Institutions, Comparative Advantage, and the Environment*

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Abstract

This paper proposes that strong institutions provide comparative advantage in clean industries, and thereby improve a country's environmental quality. I study financial, judicial, and labor market institutions. Five complementary tests evaluate and assess implications of this hypothesis. First, industries that depend on institutions are clean. Second, strong institutions increase relative exports in clean industries. Third, an industry's complexity helps explain the link between institutions and clean goods. Fourth, cross-country differences in the composition of output between clean and dirty industries explain an important share of the global distribution of emissions. Fifth, a quantitative general equilibrium model indicates that strengthening a country's institutions decreases its pollution through relocating dirty industries abroad, though increases pollution in other countries. The comparative advantage that strong institutions provide in clean industries gives one under-explored reason why developing countries have relatively high pollution levels.

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1 Introduction

This paper proposes that strong institutions provide comparative advantage in clean industries. This mechanism, in addition to existing explanations focused on environmental regulation and factor endowments, provides an important and underappreciated contributor to global patterns of pollution. I define polluting industries as those with high emissions of air and water pollution per dollar of revenue, though consider alternative definitions.[1] I study financial, judicial, and labor market institutions.

I initially show that countries with stronger national institutions have better ambient air and water quality. This is a weak test since polluted and unpolluted countries differ along dimensions besides institutions, and since institutions may affect pollution through channels besides comparative advantage.

I then use five complementary approaches to assess how institutions affect environmental quality through comparative advantage. First, I find that across industries, dependence on strong institutions is positively correlated with an industry's "clean index," i.e., how little pollution it emits per dollar of revenue. This reflects the extent to which each industry depends on each institution. Clean industries predominantly use inputs that are traded in bilateral contracts rather than in open exchanges or referenced-priced in industry catalogs, and thus clean industries disproportionately need strong judicial systems to enforce bilateral contracts. Similarly, clean industries also have disproportionately intangible assets which are more challenging than tangible assets to use as collateral, and thus clean industries disproportionately rely on financial institutions.

To clarify these cross-industry comparisons that the paper reports, consider a simple example. The Fluid Pumps industry, which builds hydraulic and pneumatic pumps used in industrial machines, emits little air or water pollution. The Gypsum Products industry, which produces drywall and plaster, emits high levels of air and water pollution. The cleaner industry in this example depends more on each type of institution. The cleaner (pumps) industry needs strong financial institutions, since a small share of its assets are tangible. The pumps industry also relies on judicial institutions, since it mainly uses specialized inputs like customized machines that require bilateral contracts with suppliers. Finally, the pumps industry depends on flexible labor market institutions, since its annual sales change substantially in most years, which can require hiring or firing workers. In comparison, the dirtier (gypsum) industry relies less on financial institutions, since a large share of its assets are tangible. The dirtier gypsum industry primarily uses homogeneous inputs like coal, stone, and paperboard, which are traded on exchanges or through industry publications. Finally, the dirtier (gypsum) industry relies less on flexible labor market institutions, since its firms have steadier mean annual sales.[2]

[1] "Clean industries" in some settings denotes solar, wind, or other forms of energy generation besides fossil fuels. I use a broader interpretation of this phrase to describe any industry with relatively low pollution emissions per dollar of revenue.

[2] This example discusses NAICS industry codes 333996 and 327420.

The paper's second general approach to studying how institutions contribute to environmental quality through comparative advantage finds that stronger national institutions increase exports in clean industries. Institutions have large estimated impacts on pollution, with comparable importance for clean industries to environmental regulation or factor endowments. Trade research assesses how the interaction of a country's endowments with an industry's reliance on that endowment (e.g, the interaction of a country's capital stock with an industry's capital intensity) predicts industry-specific trade flows. I extend this approach to study how institutions affect the comparative advantage of clean industries. I report estimates from a cross-section and panel, I study manufacturing or all industries, I compare across 15 measures of institutions and 8 measures of environmental regulation, I instrument institutions with historical natural experiments, I use US or multi-country data on pollution intensity, and I use intra-national data across states of India.

Third, clean industries depend on institutions because clean industries need sophisticated, skilled, and specialized inputs, i.e., complex inputs. These patterns help explain the first two parts' findings. Intuitively, dirty industries require large machines, plants, and other tangible assets to heat, pressurize, combust, and process raw materials like fossil fuels; this processing emits pollution as a waste byproduct and the collateral that these tangible assets provide decreases dirty industries' dependence on strong financial institutions. Similarly, polluting industries disproportionately use fossil fuels, iron, and other homogeneous inputs which are traded on open exchanges and do not rely on complex bilateral contracts for judicial institutions to enforce. Clean industries rely on flexible labor market institutions, though to a lesser extent than on other institutions, in part because polluting goods like energy have inelastic short-run supply and demand, leading to less volatile sales and need for hiring and firing.

Fourth, I decompose how cross-sectional differences in pollution across countries reflect differences in the scale of total output, the composition of output across industries, and the techniques used to produce output in a given industry. For example, this decomposition asks: how would India's pollution change if India used US production techniques versus if India's composition of output across industries matched the US distribution? The decomposition covers all sectors, including but not restricted to manufacturing.

I find that composition has importance similar to or greater than technique in explaining cross-country differences in environmental quality. This suggests that comparative advantage and its determinants could meaningfully affect global patterns of environmental quality. This decomposition helps reconcile the role of institutions and comparative advantage from this paper's first several sections with the limited scope for comparative advantage to affect pollution that some readers take from existing literature, reviewed below.

Fifth, I use a quantitative general equilibrium model to assess how improving institutions in some countries changes pollution in all countries. I use a structural gravity model with pollution (Costinot and

Rodriguez-Clare 2014; Shapiro 2021) where national institutions change a country's productivity across industries. The comparative advantage regressions of the earlier sections estimate model parameters describing the productivity benefit of institutions, so the model is interpreting quantitative implications of the comparative advantage channels that the paper's earlier sections estimate. I find that improving institutions in countries where they are initially weak decreases pollution in those countries but increases it in others, due to changing the output share of dirty industries. For example, a counterfactual which improves institutions in Latin America to the institutional quality in North America would decrease pollution in Latin America by up to 20 percent but increase pollution elsewhere, by relocating dirty industries.

The paper's five approaches complement each other. The positive correlation between an industry's dependence on institutions and its clean index provides a reason for why the trade regressions and the quantitative model find that institutions provide comparative advantage in clean industries. That positive correlation also motivates the analysis of mechanisms—why do clean industries need institutions? The trade regressions estimate parameters that the quantitative model uses. The decomposition reconciles results from the earlier regressions with prior literature. All five approaches address the same research question: how and why do institutions affect pollution through comparative advantage?

This paper's main conclusions do not point to a specific environmental or trade policy that improves environmental quality. Hence, the goal of this paper is not to provide a new perspective on the welfare consequences or optimal design of environmental or trade policy. Instead, this paper highlights how policy reforms usually thought unrelated to the environment, such as judicial reforms that improve contract enforcement, or financial reforms that improve credit markets, can improve national environmental quality through attracting clean industries.

If every country had Pigouvian taxes on all pollutants, this paper's findings would not change the national welfare consequences of institutions. To the extent that environmental policy is less stringent than optimal, especially in developing countries, this paper's findings strengthen the case for policies that improve institutions in developing countries, since this paper's results imply that such reforms help address environmental externalities. In many settings, political economy obstacles impede first-best environmental policy. Institutional reforms provide one second-best alternative. Additionally, when international organizations like the International Monetary Fund, World Bank, and bilateral aid organizations advocate for improving institutions, this paper suggests that such reforms can also help improve the environment. I also find that such reforms reallocate dirty production to high income countries, which complicates such reforms since primarily high-income countries fund the International Monetary Fund and World Bank.

Because the paper's mechanisms reshuffle pollution across countries, the paper does not find that policies improving institutions are an especially effective tool to reduce global pollution totals. At the same time, the questions of what forces contribute to the observed global distribution of environmental quality, or how improving institutions in one country affect the environment in that country, are important for research and policy, even if they do not identify a leading policy lever that decreases total global pollution. For example, the large impact of the Environmental Kuznets Curve literature (Grossman and Krueger 1995) partly reflects the high level of interest in explaining global patterns of environmental quality, even if the explanation does not immediately imply a single policy solution. Additionally, the fact that little if any existing economics research calculates the level of total global air pollution emissions suggests it is not the primary focus of existing research and policy. (Many sources do calculate global total greenhouse gas emissions, or analyze global ambient pollution concentrations.)

This paper departs from existing work in several ways. I believe it is the first comprehensive analysis of how institutions affect environmental quality through comparative advantage. Existing research on trade and the environment focuses on environmental regulation and endowments of capital and labor as the main drivers of international differences in environmental quality (Antweiler, Copeland and Taylor 2001).[3] The idea that regions may use weak levels or enforcement of environmental policy to attract dirty industries (the "Pollution Havens Hypothesis") has widespread influence, and I build on literature seeking to understand the limited empirical support for this Hypothesis (Cherniwchan, Copeland and Taylor 2017).[4] The Environmental Kuznets Curve literature (Grossman and Krueger 1995) proposes that a country's pollution has an inverted U-shaped relationship to income per capita, due to consumer preferences, structural transformation from agriculture to manufacturing to services, increasing returns to pollution abatement, or voting rules that determine environmental regulation (Arrow et al. 1995; Stokey 1998; Andreoni and Levinson 2001; Jones and Manuelli 2001). The evidence for the inverted-U pattern is mixed (Stern 2017), and pollution is higher in developing countries for some pollutants (Greenstone and Hanna 2014; Jayachandran 2022). Andersen (2016; 2017) finds that ambient air pollution declines when a country creates a credit bureau and that US manufacturing firms with better credit ratings have lower pollution emissions, and Haas and Popov (2018) relate a country's CO_2 per capita to its financial development. Unlike development-environment research, which focuses on demand-side reasons like income for why poor countries have more pollution (Greenstone and Jack 2015), I focus on how comparative advantage instead represents a supply-side story. Classic work emphasizes that property rights over natural resources increase investment (Coase 1960; Chichilnisky

[3]A few papers refer to environmental regulation, and Jones and Manuelli (2001) theoretically analyze voting rules, as types of institutions. I use "institutions" to refer to judicial, financial, and labor market institutions, which I distinguish from environmental regulation, though I carefully compare them.

[4]Given the importance of the Pollution Havens Hypothesis, a brief history is informative and I do not think is available elsewhere. The first published mention of "pollution havens" appears to be from the late 1960s, in discussions of how US states used weak environmental policy to attract industrial activity (Hughes 1967; Lieber 1968; Metzler 1968). Russell and Landsberg's (1971) paper in *Science* popularized use of the phrase to describe international industry relocation. The pollution havens "hypothesis" was introduced in the early 1990s around environmental debates involving the North American Free Trade Agreement (Molina 1993; Birdsall and Wheeler 1993; Harrison 1994).

1994).

This paper also shows that approaches in the trade literature used to study comparative advantage can shed light on environmental quality. Research has studied how factor endowments (Romalis 2004), financial institutions (Rajan and Zingales 1998; Manova 2013) judicial institutions (Nunn 2007), and labor market institutions (Cuñat and Melitz 2012) drive international specialization, and more broadly studied interactions of institutions, comparative advantage, and international trade (Berkowitz, Moenius and Pistor 2006; Levchenko 2007; Chor 2010). Broner, Bustos and Carvalho (2011) find that environmental regulation discourages dirty production, though do not examine how institutions affect dirty industries. Firms can respond to weak contracting environments through vertical integration (Grossman and Hart 1986; Hart and Moore 1990; Antras 2003); one could interpret this paper's estimates as net of any such firm adaptive responses. One explanation of this paper's conclusions is that they combine three fairly simple ideas—comparative advantage drives international trade (Chor 2010; Costinot and Donaldson 2012; Morrow 2022); institutions provide a source of comparative advantage; and industries that need strong institutions are clean. I provide the first test and evidence of the third channel. I describe plausible causal links between specific institutions and comparative advantage in clean industries, and provide suggestive evidence of these mechanisms.

Finally, I provide what I believe is the first decomposition of how scale, composition, and technique explain cross-country differences in environmental quality. The results of this decomposition differ from the prevailing view that composition is an unimportant channel for understanding broad global environmental patterns. Following Grossman and Krueger (1993) and then Copeland and Taylor (1994), research has asked whether changes in the scale of production, the composition of production across industries, or the techniques used to produce goods within industries most accounts for differences in environmental quality. Recent analyses of the US, EU, Canada and many other countries typically find that technique, rather than composition, explains most differences in environmental quality within a country and over time (Grether, Mathys and de Melo 2009; Levinson 2009; Brunel 2016; Shapiro and Walker 2018; Copeland, Shapiro and Taylor 2022). Because standard Heckscher-Ohlin models predict that comparative advantage would primarily cause differences in environmental quality through composition, some work proposes based on this empirical finding that canonical theories of comparative advantage do not primarily account for international differences in environmental quality. While those findings account for environmental change within a country and over time, this paper instead provides such a comparison across countries within a year, and finds a more important role for composition effects. This finding helps reconcile this paper's first three sections, which find that comparative advantage driven by institutions affects the global distribution of pollution, with previous literature, which finds that technique rather than composition drives most environmental change.

The decomposition also has relevance for the Environmental Kuznets Curve literature (Grossman and Krueger 1993). It is common to present graphs of an Environmental Kuznets Curve showing different countries at the same point in time. This paper highlights that technique effects may be comparatively important in the time series but composition may be relatively more important in the cross-section. Adapting analyses in the Environmental Kuznets Curve literature to test, accommodate, or study implications of possible cross-sectional and time-series differences may be informative.

Before proceeding, I clarify scope. I analyze how institutions affect environmental quality through comparative advantage. This question has reasonable internal validity in regressions interacting country and industry characteristics and provides quantitatively important effects. It also parallels trade papers on institutions mentioned earlier. I largely leave analysis of other channels besides comparative advantage for institutions to affect environmental quality to future work.

I also clarify a broad question on the importance of environmental regulation. How could institutions, which do not purposefully target clean industries, have comparable importance as environmental policy, which targets dirty production? Cost structure provides an explanation. For the dirtiest industries, environmental regulation increases costs by up to a few percent (Becker and Shadbegian 2005; Greenstone, List and Syverson 2012; Shapiro and Walker 2018). Through changing the productivity of using intermediate goods or factors, however, institutions can change a majority of a firm's costs.

I proceed as follows. Section 2 describes data. Section 3 compares the clean index and dependence on institutions across industries. Section 4 estimates trade regressions interacting national institutions with an industry's clean index. Section 5 studies mechanisms. Section 6 decomposes scale, composition, and technique. Section 7 discusses a quantitative model of institutions and the environment. Section 8 concludes.

2 Data

Appendix Table 1 summarizes variables and Appendix A provides additional data details. I scale all environmental variables so more positive values represent better environmental quality.

2.1 Country Variables

I use country-level measures of each institution for the year 2012 or closest available year.[5] I measure each institution in z-scores, with a higher value denoting better institutions. Appendix A.1 describes measures of institutions and environmental regulation for sensitivity analyses.

