appl. annual imports upon ann.	Effective date	Applicable items
List 1	818	@ 25%	$34 billion	Jul. 6, 2018	https://ustr.gov/sites/default/files/2018-13248.pdf
List 2	284; reduced to 279	@ 25%	$16 billion	Aug. 23, 2018	https://ustr.gov/sites/default/files/enforcement/301Investigations/2018-17709.pdf
List 3	5,745; reduced to 5,733	@ 10%	$200 billion	Sep. 24, 2018	https://ustr.gov/sites/default/files/enforcement/301Investigations/83%20FR%2047974.pdf
List 3		@ 25%		May 10, 2019	https://ustr.gov/sites/default/files/enforcement/301Investigations/84_FR_20459.pdf
List 4A	3229	@ 10%	$125 billion	Sep. 1, 2019	https://ustr.gov/sites/default/files/enforcement/301Investigations/Notice_of_Modification_%28List_4A_and_List_4B%29.pdf
List 4A		@7.5%		Feb. 14, 2020	
List 4B	542	@ 10%	$175 billion	Suspended & Unimplemented	https://ustr.gov/sites/default/files/enforcement/301Investigations/Notice_of_Modification_%28List_4A_and_List_4B%29.pdf

Notes: The abbreviations *appl.* and *ann.* stand for *applicable* and *annual*, respectively. China and the US made a Phase One agreement on Dec. 13, 2019. The additional *ad valorem* duty applicable to List 4A was reduced to 7.5% starting from Feb. 14, 2020, and the extra duty on List 4B items scheduled for implementation on Dec. 15, 2019, was suspended (source). Disputes against the S301 tariffs have been ongoing at the WTO, but the Court of International Trade has upheld the legality of S301 tariffs on products of China by far (source). Exclusions of items have been granted from time to time (see list), these exclusions remain valid till Sep. 2023 (source).

Table A2: Spatial Path Dependence in Urban Economic Growth

Variables	(1) Avg. Growth 2015-17	(2) Avg. Growth 2017-21	(3) Avg. Growth 2015-17	(4) Avg. Growth 2017-21	(5) Avg. Growth 2015-17	(6) Avg. Growth 2017-21
CN Dist.$_{(100km)}$	-0.331*	-0.254**			-0.204	-0.265**
	(0.174)	(0.101)			(0.178)	(0.109)
Avg. Growth,			0.432***	-0.028	0.372**	-0.094
2010-15			(0.157)	(0.104)	(0.166)	(0.104)
Avg. Growth,				0.094		0.066
2015-17				(0.080)		(0.078)
Observations	63	63	63	63	63	63
R^2	0.06	0.09	0.11	0.02	0.13	0.11
Constant	YES	YES	YES	YES	YES	YES

Note: *Avg. Growth* is measured by the average annual growth rate in output during the period. The ***, **, and * marks indicate 1%, 5%, and 10% significance. The results suggest that the average growth between 2010 and 2015 can be used to isolate spatial growth pre-trends in regression analysis on the tariff privilege's China border effect.

We can see cities' 2015-2017 output growth rates exhibit a marginally significant pairwise correlation with the distance to China (Column 1). This draws concern of a pre-trend: Even if the trade war did not occur, North Vietnam would still grow and close the gap with the South because of rising trade with powerful China. Notably, cities' growth in 2010-2015 predicts the growth in 2015-2017 (Column 3), but neither the 2010-2015 growth nor the 2015-2017 growth predicts the 2017-2021 growth (Column 4); the US-China trade war has changed Vietnamese cities' growth pattern. When past growth is controlled, the 2017-2021 growth is still significantly correlated with the distance to China (Column 6) but the 2015-2017 is not (Column 5). This finding suggests that cities' growth in 2010-2015 can be used to absorb potential spatial pre-trends and safeguard an unbiased estimate of the China border effect of the tariff privilege.