I use standard data to measure each institution (Rajan and Zingales 1998; Romalis 2004; Nunn 2007; Chor 2010; Cuñat and Melitz 2012; Manova 2013). I measure financial institutions as the ratio

[5] I use 2012 since several data come from the US Economic Census, collected in years ending in 2 and 7.

of private credit by deposit and money institutions to GDP, as reported in the World Bank's Financial Structure Database. I measure judicial institutions from the World Bank's Rule of Law index, which reflects the "quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence" (Kaufmann, Kraay and Mastruzzi 2011, p. 223). I measure labor market institutions from the Heritage Foundation (2021)'s labor market freedom index, which reflects hindrance to hiring workers; rigidity of hours; and other inflexibility.

I measure labor institutions as labor market flexibility. This contrasts with another possible concept, the presence of a strong social safety net. I can quantify the extent to which each industry benefits from flexibility, according to the volatility of firm sales (Cuñat and Melitz 2012). It is harder to measure the dependence of each industry on the safety nets measure of labor market institutions.

I use eight different measures of national environmental regulation. I primarily analyze the first principal component of the four measures of regulation with the fewest missing values. I report sensitivity analyses that aggregate all eight measures via z-scores or via percentiles; unlike principal components, these accommodate missing values. I also analyze each of the eight measures of regulation separately. The eight measures are as follows: surveys of executives about environmental policy enforcement and about environmental policy stringency; the number of environmental treaties each country has signed; the ratio of environmental tax revenue to GDP; the 24-hour numerical air quality standards for particulate matter and sulfur dioxide;[6] lead standards for gasoline; and sulfur standards for diesel. The principal components measure combines the diesel sulfur standard, environmental regulation stringency, environmental regulation enforcement, and environmental treaties.

I measure factor endowments from standard data. I measure capital endowments as the log of the value of a country's capital stock per worker and skill endowments as the Penn World Tables calculation of a country's human capital index (Feenstra, Inklaar and Timmer 2021).

I analyze air ambient pollution data on the national urban mean of particulate matter smaller than 2.5 micrometers ($PM_{2.5}$), averaged over 2014-2022. I also analyze measures of biochemical oxygen demand, which provides a common omnibus measure of water pollution (Keiser and Shapiro 2019).

Appendix Table 2, Panel A, shows correlations between country variables. Financial and judicial institutions have a large positive correlation. Labor market institutions have weaker positive correlation with other institutions. Environmental regulations are positively correlated with institutions, capital, and skills.

[6]These are the two standards with the fewest missing values across countries.

2.2 Industry Variables

I measure most industry variables for about 350 US 6-digit North American Industry Classification System (NAICS) manufacturing industries in 2012. I report sensitivity analyses using data from Exiobase, which allow industry characteristics including pollution to differ by country. Appendix A.2 discusses possible concerns about measures of industries' dependence on institutions.

The main results use US industry data for several reasons. The US has greater industry detail and better emissions data than most countries. Emissions data in Exiobase rely on imputed pollution information for many countries based on technology estimates (Stadler et al. 2018). The variables used to explain why clean industries depend on institutions are available for the US only. The US Census of Manufactures also measures cumulative capital stock, which is harder to measure well for every country×industry globally.[7] Using US data also ensures that industry rates are exogenous to conditions in other countries. Reporting results with Exiobase also addresses potential bias from assuming that US pollution rates represent all countries (Ciccone and Papaioannou 2023).

I use common measures of each industry's factor and institution intensity (Rajan and Zingales 1998; Romalis 2004; Nunn 2007; Chor 2010; Cuñat and Melitz 2012). Measures of each industry's dependence on capital and skills are straightforward. I measure an industry's dependence on financial institutions according to asset intangibility, measured as one minus the share of assets that are property, plant, and equipment in Compustat. Tangible assets can provide ready collateral for a loan, and so industries where most assets are tangible depend relatively less on financial institutions.[8] I measure an industry's dependence on judicial institutions as the share of the industry's inputs, measured from input-output tables, that are not traded on open markets or reference priced (Rauch 1999). This is positively correlated with the prevalence of contract litigation (Boehm 2022). I measure an industry's dependence on labor market institutions as the standard deviation of within-firm sales growth, using Compustat data, weighted across firms by each firm's employment.

I measure each industry's clean index from data on air and water pollution emissions. I analyze air and water pollution because they can have large local welfare effects, are a focus of the trade-environment literature, and are feasible to attribute to individual industries. In the cross-section, relative emission rates across industries primarily reflect fixed attributes of each industry; for this reason, industries like primary metal processing, petroleum processing and refining, and pulp and paper mills are among the dirtiest industries in most time periods, papers, and datasets, ranging from the earliest discussions of

[7] Focusing on manufacturing also limits concern that discovery and exports of natural resources from the mining sector could directly influence institutions through the "resource curse." A sensitivity analysis includes all industries and not just manufacturing.

[8] Manufacturing sectors with tangible assets have much lower dependence on external credit, as measured in Rajan and Zingales (1998). I work with data on asset tangibility rather than external credit dependence since it is more intuitive to interpret the pollution-related sources and consequences of asset tangibility, as in Section 5.1.

pollution havens and the Clean Air Act a half century ago through more recent work (U.S. Department of Health, Education, and Welfare, Public Health Service 1967; Conroy 1974; Greenstone 2002), including Table 1 of this paper.

Specifically, I measure the short tons of air pollution emitted from the 2011 National Emissions Inventory, a plant-level emissions dataset collected by the US Environmental Protection Agency. I consider the five "criteria" pollutants that are most widely measured and the focus of regulation: carbon monoxide, nitrogen oxides, particulate matter smaller than 2.5 micrometers ($PM_{2.5}$), sulfur dioxide, and volatile organic compounds. For each pollutant, I calculate log emissions per dollar of revenue. I measure revenues from the 2012 Census of Manufactures. I measure an industry's air pollution rate as the first principal component of the five log pollutant-specific rates. Appendix A.1 discusses reporting thresholds in the air pollution data. For water pollution, I measure the log of the total pounds of emissions from the Discharge Monitoring Reports of the US Environmental Protection Agency (EPA) per dollar of revenue (USEPA 2020). I measure an industry's clean index as minus one times the first principal component of the air and water pollution emission rates. I report sensitivity analyses using country$\times$industry data from Exiobase, which measures air but not water pollution, and using the Leontief Inverse matrix to account for emissions embodied in value chains of each industry, including electricity.

Appendix Table 2, Panel B, shows pairwise correlations between industry characteristics. Dependence on judicial and financial institutions have a positive correlation. Dependence on judicial and labor market institutions are independent. Clean industries have stronger dependence on institutions.

2.3 Other Variables

I measure bilateral trade from the *Base pour l'Analyse du Commerce International* (BACI) database, created by the *Centre d'Etudes Prospectives et d'Informations Internationales* (CEPII). I aggregate data to 134 individual countries with non-missing values of key variables, plus one rest-of-world region. I concord industries in these data to distinguish six-digit NAICS industries. I use applied tariff rate data from CEPII's Market Access Map (Macmap) database, which accounts for regional and free trade agreements, tariff rate quotas, and other detailed tariff characteristics. Applied tariffs represent the statutory tariff rate, which is weakly less than preferential (Most Favored Nation) tariffs. A 2-digit Harmonized System (HS) code version is online; I purchased the 6 digit HS code version (Guimbard et al. 2012).

I use data from Exiobase, version 3.8.1, industry-by-industry data (Stadler et al. 2018), to separate scale, composition, and technique, and calibrate the quantitative model. Exiobiase is a multi-region input-output table, like the World Input Output Database or Eora. I use Exiobase since it has 163 industries, more than other world input-output tables.

I report one analysis of state production in India, using microdata from India's 2015-2016 Annual Survey of Industry. The dependent variable in regressions measures gross sales. I measure institutions according to existing measures (Dougherty 2009; Boehm and Oberfield 2020).

2.4 Cross-Country Comparisons

Figure 1 shows a cross-sectional correlation of national institutions and environmental quality:

$$Z_i = \rho_0^C + \rho_1^C I_i + \epsilon_i \tag{1}$$

Here Z_i measures ambient air or water quality in country i and I represents national institutional quality. Equation (1) provides a starting point for research on institutions and environmental quality, and I do not believe previous research has reported it. It does not reveal causal evidence, since institutions may be correlated with other variables influencing pollution. It also provides no evidence on whether institutions affect pollution through comparative advantage or other channels.

Figure 1, which presents binned scatter plots of equation (1), shows that countries with stronger institutions have better air and water quality. Some relationships are roughly linear. Others are less clear. The financial and judicial institutional patterns are significantly different from zero, while the labor market institutional patterns are not. Panel E has a slight U shape reminiscent of the Environmental Kuznets Curve literature.[9] Appendix Figure 1 finds similar patterns for two other relevant pollutants that trade-environment research has examined—nitrogen dioxide and sulfur dioxide.

3 Cross Industry Comparisons

I first ask whether the industries that depend on institutions are clean. I measure the cross-sectional relationship of each industry's dependence on institutions with the industry's clean index—how little air and water pollution industry s emits per dollar of sales:

$$Z_s = \rho_0^I + \rho_1^I I_s + \epsilon_s \tag{2}$$

I measure Z_s, the clean index of industry s, as minus one times the first principal component of log air and water pollution per dollar. The term I_s represents the extent to which industry s depends on institutions, as discussed in Section 2.2. My estimate of equation (2) uses US data.

Table 1 describes the five cleanest and dirtiest manufacturing industries. Panel A shows that cleaner

[9] The tables and figures in Grossman and Krueger (1995) and many subsequent papers on the Environmental Kuznets Curve relate pollution to GDP per capita. The text of many of these papers interpret GDP per capita in terms of "development."

industries depend relatively more on strong institutions. For example, column (1) shows that the fluid power pumps and motors industry is 2.4 standard deviations cleaner than the mean industry. Columns (2) through (4) show that this industry depends more than the mean manufacturing industry does on financial, judicial, and labor market institutions. Panel B of Table 1 shows that dirtier industries depend less on institutions. For example, gypsum product manufacturing, one of the dirtiest manufacturing industries, depends less than the mean manufacturing industry does on all three types of institutions. Column (5) of Table 1 shows mostly positive values for clean industries in Panel A, indicating that they depend more than average on institutions; but negative values for dirty industries in Panel B, indicating that they depend less than average on institutions. Averaging across the cleanest industries and across the dirtiest industries, column (5) shows that the cleanest industries depend 2.12 standard deviations (=0.65+1.47) more on institutions overall than the dirtiest industries do.

Figure 2 shows binned scatter plots describing the relationship between an industry's clean index and its dependence on institutions. Upward-sloping lines indicate that cleaner industries depend more on stronger institutions. Panel A shows that industries that have relatively intangible assets, and thus depend relatively more on financial institutions, are cleaner. Panel B shows that industries which use inputs that are differentiated, and thus depend more on strong judicial institutions, are cleaner. Panel C shows a smaller relationship between industries which have volatile sales, so depend more on flexible labor market institutions, and an industry's clean index. As shown in the R-squared in the three graphs, the clean index explains a third of the variation in dependence on financial institutions, a fourth of the variation in judicial institutions, and little of the variation in labor market institutions.

This section finds that the industries which depend on institutions are clean. Existing research finds that strong national institutions provide comparative advantage in industries that depend on institutions. Combining these two results indirectly implies that institutions provide comparative advantage in clean industries. The next section interacts country and industry characteristics to test directly for comparative advantage in clean industries.

4 Regressions: Direct Tests of Comparative Advantage

4.1 Comparative Advantage in All Industries

As Section 7 discusses, multi-sector Ricardian trade models lead to the following gravity equation for international trade (Costinot, Donaldson and Komunjer 2012; Costinot and Rodriguez-Clare 2014):

$$X_{ij,s} = \xi \frac{T_{i,s}(c_{i,s}\phi_{ij,s})^{-\theta_s}}{(P_{j,s})^{-\theta_s}} X_{j,s} \tag{3}$$

Here $X_{ij,s}$ is the value of bilateral trade from origin country i to destination j in industry s, $T_{i,s}$ is the origin×sector technology level, $c_{i,s}$ is the unit production cost, and country×sector expenditure is $X_{j,s} \equiv \sum_i X_{ij,s}$. The full trade cost is $\phi_{ij,s} \equiv \tau_{ij,s}(1+t_{ijs})$. Goods face iceberg trade costs $\tau_{ij,s} \geq 1$, where τ goods must be shipped for one to arrive, and tariffs $t_{ij,s}$. Here θ_s describes the (trade) elasticity of bilateral trade with respect to trade costs. The importer×industry price index is $P_{j,s}$. The importer spends $X_{ij,s}$ on (ij,s) goods. The term ξ represents a constant function of model parameters.

I link equation (3) to country endowment×industry regressions through the following assumptions:

$$lnX_{j,s} - \theta_s lnP_{j,s} = \zeta_{j,s} \tag{4}$$

$$lnT_{i,s} = \alpha E_i I_s + \sum_f \beta_f E_i^f I_s^f + \pi R_i Z_s + \omega_{i,s} \tag{5}$$

$$ln\xi - \theta_s lnc_{i,s} - \theta_s ln\phi_{ij,s} = \gamma ln(1+t_{ij,s}) + \eta_{ij} + \omega_{ij,s} \tag{6}$$

$$\epsilon_{ij,s} = \omega_{i,s} + \omega_{ij,s} \tag{7}$$

Equation (4) states that the importer×industry fixed effects $\zeta_{j,s}$ equal the difference of importer×industry log expenditure and scaled prices. Equation (5) states that a country×sector's productivity reflects the interactions of endowments and industry characteristics, plus a stochastic term $\omega_{i,s}$.[10,11] Equation (6) states that tariffs, bilateral fixed effects η_{ij}, and the error $\omega_{ij,s}$ capture the effects of unit production costs and trade frictions. In these equations, E_i represents the quality of institutions in exporter i, E_i^f is a country's endowment of factor f, I_s^f is the dependence of industry s on factor f, R_i is the stringency of environmental regulation, and Z_s is the clean industry index. The left side of equations (4) through (7) describe components of equation (3). The right side of these equations describe terms that data report or regressions can estimate.

Under assumptions (4) through (7), the natural log of equation (3) becomes the following:

$$lnX_{ij,s} = \alpha E_i I_s + \sum_f \beta_f E_i^f I_s^f + \pi R_i Z_s + \gamma ln(1+t_{ij,s}) + \zeta_{j,s} + \eta_{ij} + \epsilon_{ij,s} \tag{8}$$

[10] I describe institutions and factors as affecting technology $T_{i,s}$ rather than the unit cost $c_{i,s}$ because the unit cost is a price index that only depends directly on prices and model parameters. Appendix Equation (D–5) shows that the cost function $c_{i,s}$ depends on the price of labor and intermediate goods. Put another way, institutions and factors via the industry-specific interaction terms in $T_{i,s}$ determine how much output a unit of inputs can generate; and the cost function $c_{i,s}$ describes the price of a unit of inputs. A broader analysis which investigates channels beyond comparative advantage for institutions to affect the environment could assume a production function where institutions affect factor shares or in other ways would enter the cost function. Ultimately, equations (4)-(7) provide one model-based interpretation of how to translate a canonical structural gravity model into the type of regression equation (8) that much of the empirical trade literature runs, but one could propose other versions of the assumptions in equations (4)-(7) that would result in the same regression.

[11] Equation (5) abstracts from components of technology that vary by industry but not country, since this paper focuses on differential effects of institutions across industries. Ultimately, this abstraction does not affect estimation, since the fixed effects in regressions adjust for country- and industry-specific shifters.

Many papers test for comparative advantage by interacting exporter endowments with industry characteristics. Equations (4) through (7) describe one way to derive such an equation from a Ricardian trade model. The term α reflects comparative advantage due to institutions, β_f reflects comparative advantage due to factor endowments, and π reflects comparative advantage due to environmental regulation.

I add a few practical notes. I report estimates either with an index of institutions or separating financial, judicial, and labor market institutions. Factors include a country's capital-labor ratio and skills. Regressions cluster standard errors by exporter, as in Defever, Head and Larch (2015); Do, Levchenko and Raddatz (2016), and Gerritse (2021). I show standardized beta coefficients to facilitate comparison of magnitudes across variables. I also report Poisson pseudo-maximum likelihood (PPML) versions of equation (8), partly to address possible bias from excluding the log of zero trade flows (Silva and Tenreyro 2006). Equation (8) reflects effects of one country endowment conditional on others—for example, one could think of comparing countries with similar quality institutions but different stringency of environmental regulation.

Equation (8) and extensions address three potential econometric issues. Institutions may be measured with error, correlated with other country characteristics, and affected by trade and production. To address these potential concerns, I compare different measures of institutions, construct an index of institutions, use multiple predetermined instruments for institutions, focus on interactions of a country's institutions with an industry's characteristics, and exploit variation in institutions across time within a country and across states within a country.

Should estimates of equations like (8) include additional interactions, such such as the interaction of an industry's clean index with the country's GDP per capita? One might think that such additional controls could help address omitted variables bias. At the same time, theoretical and empirical reasons argue against such controls. Theoretically, this kind of GDP interaction is not readily derived from a standard closed-form gravity model, whereas most of the other regressions are consistent with the kind of model the paper later discusses and analyzes quantitatively. GDP is an endogenous outcome of all countries' endowments, industries' intensities, and parameters in a general equilibrium model, whereas the regressions derived from the model include predetermined country endowments that determine comparative advantage. Econometrically, since institutions and factors affect log GDP per capita, the GDP interaction is a bad control in the sense of Angrist and Pischke (2009). This is because GDP per capita is an intermediate outcome that institutions affect. Despite these caveats, I do report one sensitivity analysis which interacts the log of GDP per capita with each industry's clean index.

More broadly, how should we interpret the effect of institutions? An empirical interpretation is that while institutions are not randomly assigned, the various cross-section, panel, and instrumental variables estimates represent the thought experiment of randomly changing the quality of a country's institutions, while holding other attributes of the country fixed, and holding fixed attributes of other countries. These estimates represent the effect of such random variation in a country's institutions on its production of clean versus dirty goods and other outcomes. A model-based interpretation, which justifies the use of these regressions for calibrating the quantitative model, is that institutions change the fundamental productivity $T_{i,s}$ of a country in certain industries, and these regressions estimate the magnitude of that relationship.

Results

Table 2, Panel A, examines comparative advantage in a standard setting, corresponding to equation (8). Columns (1) through (8) consider one source of comparative advantage at a time; column (9) pools the three measures of institutions; and column (9) examines the institutions index.

Table 2, Panel A finds that most institutions and factors provide comparative advantage. This echoes existing work, though incorporates environmental regulation. Column (1) shows that countries with strong financial institutions export relatively more in industries that depend on financial institutions. The coefficient indicates that for an industry that depends one standard deviation more than average on financial institutions, improving a country's endowment of financial institutions by one standard deviation increases log exports by 0.057 standard deviations. In other words, this indicates that financial institutions provide a source of comparative advantage. Columns (2) through (4) show that similar patterns hold for other institutions, though the relationship for labor is statistically insignificant. Column (5) shows that environmental regulation provides a source of comparative advantage in clean industries. Capital has less importance on its own, though is more important in the pooled regressions of columns (9) and (10). Column (7) shows a similar pattern for skills. Column (8) finds that tariffs discourage trade.

Because Table 2 shows standardized beta coefficients, we can compare magnitudes across variables. Consistent with Heckscher-Ohlin models, the largest source of comparative advantage in the pooled regression of columns (9)-(10), Panel A, is a country's skill endowment. The capital/labor ratio matters less. In all these estimates, institutions have larger predictive power for trade than environmental regulation does. The role of environmental regulation here nonetheless suggests that the Pollution Havens Hypothesis is relevant to trade and comparative advantage broadly.

These estimates for the comparative advantage of institutions are qualitatively in line with existing papers. As in Chor (2010), each of the three institutions has some role individually, although the coefficient for labor market institutions is statistically insignificant, and factor endowments and institutions matter independently. In Chor (2010), judicial institutions matter the most either when the three institutions are analyzed in separate regressions or together, while here, financial institutions matter slightly more. The magnitudes here are smaller than corresponding estimates in Nunn (2007) or Chor (2010), perhaps in part because this paper has more countries, industries, and detailed controls.

One explanation for the estimated effect of the capital/labor ratio in Table 2, column (6), is the lack of control for environmental regulation, since polluting industries have high capital/labor ratios. Adding the environmental regulation endowment×intensity variable to this regression increases the coefficient on the capital/labor ratio to be larger and statistically significant. The estimate for the capital/labor ratio in columns (9)-(10) also fits this explanation. This pattern again demonstrates the relevance of environmental policy in explaining comparative advantage overall.

4.2 Comparative Advantage in Clean Industries

The findings in Section 4.1 and previous work that institutions provide comparative advantage, and in Section 3 that the industries benefiting from institutions are clean, together imply that institutions provide comparative advantage in clean industries. I now report the following direct test of this hypothesis:

$$lnX_{ij,s} = \alpha^C E_i Z_s + \sum_f \beta_f^C E_i^f I_s^f + \pi^C R_i Z_s + \gamma^C t_{ij,s} + \zeta_{j,s}^C + \eta_{ij}^C + \epsilon_{ij,s}^C \tag{9}$$

Equation (9) tests whether countries with strong institutions export more in clean industries. It resembles the canonical gravity equation (8), but interacts institutions with an industry's clean index, rather than an industry's dependence on institutions. I calculate the clean index from US data. The coefficient α^C represents the mean increase in log exports for an exporter with institutional quality E_i in an industry with clean index Z_s. The country-pair fixed effects η_{ij}^C adjust for effects of the exporter's institutional quality. The destination×sector fixed effects $\zeta_{j,s}^C$ adjust for the industry's clean index Z_s.

Results

Figure 3, Panels A and B, graph raw data. Each graph describes three variables: the horizontal axis describes an industry's clean index; the vertical axis plots a country's exports in each industry, normalized to mean zero; and the two lines describe regions with strong versus weak institutions. Panel A describes two example countries: Tajikistan, with weak institutions; and Switzerland, with strong institutions. I plot a nonparametric local linear regression across industries within each region. The upward-sloping dashed line in Panel A indicates that Switzerland exports more in clean than dirty industries. The downward-sloping solid line in Panel A indicates that Tajikistan exports relatively less in clean industries. The difference in exports between clean and dirty industries is economically large. The use of US data for calculating the industry clean index adds measurement error, so it is notable that this graph shows clear patterns for even a country like Tajikistan where a US-based index may differ more than average from local patterns.

Figure 3, Panel B, finds similar patterns for all countries. This panel separates countries into two groups: the dashed red line describes countries with stronger national institutions than the median country; the solid blue line describes countries with weaker institutions than the median country. The X-shaped figure in the global graph in Panel B echoes the shape of the two-country graph in Panel A—countries with strong institutions specialize in clean industries, and countries with weak institutions specialize in dirty industries. Appendix Figure 2 shows two theoretically-derived measures of revealed comparative advantage. In both cases, countries with weak institutions specialize in dirty industries, though the specialization of countries with strong institutions in clean industries is clearer in the measure of Costinot, Donaldson and Komunjer (2012) than in that of Balassa (1965).

Table 2, Panel B, estimates equation (9). Columns (1) through (8) analyze one source of comparative advantage at a time; column (9) includes all three measures of institutions as separate variables in a single regression; and column (10) uses the institutions index.

These Table 2, Panel B estimates find that countries with strong institutions specialize in clean industries. Most estimates for institutions are positive and statistically significant. Estimates separating institutions in columns (1) through (3) and pooling them in column (9) suggest that financial institutions provide a larger source of comparative advantage in clean industries than judicial or labor market institutions do. In the regression including each of the three institutions simultaneously in column (9), only financial institutions are statistically significant, though all have positive coefficients that are similar to the coefficient for environmental regulation.

It is unclear what existing evidence would predict regarding this greater role for financial institutions in clean production. Figure 2 finds that dependence on financial institutions has the strongest correlation with an industry's clean index, closely followed by dependence on judicial institutions. Appendix Table 2 also finds that financial institutions have the strongest correlation with an industry's clean index. At the same time, several of these institutions have strong positive correlation, which can make them complex to separate empirically when jointly included in the same regression (Chor 2010). Existing work does highlight the direct importance of financial institutions for clean production (Andersen 2016, 2017; Haas and Popov 2018).

Panel B of Table 2, Column (10), shows that for an industry one standard deviation cleaner than the mean, a country with one standard deviation stronger institutions has about 4 percent of a standard deviation higher log exports. Column (5) supports the Pollution Havens Hypothesis by finding that environmental regulation drives specialization in clean industries. Column (10) finds that institutions are at least as important as environmental regulation to explaining countries' specialization in clean versus industries.

Table 2 allows a couple other interpretations. One sees how changing national institutions from the tenth to the ninetieth percentile of institutional quality affects emissions. I calculate a country's baseline environmental quality as $Z_i = \sum_{j,s} X_{ijs} Z_s$, and counterfactual environmental quality as

$$Z' = \sum_{j,s} [X_{ij,s} Z_s + e^{\hat{\alpha}^C Z_i [E^e_{0.9} - E^e_{0.1}]} Z_s] \tag{10}$$

Here $\hat{\alpha}$ is from equation (9), $E^e_{0.9}, E^e_{0.1}$ are the ninetieth and tenth percentile of institutional quality, and I calculate the proportional change in a country's pollution due to changing institutions as $(Z'_i/Z_i - 1)$.[12] The fitted effect row at the bottom of Table 2, Panel B, columns (9) and (10), suggests that this counterfactual would decrease a country's emissions by about 25 percent. This calculation makes strong assumptions. It only analyzes traded manufacturing goods. It assumes other sources of technology, factors, and determinants of specialization are fixed. It assumes institutions have log-linear effects, and it comes from a partial equilibrium calculation. The quantitative model in Section 7 helps relax these assumptions.

A second interpretation of Panel B of Table 2, column (10), observes that the coefficient on institutions is just under half as large as the tariff coefficient. Globally, one standard deviation of tariffs is 9 percentage points weighted by trade value and 15 percentage points unweighted. Hence, for an industry one standard deviation cleaner than average, improving institutions by one standard deviation would increase exports by about the same amount as decreasing tariffs by 4 to 7 percentage points. This would be similar to ending a trade war or granting a country Most Favored Nation status, and implies that institutions have effects on clean industries comparable to large changes in trade policy.

4.3 Alternative Research Designs and Sensitivity Analyses

Panel Data Estimates

I use 1996-2015 panel data to test if clean exports increase in countries where institutions improve:

$$lnX_{ij,sy} = \alpha^P E_{i,y} Z_s + \sum_f \beta^P_f E^f_{i,y} I^f_s + \zeta^P_{j,sy} + \eta^P_{ij,y} + \epsilon^P_{ij,sy} \tag{11}$$

Here trade flows X, institutions E, factors E^f, and the fixed effects ζ and η vary by year y. I assume the clean industry index Z, factor intensities I^f_s, and tariffs t are time-invariant, due to limited data availability for the full panel. The comparative advantage parameter α^P is identified from differences in institutional quality within a country, interacted within an industry's clean index. One motivation for these estimates is that a country's institutions could correlate with time-invariant country characteristics, such as geography, which differentially encourage specialization in clean industries.

[12] I measure the tenth percentile of institutions as the mean institution index for countries between the fifth and fifteenth percentile of that index, and the ninetieth percentile as the mean institution index for countries between the eighty-fifth and ninety-fifth percentile of that index.

I also estimate a long-difference version of equation (11), with years 2000 and 2015.[13] This may provide a more accurate estimate than the full panel regression, for two reasons. Because institutions may be measured with error, panel estimates like equation (11) can exacerbate attenuation bias due to measurement error (Griliches and Hausman 1986). Additionally, institutions can change gradually, and trade may respond gradually to institutions. Cross-sectional estimates like equation (9) obtain a long-run relationship between institutions and trade, while panel data estimates like equation (11) estimate the short-run relationship. The long-difference estimate obtains medium-run estimates.

Although a country's institutions have path dependence, the mean country has reasonable-sized changes in institutions over 20 years, which suggests that changing institutions has scope to affect pollution. Between 1996 and 2015, the absolute value of institutions in the mean country changed by half a standard deviation.[14] Institutions improved in about two-thirds of countries and worsened in a third of countries. For comparison, in the mean country between 1996 and 2015, the absolute value of capital and skill endowments changed by a similar amount of 0.6 and 0.4 standard deviations.

Figure 3, Panel C, shows a panel graph relating panel changes in trade to changes in institutions. For example, Rwanda had among the most rapid improvements in institutions in this period, while Egypt had among the most rapid deterioration of institutions. This graph divides countries into two groups: countries where institutions improve and countries where institutions worsen. For each industry, I calculate the share of global exports from each group of countries in 1996 and in 2015. I then plot a nonparametric regression of the change over time in these shares for each country×industry.

Figure 3, Panel C, shows that countries where institutions improve have faster export growth in all industries, since the solid blue line lies above the x-axis. Countries where institutions worsen have slower export growth in all industries, since the dashed red line lies below the x-axis. The slopes show that countries where institutions improve disproportionately increase exports in clean industries.

Appendix Table 3, row 2, exploits panel variation in institutions, capital, labor, and other variables within a country and over 20 years, corresponding to equation (11). Row 3 uses the long difference sample in 2000 and 2015. The panel data estimate obtains precise results, with smaller magnitudes in the full panel but larger magnitudes in the long-difference estimates. The comparative advantage that institutions provide in clean industries is 0.038 (0.012) in the baseline estimates, 0.013 (0.005) in the full panel estimates, and 0.062 (0.031) in the long-difference estimates. The smaller magnitude of the full panel versus long difference is consistent with measurement error in institutions. It is also consistent with the idea that trade responds gradually to institutions.

[13] I use 2000 rather than 1996 for the first year of the long-difference estimate since the data coverage is much lower in 1996 than in 2000.

[14] This statistic reports the mean across countries of $|E_{i,2015} - E_{i,1996}|$,where $E_{i,y}$ is a measure of institutions or factor endowments in country i and year y. For comparability with most of the paper, these values are normalized to have mean zero and standard deviation one in the year 2012.

Cross-State, Intranational Institutions

I also compare institutions across states within a single country, India. Comparing across states within a country helps address the concern that some determinants of specialization may vary across countries in ways that are difficult to observe. I study India since its institutions vary across states and existing work has measured them. I use production data to estimate the following test:

$$lnX_{i,s} = \alpha^I E_i I_s + \sum_f \beta_f^I E_i^f I_s^f + \pi^I R_i Z_s + \eta_i^I + \zeta_s^I + \epsilon_{i,s}^I$$

Here $X_{i,s}$ represents the gross output of industry s in state i. I analyze gross output rather than bilateral trade here since this is what India's Annual Survey of Industry reports. One limitation is that India only has 28 states, 26 with data available.

Appendix Table 3, row 4, estimates comparative advantage due to institutions across states in India. The magnitude of the overall comparative advantage of institutions in column (1), and the comparative advantage that institutions provide in clean industries in column (2), are both moderately larger than the global baseline estimate from row 1. The global and intra-national India estimates differ in several ways, including the use of trade versus production data and different measures of institutions and controls. While this makes it difficult to provide an apples-to-apples comparison, these magnitudes do not support the concern that the global estimates of institutions' comparative advantage is due to unobserved country-level variables that are correlated with institutions.

4.4 Additional Sensitivity Analyses

Appendix B discusses a range of sensitivity analyses, which largely leave qualitative conclusions unchanged. These include varying data sources and econometric assumptions, including controlling for interactions of the exporter's log GDP per capita and an industry's clean index, and estimating the relationship between institutions and clean production techniques within an industry (Appendix Table 3); alternative measures of environmental regulation (Appendix Table 4); using other measures of institutions, including historical instrumental variables for institutions (Appendix Table 5); and using randomization inference (Appendix Figure 3).[15]

Appendix Table 3, rows 16-20, includes interactions of a country's institutions with both the clean industry index and the measures of each industry's dependence on institutions in the same regression. In other words, it combines the main explanatory variables from Table 2, Panels A and B, into a single

[15]In general equilibrium frameworks like the model that Section 7 studies, changes in the institutional quality of a country's trading partners would affect the country's own specialization in dirty industries. I investigated the feasibility of testing this mechanism in the regressions of this section. I concluded that this setting lacks sufficient statistical power to quantify these general equilibrium spillovers with meaningful precision, since the resulting estimates did not rule out economically meaningful impacts of either sign.

regression. In most of these estimates, the interaction of institutions with the clean industry index becomes small and statistically insignificant, although the financial interactions term remains marginally significant. These estimates are generally in line with the paper's interpretation that institutions encourage specialization in clean industries primarily because clean industries depend on institutions. This is why controlling for the country institutions × industry dependence term attenuates the coefficient on country institutions × industry clean index. Of course, the empirical measures of each industry's dependence on institutions are proxies which may have some degree of measurement error, and which may account for the positive but small coefficients on some of the country institutions × industry clean index terms in these regressions.

5 Explanations

The previous sections summarize evidence that institutions provide comparative advantage in clean industries but do not explain why. Investigating explanations is important on its own and helps increase the plausibility of results in the earlier sections. I now use information on industry characteristics to provide some insight. These are primarily variables relevant to trade policy and associated political economy (Rodrik 1995; Shapiro 2021).

5.1 Intuitive Explanations

Intuitively, why do clean industries depend on financial institutions? Polluting industries, often described as "heavy industry," use large, long-lived, tangible assets like machines and boilers to process and convert dense raw materials into finished products. Plant-level increasing returns may contribute to these industries' large investments in tangible assets. The tangibility of dirty industries' assets provides collateral that helps these industries borrow money even in settings with weak financial institutions. For example, cement is among the dirtiest manufacturing industries and has large plant-level returns to scale, partly because cement kilns are among the world's largest pieces of industrial machinery (Norman 1979; Ganapati, Shapiro and Walker 2020). To give other examples, cracking units in oil refineries, blast furnaces for metal smelting, ammonia synthesis in chemical manufacturing, ethylene production at petrochemical plants, and many other polluting industrial processes require temperatures near or far above 1,000 degrees Fahrenheit and immense pressure. Intangible assets like patents, copyrights, trademarks, or brand equity alone cannot safely generate such physical chemical reactions, which is why the dirty industries using such reactions rely disproportionately on tangible assets. Conversely, consider a clean industry like instruments for industrial processes (listed in Table 1, Panel A), which makes instrumental systems for laboratory analysis of samples and other sophisticated manufactured goods. Such clean industries invest in research and development and skilled workers, but depend less on tangible assets that they could use as collateral, and thus they rely on strong financial institutions.

Why do clean industries depend on judicial institutions? Dirty industries disproportionately use raw materials that are relatively homogeneous because natural processes form identical materials under identical conditions across the planet. Many raw materials used in dirty industries' production, like the iron used to make steel or the lead used to manufacture batteries, are elements of the periodic table that consist of one type of atom present throughout the Earth's crust. Of course, marketed steel, iron, and other dirty products still have some degree differentiation to fit customer needs (Conway 2023). But because dirty inputs are more homogeneous than other types of inputs, they are less often exchanged through specialized contracts that depend on judicial institutions to enforce, and are more often bulk commodities that can be traded through open markets. Put another way, if one considered factors embodied in value chains of intermediate inputs, the complex inputs used in clean industries more intensively use clean factors like skills and intellectual property, which require judicial institutions to enforce complex contracts. By contrast, the simpler inputs used in dirty industries more intensively use dirty factors like fossil fuels, metals, and related natural resources, which are less often exchanged through bilateral contracts and thus depend relatively less on judicial institutions.

The estimated relationship between an industry's clean index and its dependence on labor market institutions is weaker than the relationships I find for financial and judicial institutions, and correspondingly, I believe the intuition for clean industries' dependence on labor market institutions is less direct. Regardless, an intuitive explanation is that polluting industries like energy produce goods with inelastic short-run supply and demand, partly because these goods are necessities. Economies buy energy-intensive and dirty goods year after year, making these industries less likely to hire and fire workers each year. Cleaner goods may have more elastic short-run demand and thus more volatile sales that require hiring and firing workers.

5.2 Statistical Explanations

To assess explanations empirically, I first regress an industry's clean index on other industry characteristics, one at a time:

$$Z_s = \rho_0^W + \rho_1^W W_s + \epsilon_s^W \tag{12}$$

This comparison indicates which industry characteristics W are correlated with being clean. I then adapt equation (2) by assessing how controlling for one industry characteristic changes the association of an industry's clean index with the industry's dependence on institutions:

$$Z_s = \rho_0^{IW} + \rho_1^{IW} I_s + \rho_2^{IW} W_s + \epsilon_s^{IW} \tag{13}$$

The additional control W_s varies by regression. I investigate how each control W_s changes the association of institutional dependence and the clean industry index. Finally, I adapt equation (9) by controlling for the interaction of one additional industry characteristic W_s with a country's institutional quality E_i:

$$lnX_{ij,s} = \alpha^W E_i Z_s + \alpha^W E_i W_s + \sum_f \beta_f^W E_i^f I_s^f + \pi^W R_i Z_s + \gamma^W t_{ij,s} + \zeta_{j,s}^W + \eta_{ij}^W + \epsilon_{ij,s}^W \tag{14}$$

My estimates of equations (12) and (13) use US data; estimates of equation (14) use international trade data across countries combined with US industry characteristics.

Table 3, column (1), shows that clean and dirty industries differ along many dimensions. Clean industries have more processed, complex inputs. Specifically, clean industries have lower cost shares of energy and raw materials, more differentiated products (higher inverse export supply elasticity), lower shipping costs, and are less upstream.

Table 3, columns (2) through (4), assesses whether these characteristics account for the relationship between an industry's dependence on institutions and its clean index, as in equation (13). They show that differentiated, processed, and downstream industries are clean and depend on institutions. The most important industry characteristics here again are the industry's energy shares and shipping costs. No one industry characteristic alone fully accounts for most of the association between an industry's institutional dependence and its clean index, though all these characteristics together do, as indicated by the small magnitudes in the final "all at once" row.

Column (5) of Table 3 estimates equation (14). The last row of Table 3 controls for all these variables at the same time. Again, no single variable completely accounts for the comparative advantage that strong institutions provide in clean industries. An industry's raw materials share and shipping costs account for meaningful shares of the comparative advantage of clean industries; and including all variables together accounts for about 25 percent of this comparative advantage. Given the many hypothesis tests in Table 3, Appendix Table 6 obtains similar conclusions from p-values adjusted for multiple hypothesis testing (Anderson 2008).

Appendix Table 7 repeats this analysis but controls for variables cumulatively. Each row in Appendix Table 7, in other words, controls for the indicated variable, in addition to all variables listed in earlier rows. The qualitative conclusions are similar, although point estimates vary somewhat from those of Table 3, especially for variables further down in the table which in Appendix Table 7 have more controls from earlier rows.

Appendix Table 8 examines the importance of industry characteristics for comparative advantage of clean industries, separately for each type of institution. It obtains similar findings that the energy and raw materials shares, shipping costs, and related variables account for much of the clean-institutions relationship. As in much of the paper, these patterns are clearer for financial and judicial than for labor market institutions.

In studying trade policy and CO_2, a single industry characteristic, upstreamness, primarily accounts for the lower trade protection of dirty industries (Shapiro 2021). This is not the case here—many variables together account for why countries with strong institutions specialize in clean industries. The most important variables reflect the idea that clean industries are specialized, skilled, and downstream, or in one word, complex. One possible reason for the difference between the analysis of trade policy and CO_2 versus this paper is that the local pollutants studied here depend on end-of-pipe pollution control technology, which varies substantially and idiosyncratically across industries based on many forces. CO_2, by contrast, has no economically viable end-of-pipe abatement technology, and depends only on energy inputs, which vary more systematically across industries.

The paper could conclude here, and has already used several methods to test its hypothesis. An important consideration, however, is that this paper's main findings appear to conflict with prior research. Research on trade and the environment in many countries finds that the technique of producing goods within an industry, rather than the composition of output across industries, accounts for most aggregate patterns of environmental quality (Levinson 2009; Grether, Mathys and de Melo 2009; Shapiro and Walker 2018; Brunel 2016; Copeland, Shapiro and Taylor 2022). This finding of prior research suggests that the composition of production across industries plays only a modest role in explaining global patterns of environmental quality. How can we reconcile this finding from prior research with the finding from the previous sections that cross-country differences in the composition of production, driven by institutions, play an important role in explaining global patterns of environmental quality?

The next section highlights an underappreciated feature of prior work—existing decompositions look within a country and over time, and largely avoid cross-country contemporaneous comparisons. For example, existing work studies the extent to which scale, composition, and technique explain the change in US pollution emissions between 1990 and 2008, and provides similar decompositions for other countries. The next section adapts this decomposition used in prior work to instead ask, for example, to what extent scale, composition, and technique explain the difference in pollution emissions from India versus the US. In other words, the next section performs a cross-country, cross-sectional decomposition, whereas prior work has reported a within-country, time-series decomposition. The decomposition in the next section does not primarily distinguish the role of institutions versus other forces in driving composition. It does, however, ask whether there is scope for any driver of comparative advantage, including institutions, to substantially affect environmental quality, and thus could help reconcile the results of the previous sections with existing literature which finds little role for composition.

6 Decomposing Scale, Composition, and Technique

I decompose pollution in a cross section of countries as follows. Let $\mathcal{E}$ denote a country's total pollution emissions, which equal the sum of industry-specific emissions $\mathcal{E}_s$ across all industries in the economy. This includes but is not restricted to manufacturing, agriculture, utilities, and household production.[16]

An industry's emissions $\mathcal{E}_s$ equal the product of sales x_s and emissions intensity, $e_s = \mathcal{E}_s/x_s$. I write an industry's sales as $X\kappa_s$, where κ_s is the share of the economy's sales from industry s:

$$\mathcal{E} = \sum_s \mathcal{E}_s = \sum_s x_s e_s = X \sum_s \kappa_s e_s \tag{15}$$

Totally differentiating then dividing by $\mathcal{E}$ yields

$$d\mathcal{E} = \kappa' \mathbf{e} dX + X\mathbf{e}' d\kappa + X\kappa' d\mathbf{e} \tag{16}$$

The first term on the right of (16) represents scale, the second represents composition, and third represents technique.

Research typically takes equation (16) to data by measuring emission rates e_s for each industry in a reference year then projecting onto future years within a country. I instead take industry emission rates in a reference country r. I project those rates onto the same industry in other countries in order to distinguish scale, composition, and technique effects. I implement this comparison for each country i separately:

$$Scale_{i,r} = \frac{\sum_s x_{is}}{\sum_s x_{rs}} \tag{17}$$

$$Composition_{i,r} = \frac{\sum_s \kappa_{is} e_{rs}}{\sum_s \kappa_{rs} e_{rs}} = \frac{\sum_s \kappa_{is} e_{rs}}{Z_r/X_r} \tag{18}$$

$$Technique_{i,r} = \frac{\sum_s \kappa_{is} e_{is}}{\sum_s \kappa_{is} e_{rs}} = \frac{Z_i/X_i}{\sum_s \kappa_{is} e_{rs}} \tag{19}$$

Here r indexes a reference country, x_{is} represents the gross output of focal country i in industry s, κ_{is} represents the share of country i's gross output from industry s, and e_{is} are emissions per dollar of gross output. In presenting estimates of equations (17) through (19), I subtract one, so the results can be interpreted as the percentage change in pollution relative to the reference country. Appendix C derives equations (18)-(19) from equations used in prior literature that compares within a country and over time.

The scale effect in (17) equals the difference in gross output between country i and reference country

[16] I treat a country as the unit of observation in part because Exiobase and other global multi-region input-output tables lack sub-national geography on where within a country emissions and economic activity occur. At the same time, global emission and pollution rates reach especially high levels in large cities and near population centers (UNEP 2016), so it is likely that these emissions data reflect pollution that affects households.

r. This describes how emissions would change if country i had the total output of country r, but the composition of output across industries and the emissions per unit output within an industry were identical across countries.

The composition effect in equation (18) equals the difference in emission rates between countries i and r due to the difference in the share of output κ from each industry between the two countries. The composition effect weights output shares by the reference rates, e_{rs}. I use these weights since they are common in the literature comparing environmental change within a country and over time (Appendix C).

The technique effect in equation (19) equals the difference in emissions between countries i and r due to the difference in emission rates e from each industry. Equation (19) uses weights from the focal country κ_{is} for consistency with the existing literature (Appendix C). Thus, the technique effect can be interpreted as holding composition fixed at the focal country level κ_{is}, then comparing the ratio in emissions as the ratios of technique for the focal versus reference countries (e_{is} versus e_{rs}). To help assess the relative importance of composition versus technique overall, I report the absolute value of the technique effect and the absolute value of the composition effect.[17] To compare them, I present the ratio $|Composition|/(|Composition| + |Technique|)$.

Consider the example of sulfur oxides emissions in India and the US. Using Exiobase, the scale effect from (17) indicates that India produced 87 percent less output than the US. Sulfur oxides emissions, however, were 12 percent higher in India than the US. The composition effect from equation (18) indicates that India emitted 162 percent more sulfur oxides than the US did because a larger share of India's output comes from dirtier industries. The technique effect from equation (19) indicates that India produced 216 percent more pollution than the US because a given industry emits relatively more pollution per dollar of gross output in India than in the US does. Thus, although India produces much less output than the US economy (scale effect), it emits more sulfur both because it is more concentrated in polluting industries (composition effect) and because a given industry emits more pollution in India (technique effect). Here, composition accounts for 43 percent (=162/(162+216)) of the composition+technique total.

Table 4 provides such comparisons for all countries and pollutants, with the US as reference. Row 1 shows that the mean country has 72 percent lower total pollution emissions than the US, a proportion which varies across pollutants from 45 to 89 percent. Row 2 shows that the mean country has 89 percent lower gross output than the US does. Row 3 shows that the composition of output across

[17] Existing research focuses on the composition and technique effects in levels, not absolute values. The absolute values here are useful because they summarize the importance of these effects in explaining cross-country differences in pollution, even if some relative comparisons are positive and others are negative. For example, if the composition effect increased pollution in half of countries relative to the US and decreased pollution in half of countries relative to the US, and both by similar amounts, then the mean value of the composition effect between the US and other countries would be zero, but the absolute value of the composition effect would not be.

industries in the mean country increases emissions 175 percent relative to the US, i.e., most countries concentrate production more in dirty industries than the US does. Row 4 shows that the technique effect for the mean country does not substantially change emissions relative to the US, i.e., some countries use cleaner techniques and others dirtier, but the mean is comparable. While some countries have a positive composition effect (dirtier than the US) and others negative, Row 5 shows that the composition effect in the mean country changes emissions relative to the US by 176 percent. Row 6 shows that in the mean country, the absolute value of the technique effect increases emissions relative to the US by 47 percent. Comparing Rows 5 and 6 indicates that in absolute values, the composition effect accounts for 79 percent (=176/(176+47)) of the combined composition and technique effect magnitudes from comparing the US to other countries.

Figure 4 describes the distribution of the ratio $|Composition|/(|Composition| + |Technique|)$ across all possible country pairs. For example, comparing the US to India creates one data point, and the US versus France is another. Each observation underlying Figure 4 is a country pair rather than a country because equations (17), (18), and (19) involve comparing a reference to a focal country (e.g., the US versus India).

Figure 4 finds that across all country pairs, composition accounts for more of cross-national differences in pollution than technique does. The distribution is roughly a truncated bell curve shape. The mean and median composition share are about 0.70. No mechanical reason makes these shares near half. Given prior literature discussed earlier, which finds that technique explains much of the time series change in pollution within country and over time, one might expect technique rather than composition to account for most of this difference.

Appendix Figure 4 separately shows this comparison for several important countries—China, Germany, India, and the US. For example, Panel A of Appendix Figure 4 shows all country pairs where China is the focal or reference country. Although the panels of Appendix Figure 4 reveal modest differences – for example, the US has more outlier comparisons where composition plays a relatively smaller role, while India has fewer – these panels have similar overall patterns.

Is the variation in these graphs mostly driven by reference countries or by differences across focal countries for a given reference country? As one indication, I regress the $|Composition|/(|Composition| + |Technique|)$ ratio from the data underlying Appendix Figure 4 on reference country fixed effects, focal country fixed effects, or both, in a dataset where each observation is a country pair. I find that reference country fixed effects obtain an R-squared of 0.37, focal country fixed effects obtain an R-squared of 0.14, and both together obtain an R-squared of 0.50. Thus, in comparing across country pairs, half the variation in the relative importance of composition comes from features specific to the individual countries, while the remaining half reflects pairwise interactions.

Why does Figure 4 find a large role for composition, while prior literature finds a larger role for technique? One reason is that Figure 4 compares across countries and within a time period, while prior literature looks within a country and over time. A less immediate explanation is that the effectiveness of pollution control technologies like scrubbers or selective catalytic reduction mean that a source can decrease its pollution emissions by more than 95 percent almost immediately, while a country's institutions change less rapidly. Although institutions do have a reasonable degree of variation within country and over time, as described earlier, institutions also have a reasonable degree of persistence. This is one reason the legal origins, settler mortality, and year 1500 population density instruments discussed in the appendix strongly predict institutions today.

A second explanation is that technique depends on a country's absolute emissions rate, while composition depends on countries' relative comparative advantage. If environmental policy and institutions strengthen similarly in all countries over time, technique could matter more in the time series but composition could matter more in the cross section. Because these are decompositions and not regressions, the aforementioned findings do not reflect differences in regression assumptions about omitted variables bias, measurement error, or other forces that differ between cross section and panel data regressions, but instead represent some forces (potentially including institutions) which make composition more important in the cross section across countries than time series within a country to explain the global distribution of environmental quality.

Could this finding about the importance of composition across countries reflects measurement error in Exiobase's emissions data? Exiobase uses observed pollution information from North America, Europe, and Asia where available, and obtains pollution measures for other countries using information on production technologies by sector and aggregate emissions (Stadler et al. 2018). Measurement error in observed emissions could overstate the true importance of technique, by adding noise within an industry and across countries. By contrast, errors due to mismeasurement of differences in production technology could understate the true importance of technique, by masking differences in countries' methods within an industry. As one way to learn about the possible role of measurement error here, I compare composition and technique using only focal and reference countries in North America and high-income Europe, where a greater share of emissions data come from direct reports than technology imputation, and therefore where measurement error is less likely to overstate the importance of composition. The ratio $|Composition|/(|Composition| + |Technique|)$ calculated using only high-income countries equals 0.63, which is not dramatically different from the global ratio. At least in regions with better-quality emissions data, composition still plays a large role in accounting for international differences in emissions rates.

This section's cross-country decomposition reach out of sample. In the literature's application of this decomposition to a country's time series, endowments like factors and institutions change gradually, while policies or other shocks may change more rapidly. Because the decomposition here compares two arbitrary countries in a cross-section, endowments including institutions differ considerably between focal and comparison countries. For example, this decomposition does not imagine that plausible short-term policies could transform India's composition to match that of the US. At the same time, comparing the composition versus technique of industries between countries can provide useful insights about potential mechanisms for realistic counterfactuals. To give one point of reference, the Environmental Kuznets Curve literature (Grossman and Krueger 1993) makes cross-sectional comparisons across countries. While the Environmental Kuznets Curve literature motivated discussions of scale, composition, and technique, ensuing decompositions to date have focused on the time series rather than the cross section.

How do this section's decompositions quantitatively relate to the analysis of institutions in earlier sections? Appendix Table 9 finds that across countries, national financial and judicial institutions, though not labor market institutions, are correlated with cleaner industrial composition. This table calculates the mean composition effect from equation (18) for each focal country, across all reference countries. One could interpret this as the percentage pollution differential that this country experiences relative to other countries due to differences in industrial composition. I report a cross-sectional regression of this composition value on the national institutions values. Panels A and B indicate that countries with strong financial and judicial institutions have significantly cleaner industrial composition. Panel C finds insignificant and positively signed patterns for labor market institutions. Panel D finds that judicial institutions have the strongest negative correlation with composition effects. The institutions index in Panel E is negatively correlated with composition effects, though precision varies by pollutant. Because each cross-sectional correlation has 46 observations without any research design or other countries, these estimates do not represent a causal relationship, and I therefore interpret them cautiously.

7 Counterfactual Institutions: Model-Based Estimates

The previous sections find that institutions provide comparative advantage in clean industries, that industry complexity provides an important explanation, and that differences in the industrial composition of output across countries account for an important share of differences in pollution. I now use a model which incorporates estimates from previous sections to quantify how improving institutions affects environmental quality through comparative advantage. This section does not introduce new tools, but instead combines leading models with estimates of the previous sections to enable analysis of specific counterfactual changes in institutions.

The model has typical features—multiple industries, intermediate goods, input-output links, trade imbalances, tariffs, and pollution emission rates for each country$\times$industry, in all sectors of the economy.

Because many model details are common in the structural gravity literature, I describe them in Appendix D. Here I highlight key features and focus on aspects which differ from a standard trade setting.

Each country has a representative agent who maximizes utility that is a constant elasticity of substitution (CES) aggregate across varieties and Cobb-Douglas across sectors. The representative agent experiences disutility from pollution. This is a multi-country, multi-sector Ricardian trade model of perfect competition (Eaton and Kortum 2002)—buyers source a variety from the lowest-price producer and trade faces iceberg trade costs and tariffs. Production is Cobb-Douglas in labor and intermediate goods, which use inputs from all sectors as dictated by an input-output table. Productivity has a Fréchet distribution with location parameter $T_{i,s}$ and dispersion parameter θ_s. I describe $T_{i,s}$ as each country×industry's technology or productivity level. Given the absence of firm-level emissions data in most countries, and in order to have a single elasticity governing the response of pollution to institutions, I assume firms within a country×industry have the same emissions intensity.

I interpret institutions as changing country×industry productivity in potentially every sector, including non-tradable goods. Equation (5) implies that reforming institutions proportionally changes productivity for exporter i and industry s via

$$\hat{T}_{i,s} = exp\left\{\alpha I_s(E_i^{'} - E_i)\right\} \tag{20}$$

To estimate equation (20), I use estimates of α from equation (8), data on an industry's dependence on institutions I_s, and a country's baseline quality of institutions E_i. I then choose $E_i^{'}$ to define a counterfactual. Because I measure I_s in z-scores, improving institutions effectively diminishes this measure of relative productivity in some industries. Equation (20) is the only part of the model which uses information on institutions. I therefore emphasize the caveat that the model-based analyses of counterfactuals abstract from the mean effect that institutions have on productivity or pollution intensity that is uniform across industries. The counterfactual analyses therefore reflect differences in effects of institutions across industries, in line with the paper's focus on comparative advantage.

Country i's pollution emissions are

$$\mathcal{E}_i = \sum_s \frac{\gamma_{i,s} R_{i,s}}{c_{i,s}}$$

where $\gamma_{i,s}$ measures the baseline units of pollution emitted per real dollar of revenue, $R_{i,s}$ describes country×sector revenue, and $c_{i,s}$ is the unit cost function. In baseline data, $\gamma_{i,s}$ equals the units of pollution per dollar of revenue. Counterfactuals can change revenues $R_{i,s}$ and costs $c_{i,s}$, so I interpret changes in $R_{i,s}/c_{i,s}$ as real revenue, with $c_{i,s}$ as the deflator. Pollution depends on the ratio $R_{i,s}/c_{i,s}$ since it reflects units rather than value of sectoral output. The model can accommodate changes in pollution intensity $\gamma_{i,s}$ due to changes in institutions. Following the muted technique regression estimates discussed near the end of Section 5, however, I assume that the pollution intensity $\gamma_{i,s}$ of exporter i in industry s is invariant to counterfactual changes in institutions. If stronger institutions generated cleaner production techniques, this assumption would tend to understate institutions' environmental benefits.

I study a competitive equilibrium. Consumer utility maximization implies the gravity equation (3). Total country×sector expenditure equals the sum of spending on final and intermediate goods, accounting for revenues from fixed trade deficits and tariffs. I study counterfactual policies by expressing variables in changes, i.e., using exact hat algebra (Dekle, Eaton and Kortum 2008). I focus on counterfactuals which change technology in certain country×industry pairs due to changes in institutions. The change in pollution due to changing institutions is

$$\hat{\mathcal{E}}_i = \frac{\sum_s (\hat{R}_{i,s}/\hat{c}_{i,s})\mathcal{E}_{i,s}}{\sum_s \mathcal{E}_{i,s}} \tag{21}$$

where $\mathcal{E}_{i,s}$ is the baseline observed pollution for a country×sector. Equation (21) means that the proportional change in a country's pollution is the sum across industries of baseline pollution from an industry times the industry's change in real output, all divided by the country's baseline pollution.

I apply the model empirically using trade, production, and air pollution data from Exiobase, aggregated to 10 regions and 21 industries. I use this aggregation, following Costinot and Rodriguez-Clare (2014) and Shapiro (2021), since it easily summarizes broad geographic patterns.[18] With far more detailed regions or industries, the algorithm for analyzing counterfactuals does not always converge. The quantitative model uses sector-specific trade elasticities aggregated across four studies (Caliendo and Parro 2015; Shapiro 2016; Giri, Yi and Yilmazkuday 2020; Bagwell, Staiger and Yurukoglu 2021; see also Bartelme et al. 2021 and Shapiro 2021).[19]

Counterfactuals and Results

I study several sets of counterfactuals. The first set of counterfactuals improves institutions in each region by one standard deviation, one region at a time. For example, I consider a scenario where Chinese institutions improve by one standard deviation, then assess how pollution changes in each region, including China, and in the world overall. I then consider a scenario where institutions in North America improve, and I analyze pollution changes in each region and globally.

[18] The regions include the following countries. The Pacific Ocean includes Australia, Japan, South Korea, and Taiwan. Western Europe includes Austria, Belgium, France, Germany, Luxembourg, and the Netherlands. Eastern Europe includes Bulgaria, Czechia, Estonia, Hungary, Lithuania, Latvia, Poland, Romania, Russia, the Slovak Republic, and Slovenia. Latin America includes Brazil and Mexico. North America includes Canada and North America. China has its own region. Southern Europe includes Cyprus, Spain, Greece, Italy, Malta, Portugal, and Turkey. Northern Europe includes Denmark, Finland, the United Kingdom, Ireland, Norway, and Sweden. The Indian Ocean includes India and Indonesia. All other countries, including the Exiobase regions of South Africa, Switzerland, Croatia, Rest of World Asia and Pacific, Rest of World Europe, Rest of World Africa, Rest of World Americas, and Rest of World Middle East, are in the Rest of the World region.

[19] The sectors and elasticities appear in Appendix Table 7, column (1) of Shapiro (2021), and range from 2.99 to 13.53 across sectors.

The remaining four sets of counterfactuals examine particularly interesting changes in institutions for specific regions or groups of regions. The first of these sets all regions to have the same quality of institutions, equal to the global mean. This provides a benchmark to think about the signs and magnitudes of more realistic changes in institutions. The second of these counterfactuals takes regions with below-median institutional quality and improves their institutions to the level of North America, the region with the strongest baseline institutions. The third in this group of counterfactuals takes Latin America, the region with the lowest-quality institutions, and improves its institutions to match those of North America. The last changes each region's institutions by the observed, historical improvement in the region's institutions between 1996 and 2015.

Table 5 shows results from the first set of counterfactuals. Each column shows a different scenario– column 1 shows effects of improving institutions in Pacific Ocean countries by one standard deviation; column 2 shows effects of improving institutions in Western Europe by one standard deviation; etc. Each row shows effects of a given counterfactual on pollution emissions in the region listed in the row— the first row shows how each counterfactual affects pollution emissions in the Pacific Ocean, the second row shows how each counterfactual affects emissions in Western Europe, etc.

Table 5 shows that improving institutions a region decreases pollution in that region. The magnitude of the decrease ranges from 4% to 8%, depending which region experiences the improvement.

In all ten counterfactuals from Table 5, all regions where institutions do not change experience increases in pollution. These increases occur because improving institutions in one region makes dirty industries relocate to other regions. These increases in pollution for regions where institutions do not improve range from 0.1% to 1.3%. Due to gravity, the regions experiencing relatively large increases in pollution are typically geographically closer to the region where institutions improve. For example, column (6) shows that when Chinese institutions improve, Pacific Ocean countries (Australia, Japan, South Korea, and Taiwan) experience relatively large increases in pollution. Similarly, column (2) shows that when Western European institutions improve, pollution increases most in Northern Europe. The counterfactuals that change institutions for regions with large GDP, like for North America or China as listed in columns (5) and (6), cause large increases in pollution in other regions. Counterfactuals that change institutions for regions with smaller total GDP, like the Indian Ocean (India and Indonesia) shown in column (9), affect pollution in other regions less.

Figure 5 depicts these effects of improving institutions in one region by one standard deviation. This graph shows the effects of 10 separate counterfactuals, identified by the horizontal axis labels. Each counterfactual improves institutions in one region by one standard deviation. The bars in the graph show how a counterfactual affects pollution in each region, and the bar colors help identify regions. For example, the left-most group of bars shows how improving institutions in the Pacific Ocean region by one standard deviation affects pollution in each region, where each bar shows the pollution change for one region.

Figure 5 visually shows two of the main conclusions from these counterfactuals. First, for each counterfactual, pollution decreases in the region where institutions improve. Second, pollution increases in all other regions. This can be seen because within each group of bars, all regions have positive value except the bar for the region where institutions in a given counterfactual improve.

Appendix Figure 5 maps two of these counterfactual scenarios—improving Chinese institutions by one standard deviation (Panel A) and improving Western European institutions by one standard deviation (Panel B). Both maps show that the largest environmental spillovers occur to countries that are geographically near and connected by trade to the region where institutions change. In Panel A, the decrease in China's pollution, shown in red, contrasts with the large increases in pollution in Southeast Asia and South Asia. In Panel B, the decrease in Western Europe's pollution, shown in red, contrasts with the large increases in pollution in other parts of Europe.

The bottom row of Table 5, columns (1) through (10), shows that global emissions fall when dirty countries improve institutions, and rise when clean countries improve institutions. This makes sense since each counterfactual reshuffles dirty production to regions where institutions do not improve. Because regions with strong baseline institutions have clean baseline production techniques, when a counterfactual reallocates dirty production away from such regions, global pollution tends to rise; whereas when a counterfactual reallocates dirty production to such regions, global pollution tends to decline. The magnitudes of changes in global emissions range from -1.5% to +0.3%. They underscore the idea that effects of these counterfactuals on the allocation of pollution across countries have larger magnitude than effects of these counterfactuals on total global pollution emissions.

Table 6 shows effects of the four other counterfactuals. Each panel describes a different counterfactual. Each row within a panel shows effects on different regions, and the last row of each panel shows the global total. Column (1) shows baseline data on institutional quality. Column (2) shows the change in institutional quality chosen to define the counterfactual. Column (3) shows the model-estimated percentage change in emissions due to the counterfactual. Columns (4) through (6) describe the counterfactual's effect on the share of output from three groups of industries—the dirtiest, middle, and cleanest third.

Panel A of Table 6 shows that the first counterfactual, which equalizes institutions across regions, also helps equalize pollution across regions. Column (1) shows that Northern Europe, North America, and Pacific countries like Japan and Korea have the strongest baseline institutions. Column (2) shows that in this counterfactual, institutions in these regions worsen the most. Column (3) shows that this counterfactual increases pollution in these regions. This counterfactual increases emissions in Northern Europe and decreases emissions in Latin America, both by around 10 percent. Columns (4) through (6) show that these changes come from reallocating production between clean and dirty industries in each country.

Panel B of Table 6 considers the second counterfactual, which improves institutions in regions with below-median institutions to equal the mean quality of institutions for regions with above-median quality institutions. Column (2) shows that this improves institutions in targeted regions by one to two standard deviations. Column (3) shows that this counterfactual decreases emissions in targeted regions by 3 to 10 percent. In regions where institutions remain unchanged, this counterfactual increases pollution emissions by 3 to 4 percent. The second counterfactual increases pollution in regions where institutions do not change because it works through comparative advantage. As institutions improve in Latin America and Eastern Europe, those regions gain comparative advantage in clean industries. This leads some clean production to move to these targeted regions, and some dirty production to move elsewhere.

Table 6, Panel C, analyzes the third counterfactual, where institutions in Latin America improve to match those of Northern Europe. This counterfactual decreases pollution emissions by nearly 20 percent in Latin America. This counterfactual also makes clean industries move to Latin America and dirty industries move elsewhere. Emissions rise by up to 1 percent in regions outside Latin America, due to comparative advantage-driven reallocation of clean and dirty production.

Panel D of Table 6 calculates the mean change in institutions for each region between 1996 and 2015, where I take the export-weighted mean across countries within each region. I then change each region's institutions by this amount. This counterfactual provides a benchmark for how institutional changes over the last two decades affected environmental quality. Because it averages across countries within a region, the institutional changes for each region are not especially large. Column (2) shows that institutions have improved most in China and in Eastern and Northern Europe. Column (3) finds that these have decreased pollution emissions by several percent. Institutions slightly deteriorated in the Indian Ocean region (India and Indonesia), and emissions correspondingly increased.

Appendix Table 10 shows effects of these four counterfactuals on each air pollutant in Exiobase separately. Most counterfactuals have the same sign impact on global emissions across all these pollutants, although magnitudes differ. For example, particulate matter smaller than 2.5 micrometers ($PM_{2.5}$) changes more than non-methane volatile organic compounds (NMVOCs) globally in most counterfactuals, perhaps in part because more of NMVOCs comes from transportation, which is less widely traded.

These counterfactuals primarily change pollution by reallocating dirty production between regions, but Table 6 shows that they decrease total global emissions. The second counterfactual, for example, decreases global emissions by 4 percent. The global decreases occur in part because regions with strong baseline institutions have low baseline emission rates. Thus, reallocating one dollar of dirty production from countries with weak to strong baseline institutions tends to decrease total global production.

While most research on greenhouse gases analyzes global total emissions, I am not aware of prior analysis of the global sum of local air pollution emissions. In part this is because greenhouse gases create the same climate damages regardless of where they originate, while damages from local air pollutants vary by the location of emissions since they depend on population density, wind, and many other variables.

Decreasing a country's emissions via technique effects will typically decrease global emissions. Decreasing a country's emissions via composition effects, however, has ambiguously-signed effects on global emissions, since the composition effect is likely to reshuffle dirty industries to other countries. The counterfactual results clearly show this channel, since improving institutions in countries with weak initial institutions reduces emissions in those countries but increases them in other countries. Because dirty industries have lower emissions intensity in countries with strong baseline institutions, I do find that this global reallocation decreases total global pollution. At this same time, it is worth highlighting that this general equilibrium effect dampens the effect of institutions on global emissions that one might calculate from the reduced-form regressions earlier in the paper. For this reason, this paper's findings do not change the received wisdom from the literature that if the primary goal of analysis or policy is decreasing global emissions, then reforms that change technique may be most effective. At the same time, if the primary goal of analysis or policy is explaining or decreasing one country's emissions, then composition effects become more relevant.

8 Conclusions

Existing research highlights three forces that help explain international patterns of environmental quality—weaker environmental regulation in some countries increases their pollution (the Pollution Havens Hypothesis); greater capital endowments in some countries attract capital-intensive, dirty industries (Heckscher-Ohlin); and trade openness increases per capita GDP, which has nonlinear effects on the concentration of polluting industries (the Environmental Kuznets Curve).

This paper proposes and evaluates an additional explanation for international patterns of environmental quality—institutions improve international environmental quality through comparative advantage. Clean industries depend on strong institutions to operate efficiently, and so disproportionately locate in countries with strong institutions. Quantitatively, institutions have similar importance to environmental policy in explaining international specialization of dirty industries. Estimates indicate that if countries with the world's weakest institutions instead had some of the world's strongest institutions, their pollution emissions would fall by up to 20 percent. I find an important role for institutions across countries, over two decades of institutional change within countries, and when instrumenting institutions with historical natural experiments. Financial and to a lesser extent judicial institutions seem most important to the location choices of clean industries; flexible labor market institutions play a less central role.

This paper calls attention to interactions between two areas of intense scholarly interest that previous work has largely studied separately: political institutions and pollution. More broadly, it suggests how institutions could affect a range of social outcomes through comparative advantage.

How important is the general idea that an industry's dependence on institutions may be correlated with other socially valuable or costly attributes? For example, what if industries that depend more on institutions are more gender equal, or involve fewer workplace injuries, or lead to interactions of artificial intelligence with autocracy (Beraja et al. 2023*a*,*b*)? Would such findings meaningfully change the analysis of institutions, gender equality, workplace injuries, or artificial intelligence? I believe the basic concept this paper proposes has potentially broader application—economic endowments like institutions can have meaningful effects on market failures like externalities through correlation across industries in externalities' dependence on institutions. While this idea need not be applied to numerous other market failures, the general idea is important and the welfare consequences of environmental externalities makes them a powerful setting to demonstrate the idea's importance.

I conclude with a few open questions for future work. First, how do institutions affect environmental quality through channels besides comparative advantage? Institutions may affect innovation, Coasian bargaining, and other channels. Just as research has found many channels for institutions to affect growth and economic activity, institutions may affect environmental quality through channels besides comparative advantage as well.

Second, can a case study of a shock to a region's institutions provide additional insight on which institutions affect environmental outcomes, mechanisms for such effects, and the importance of comparative advantage versus other channels? This could involve within-country research designs or specific episodes where institutions improve (e.g., Dell (2010); Acemoglu et al. (2019)). Unlike this paper's framework, which exploits all the variation in institutions across countries (and, in longitudinal regressions, across years), abrupt changes in institutions would also allow event study analyses.

Third, how do choices inside the firm mediate or magnify the effects of institutions on environmental quality? Firms respond to weak institutions in many ways, for example, by changing how transactions are financed (Antras and Foley 2015) or through vertical integration (Boehm and Oberfield 2020). Do firms in dirty and clean industries respond differently to the strength of a country's institutions? And how do such firm responses shape the intensity of pollution and international specialization in clean versus dirty production?

Data Availability Statement: The data and code underlying this research is available on Zenodo at `https://doi.org/10.5281/zenodo.14782004`.

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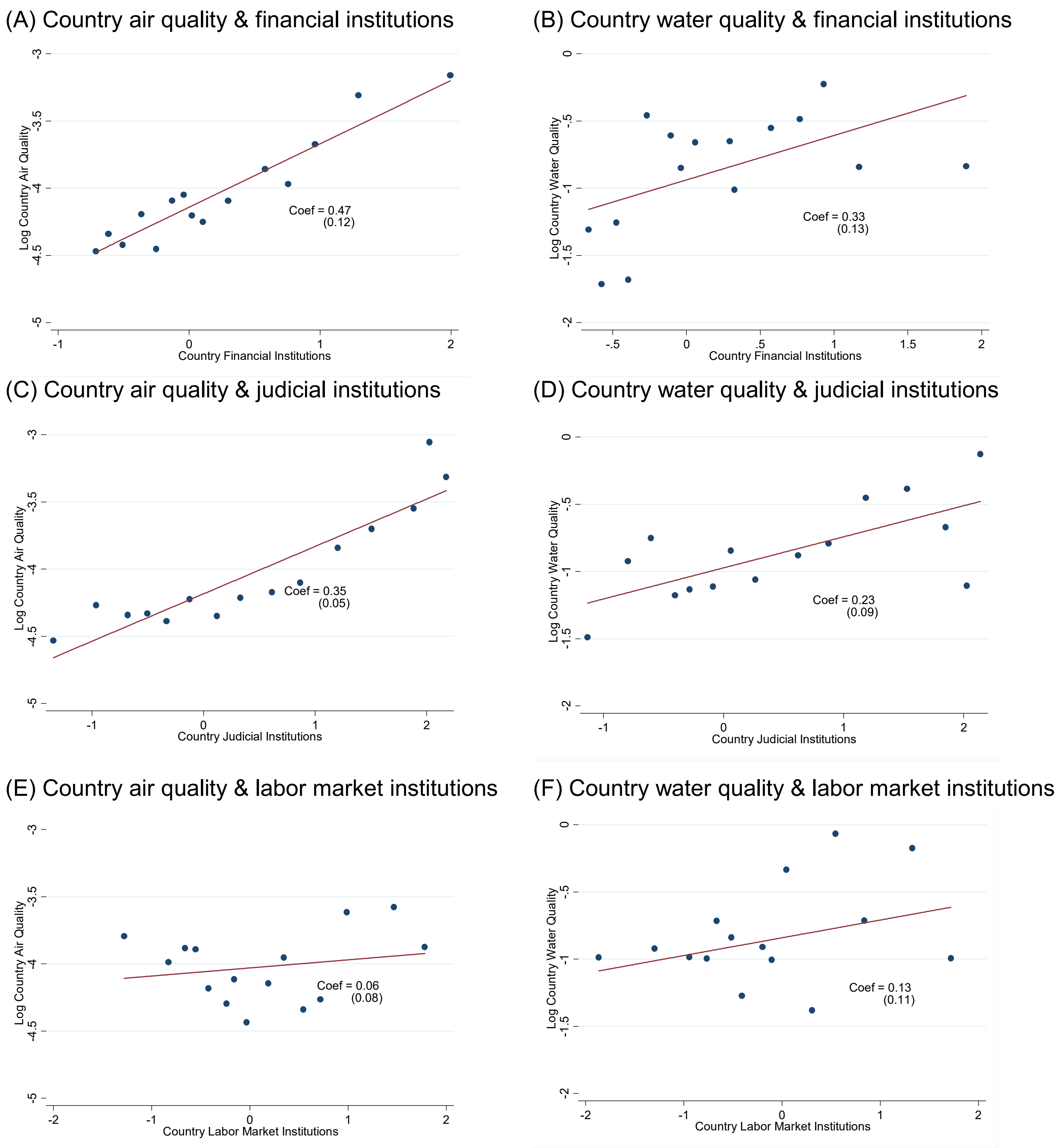
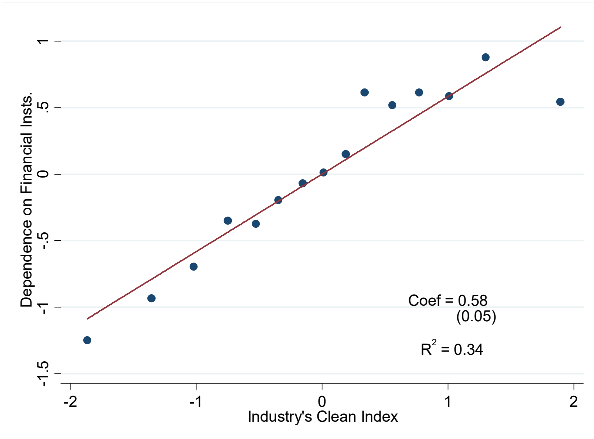
Figure 1. Country Environmental Quality and Country Institutions



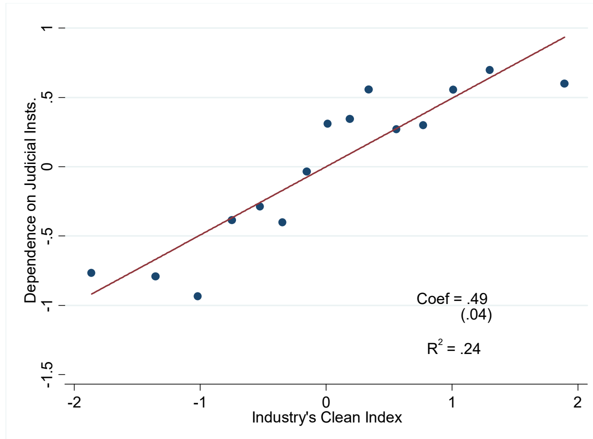
Notes: Graphs show binned scatterplots—blue circles are means of 15 bins, each with approximately equal number of countries. Red line is linear trend. Log of country environmental quality is negative one times the log of the country's mean $PM_{2.5}$ in µg/m^3 (Panels A, C, and E); or times the log of the country's mean biochemical oxygen demand in mg/L (Panels B, D, and F). "Coef" shows line slope and its robust standard error. Institutions are in z-scores. The number of observations for Panels A through F, in order, is as follows: 86, 66, 88, 66, 82, and 66.

Figure 2. Industry Dependence on Institutions and Industry Clean Index

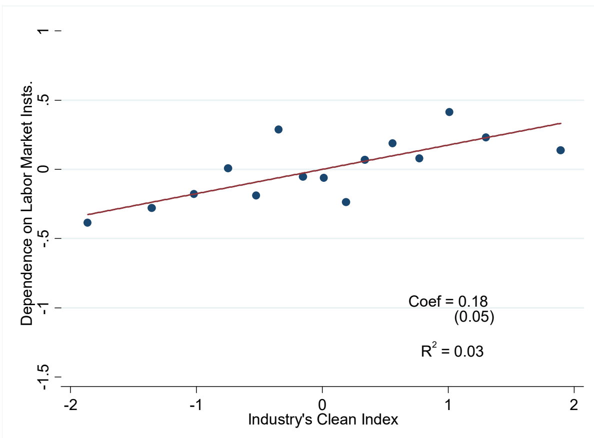
(A) Financial institutions



(B) Judicial institutions

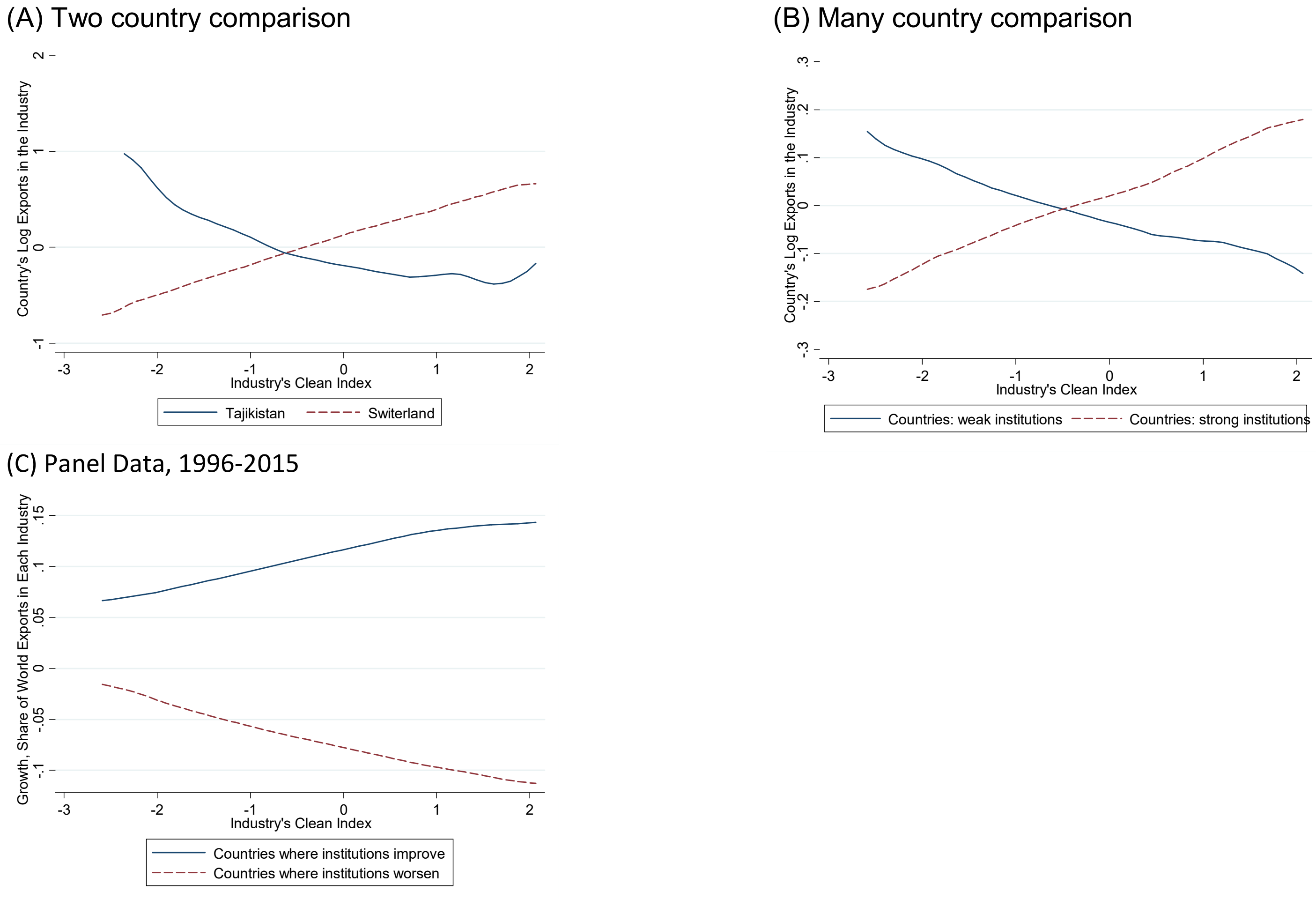


(C) Labor market institutions



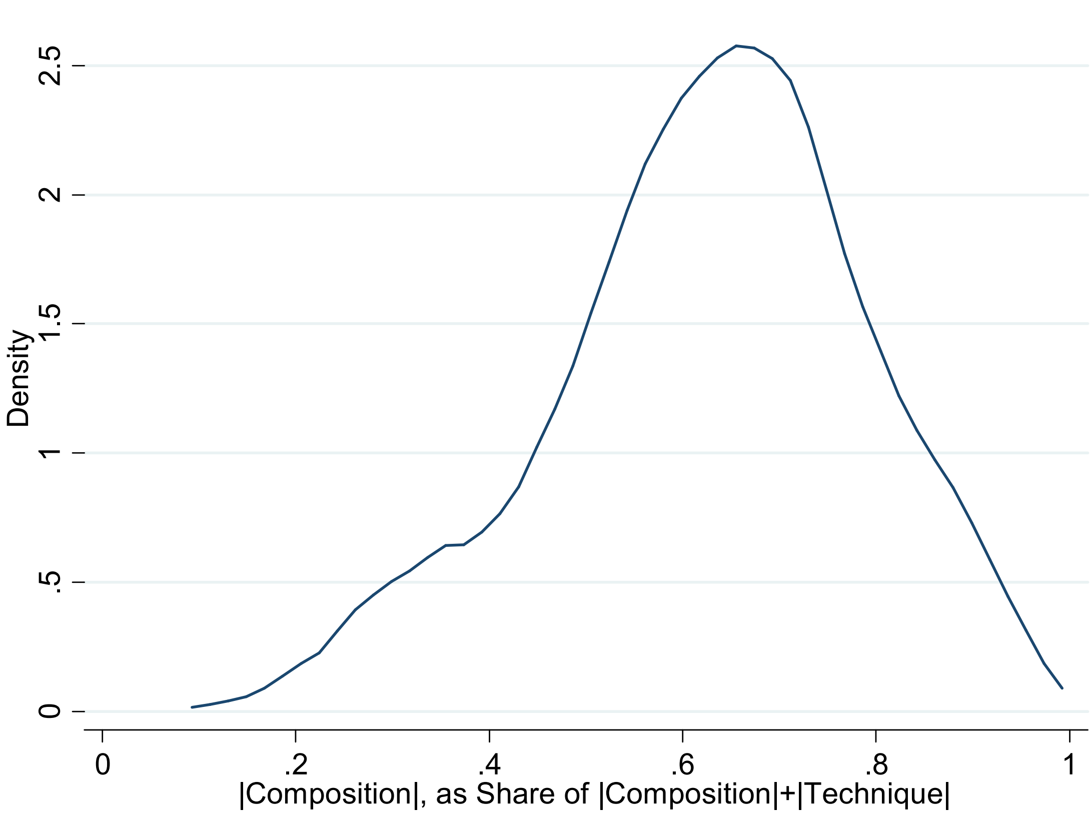
Notes: Graphs use US data and show binned scatterplots—blue circles are means of 15 bins, each with equal number of industries. Each observation in the underlying data represents a manufacturing industry. Blue circles show means of 15 bins, each with an equal number of countries. Red line is linear fit. Dependence on institutions variables are in z-scores.

Figure 3. Industry Clean Index and Exports, by Strength of Country Institutions



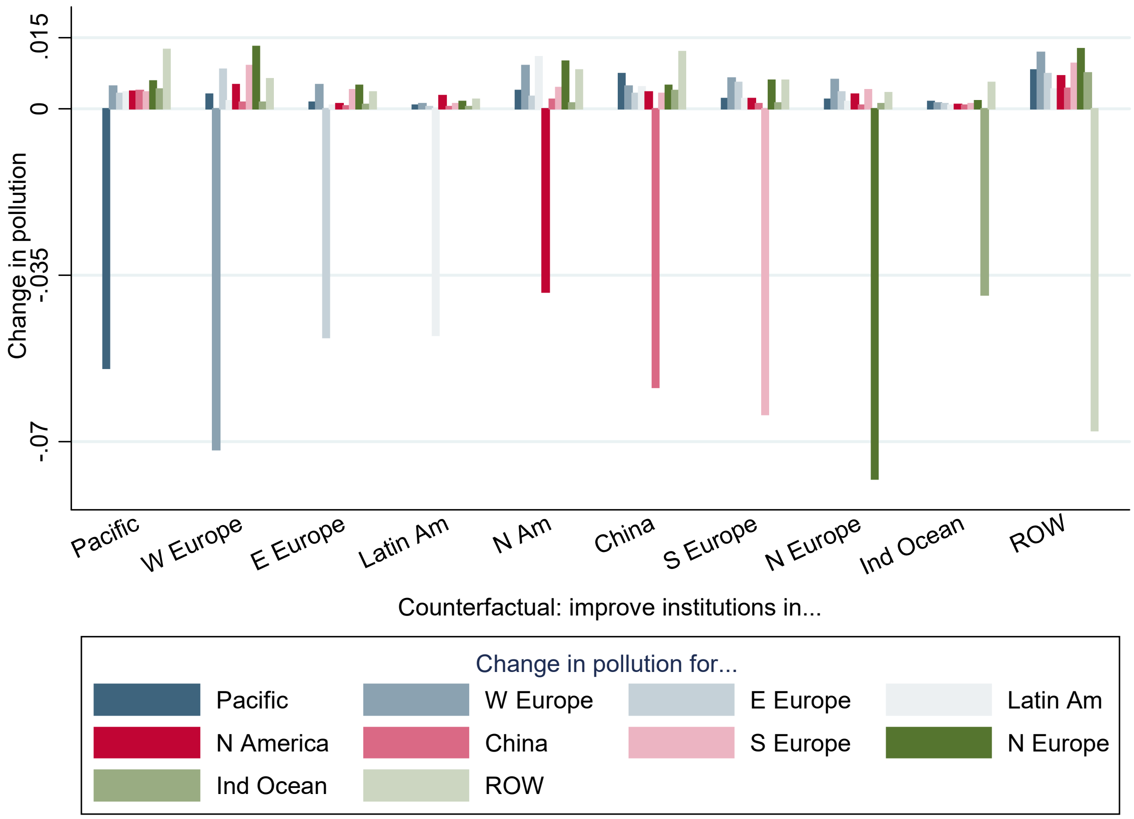
Notes: industry clean index is calculated using US data. In Panel A, Tajikistan has weak institutions and Switerland has strong institutions. In Panel B, "Countries: weak institutions" includes all countries with below-median quality institutions, while "Countries: strong institutions" includes all countries with above-median quality institutions. Each graph shows two local linear regressions, with bandwidth of one, for manufacturing industries. For each line, the mean of log exports across industries is normalized to zero. Panel C divides countries into two groups: countries where national institutions improve between 1996 and 2015 and countries where institutions worsen. Institutions are measured by the first principal component of financial, judicial, and labor market institutions. This analysis calculates the share of world exports in each manufacturing industry that each of these two groups of countries represents in each year (1996 and 2015). Local linear regression is used to calculate nonparametrically smoothed export shares in each year, for each of the two groups of countries. The graph plots the change in that export share for each country group and industry between 1996 and 2015.

Figure 4. Importance of Composition Versus Technique, Distribution Across Country Pairs



Notes: the graph plots the distribution across all possible reference countries and local pollutants. For each reference country *r*, the analysis calculates |*composition*| averaged across all focal countries while using *r* as reference, divided by |*composition*|+|*technique*| averaged across all countries while using *r* as reference. Each underlying point averages across (r,i) and (i,r) country pairs (e.g., US-China and China-US), and across air pollutants in Exiobase. Calculations cover all industries. Pollution emission rates are winsorized at the 99.9th percentile and calculation excludes industry×country cells with less than $10,000 in annual sales.

Figure 5: Pollution Impacts of Counterfactual Changes in Institutions, Model-Based Estimates



Notes: graph shows model-based estimates of the impact of the first ten counterfactuals listed in Table 5 on pollution in each region. Each counterfactual improves institutions in one region, indicated by the x-axis labels, by one standard deviation. The bars show the resulting change in pollution for each region, identified by the different color bars. For example, the first group of bars on the left of the graph show how improving institutions in the Pacific Ocean region by one standard deviation affect pollution in the Pacific Ocean region (dark blue), Western Europe (moderate blue), Eastern Europe (light blue), etc. Pacific is shorthand for Pacific Ocean; Latin Am is Latin America; Ind Ocean is Indian Ocean; ROW is Rest of World.

Table 1—Industry Clean Index and Industry Dependence on Institutions

	Clean index	Industry dependence on institutions			
		Financial	Judicial	Labor markets	Index
	(1)	(2)	(3)	(4)	(5)
Panel A. Cleanest industries					
Office supply manufacturing	2.64	0.68	0.07	0.22	0.35
Instruments for industrial processes	2.58	1.48	1.18	-0.59	1.16
Fluid power pumps and motors	2.42	0.21	0.66	1.00	0.80
Curtain and linen mills	2.40	0.53	0.54	1.51	0.98
Precision turned product manufacturing	2.23	-0.61	0.15	0.19	-0.07
Mean for cleanest industries	*2.46*	*0.46*	*0.52*	*0.47*	*0.65*
Panel B. Dirtiest industries					
Aluminum refining and production	-2.17	-1.84	-1.63	-0.96	-2.03
Gypsum product manufacturing	-2.18	-2.19	-1.16	-1.18	-1.91
Pulp mills	-2.22	-2.08	-0.48	-0.09	-1.10
Newsprint mills	-2.30	-3.12	-0.60	-0.80	-1.76
Other petroleum, coal products	-2.43	0.10	-1.26	0.96	-0.55
Mean for dirtiest industries	*-2.26*	*-1.83*	*-1.03*	*-0.41*	*-1.47*

Notes: table includes manufacturing industries with non-missing values of all listed variables. Table uses US data.

Table 2—Sources of Comparative Advantage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Comparative advantage in all industries										
Country endowment × industry intensity:										
Institutions: financ.	0.057***	—	—	—	—	—	—	—	0.036**	—
	(0.012)	—	—	—	—	—	—	—	(0.015)	—
Institutions: judicial	—	0.054***	—	—	—	—	—	—	0.025**	—
	—	(0.010)	—	—	—	—	—	—	(0.010)	—
Institutions: labor	—	—	0.006	—	—	—	—	—	0.004	—
	—	—	(0.004)	—	—	—	—	—	(0.004)	—
Institutions: index	—	—	—	0.057***	—	—	—	—	—	0.038***
	—	—	—	(0.007)	—	—	—	—	—	(0.008)
Environmental reg.	—	—	—	—	0.048***	—	—	—	0.017*	0.022**
	—	—	—	—	(0.009)	—	—	—	(0.010)	(0.009)
Factor capital/lab.	—	—	—	—	—	-0.025	—	—	0.186**	0.172*
	—	—	—	—	—	(0.096)	—	—	(0.089)	(0.098)
Factor: skills	—	—	—	—	—	—	0.348***	—	0.282***	0.285***
	—	—	—	—	—	—	(0.036)	—	(0.035)	(0.033)
Log(1+tariffs)	—	—	—	—	—	—	—	-0.085***	-0.084***	-0.085***
	—	—	—	—	—	—	—	(0.009)	(0.009)	(0.009)
Panel B: Comparative advantage in clean industries										
Country endowment × clean industry index:										
Institutions: financ.	0.051***	—	—	—	—	–	–	–	0.035**	—
	(0.010)	—	—	—	—	–	–	–	(0.015)	—
Institutions: judicial	—	0.054***	—	—	—	–	–	–	0.008	—
	—	(0.010)	—	—	—	–	–	–	(0.031)	—
Institutions: labor	—	—	0.018**	—	—	–	–	–	0.006	—
	—	—	(0.008)	—	—	–	–	–	(0.008)	—
Institutions: index	—	—	—	0.054***	—	–	–	–	—	0.038***
	—	—	—	(0.007)	—	–	–	–	—	(0.012)
Environmental reg.	—	—	—	—	0.048***	–	–	–	0.008	0.008
	—	—	—	—	(0.009)	–	–	–	(0.028)	(0.014)
Country endowment × industry intensity:										
Factors capital/lab.	—	—	—	—	–	-0.025	–	–	0.112	0.115
	—	—	—	—	–	(0.096)	–	–	(0.086)	(0.094)
Factors: skills	—	—	—	—	–	–	0.348***	–	0.307***	0.302***
	—	—	—	—	–	–	(0.036)	–	(0.034)	(0.034)
Log(1+tariffs)	—	—	—	—	–	–	–	-0.085***	-0.084***	-0.085***
	—	—	—	—	–	–	–	(0.009)	(0.009)	(0.009)
Fitted effect 10→90%	-20.5%	-38.1%	-14.8%	-34.5%	–	–	–	–	-21.4%	-24.7%
Importer×exporter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer×industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each observation is an importer×exporter×manufacturing industry. Dependent variable is log of bilateral trade. Industry intensity and industry clean index are calculated from US data. Table shows beta coefficients. N=1,875,532. In Panel A, the main explanatory variables are the interaction of an exporter's endowment with the industry's intensity. Fitted effect 10→90% implements equation (10). Columns (5) through (8) of Panel B repeat those of Panel A. Standard errors are clustered by exporter. Asterisks denote p-value * < 0.10, ** < 0.05, *** < 0.01.

Table 3—Which Industry Characteristics Explain the Importance of Institutions for Clean Industries?

	Association with clean index	Dependence of clean industries on institutions:			Comparative advantage of clean industries
		Financial	Judicial	Labor	
	(1)	(2)	(3)	(4)	(5)
Baseline	—	0.58***	0.49***	0.18***	0.041***
	—	(0.05)	(0.04)	(0.05)	(0.010)
Energy share	-0.37***	0.50***	0.42***	0.16***	0.042***
	(0.12)	(0.05)	(0.04)	(0.05)	(0.010)
Raw materials share	-0.36***	0.49***	0.33***	0.17***	0.031***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.009)
Upstreamness	-0.33***	0.49***	0.41***	0.20***	0.049***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.010)
Inverse export supply elasticity	0.27***	0.61***	0.50***	0.15**	0.048***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.011)
Mean wage	0.06	0.57***	0.49***	0.17***	0.037***
	(0.06)	(0.04)	(0.04)	(0.05)	(0.010)
Unemployment (%)	-0.08*	0.58***	0.49***	0.16***	0.038***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.010)
College educated	0.18***	0.53***	0.46***	0.16***	0.033***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.009)
Union membership	-0.28***	0.51***	0.48***	0.16***	0.043***
	(0.05)	(0.04)	(0.04)	(0.05)	(0.009)
Intra-industry share	0.06	0.66***	0.56***	0.15**	0.050***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.011)
Geographic dispersion	-0.03	0.59***	0.50***	0.17***	0.041***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.010)
Labor share	0.29***	0.58***	0.43***	0.17***	0.048***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.011)
Capital share	-0.06	0.58***	0.50***	0.17***	0.041***
	(0.09)	(0.05)	(0.04)	(0.05)	(0.010)
Log shipping cost per ton×km	-0.41***	0.51***	0.44***	0.10	0.038***
	(0.07)	(0.06)	(0.06)	(0.07)	(0.008)
Mean firm size	-0.10**	0.57***	0.48***	0.17***	0.042***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.010)
Std. dev. Firm size	-0.12**	0.58***	0.49***	0.17***	0.042***
	(0.06)	(0.05)	(0.04)	(0.05)	(0.010)
Concentration ratio	-0.15***	0.59***	0.49***	0.17***	0.040***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.010)
Log output	-0.06	0.58***	0.48***	0.18***	0.044***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.011)
Output trend 1977-2007	-0.15***	0.60***	0.51***	0.16***	0.039***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.010)
All at once	—	0.21***	0.16***	0.07	0.031***
	—	(0.05)	(0.05)	(0.09)	(0.008)

Notes: Columns (1) through (4) use US data; column (5) uses international trade data across countries combined with US industry characteristics. Each table entry shows beta coefficients from a separate regression, limited to manufacturing. Column (1) regresses each variable on an indicator for whether the industry's clean index is above median. Columns (2)-(4) regress institutional dependence on the clean industry index and one additional variable shown in a given row; table entries show coefficient on the clean index. Column (5) estimates equation (4), but also controlling for the interaction of institutions with the variable indicated in each row. Parentheses show robust standard errors in columns (1)-(4) and standard errors clustered by exporter in column (5). Asterisks denote p-value * < 0.10, ** < 0.05, *** < 0.01.

Table 4—Decomposition: Scale, Composition, and Technique, US as Reference

	All	CO	NO_x	$PM_{2.5}$	SO_x	VOCs
	(1)	(2)	(3)	(4)	(5)	(6)
1. Scale, composition, and technique	-0.72	-0.75	-0.83	-0.45	-0.67	-0.89
	(0.70)	(0.67)	(0.35)	(1.53)	(0.87)	(0.19)
2. Scale	-0.89	—	—	—	—	—
	(0.19)	—	—	—	—	—
3. Composition	1.75	1.20	2.11	2.75	2.11	0.55
	(1.23)	(1.21)	(1.46)	(1.98)	(2.23)	(0.55)
4. Technique	-0.02	0.10	-0.36	0.25	0.20	-0.32
	(0.59)	(0.76)	(0.44)	(1.07)	(1.19)	(0.31)
5. |Composition|	1.76	1.24	2.11	2.77	2.11	0.59
	(1.21)	(1.17)	(1.45)	(1.95)	(2.23)	(0.51)
6. |Technique|	0.47	0.51	0.49	0.74	0.88	0.38
	(0.36)	(0.57)	(0.28)	(0.81)	(0.82)	(0.22)

Notes: calculations use full Exiobase data. Scale, composition, and technique are all proportional difference relative to US. Row 2 uses production but not pollution data, so it is identical across pollutants. Emission rates are winsorized at 99.9th percentile. Calculations cover all industries. CO is carbon monoxide, NO_x is nitrogen oxides, $PM_{2.5}$ is particulate matter smaller than 2.5 micrometers, SO_x is sulfur oxides, and VOCs are volatile organic compounds.

Table 5—Effects of Counterfactual Institutions on Emissions: Model-Based Analysis

Counterfactua scenario: improve institutions by 1 s.d. in …	Pacific Ocean	Western Europe	Eastern Europe	Latin America	North America	China	Southern Europe	Northern Europe	Indian Ocean	Rest of World
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Effect on emissions in…										
Pacific Ocean	-5.5%	0.3%	0.1%	0.1%	0.4%	0.7%	0.2%	0.2%	0.2%	0.8%
Western Europe	0.5%	-7.2%	0.5%	0.1%	0.9%	0.5%	0.7%	0.6%	0.1%	1.2%
Eastern Europe	0.3%	0.8%	-4.8%	0.1%	0.3%	0.3%	0.6%	0.4%	0.1%	0.7%
Latin America	0.3%	0.2%	0.1%	-4.8%	1.1%	0.5%	0.2%	0.1%	0.1%	0.4%
North America	0.4%	0.5%	0.1%	0.3%	-3.9%	0.4%	0.2%	0.3%	0.1%	0.7%
China	0.4%	0.1%	0.1%	0.1%	0.2%	-5.9%	0.1%	0.1%	0.1%	0.4%
Southern Europe	0.4%	0.9%	0.4%	0.1%	0.4%	0.3%	-6.4%	0.4%	0.1%	1.0%
Northern Europe	0.6%	1.3%	0.5%	0.2%	1.0%	0.5%	0.6%	-7.8%	0.2%	1.3%
Indian Ocean	0.4%	0.1%	0.1%	0.0%	0.1%	0.4%	0.1%	0.1%	-3.9%	0.8%
Rest of World	1.3%	0.6%	0.4%	0.2%	0.8%	1.2%	0.6%	0.3%	0.6%	-6.8%
Global	*0.3%*	*0.2%*	*-0.1%*	*-0.3%*	*0.1%*	*-1.5%*	*0.1%*	*0.1%*	*-0.1%*	*-1.0%*

Notes: Each column shows a separate counterfactual. Each counterfactual improves institutions in the region indicated in the column by one standard deviation. Each row shows the percentage change in emissions from a given region due to the counterfactual indicated in a given column. Data from Exiobase.

Table 6—Effects of Counterfactual Institutions on Emissions: Additional Scenarios

		Counterfactual change in…		Change: share output from…		
	Baseline institutions (z-score)	Institutional quality (z-score)	Emissions (%)	Dirty industries	Moderate industries	Clean industries
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Counterfactual: remove institutional differences between countries						
Pacific Ocean	1.9	-1.0	6.2%	1.0%	0.6%	-1.6%
Western Europe	1.3	-0.4	2.1%	0.3%	0.1%	-0.4%
Eastern Europe	0.2	0.6	-3.9%	-0.9%	-0.1%	1.1%
Latin America	-0.6	1.5	-8.9%	-1.1%	-0.9%	2.1%
North America	2.4	-1.6	6.5%	0.7%	0.7%	-1.4%
China	0.7	0.2	-1.7%	-0.3%	-0.2%	0.5%
Southern Europe	0.7	0.1	-1.8%	-0.3%	-0.1%	0.4%
Northern Europe	2.2	-1.4	10.6%	1.5%	0.5%	-2.0%
Indian Ocean	-0.3	1.2	-4.8%	-0.9%	-0.8%	1.6%
Rest of World	0.2	0.7	-6.8%	-1.0%	-0.5%	1.6%
Global	—	—	*-2.3%*	—	—	—
Panel B. Counterfactual: improve institutions in countries with below-median baseline institutions						
Pacific Ocean	1.9	0.0	2.9%	0.6%	0.3%	-0.9%
Western Europe	1.3	0.0	3.7%	0.7%	0.2%	-0.8%
Eastern Europe	0.2	1.5	-5.4%	-1.1%	-0.1%	1.2%
Latin America	-0.6	2.4	-9.6%	-1.1%	-0.9%	2.0%
North America	2.4	0.0	2.5%	0.3%	0.3%	-0.6%
China	0.7	1.1	-5.3%	-0.4%	-0.2%	0.5%
Southern Europe	0.7	0.0	3.0%	0.7%	0.1%	-0.8%
Northern Europe	2.2	0.0	4.0%	0.6%	0.3%	-0.9%
Indian Ocean	-0.3	2.0	-6.0%	-0.7%	-0.9%	1.6%
Rest of World	0.2	1.6	-7.3%	-1.1%	-0.4%	1.4%
Global	—	—	*-4.3%*	—	—	—
Panel C. Counterfactual: improve institutions in Latin America						
Pacific Ocean	1.9	0.0	0.4%	0.1%	0.0%	-0.1%
Western Europe	1.3	0.0	0.4%	0.1%	0.0%	-0.1%
Eastern Europe	0.2	0.0	0.2%	0.1%	0.0%	-0.1%
Latin America	-0.6	3.1	-18.5%	-2.1%	-0.9%	3.0%
North America	2.4	0.0	1.0%	0.1%	0.1%	-0.2%
China	0.7	0.0	0.3%	0.1%	0.0%	-0.1%
Southern Europe	0.7	0.0	0.4%	0.1%	0.0%	-0.1%
Northern Europe	2.2	0.0	0.5%	0.1%	0.0%	-0.1%
Indian Ocean	-0.3	0.0	0.3%	0.1%	0.0%	-0.1%
Rest of World	0.2	0.0	0.9%	0.1%	0.0%	-0.2%
Global	—	—	*-0.9%*	—	—	—

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Table 6—Effects of Counterfactual Institutions on Emissions: Additional Scenarios (Continued)

		Counterfactual change in…		Change: share output from…		
	Baseline institutions (z-score)	Institutional quality (z-score)	Emissions (%)	Dirty industries	Moderate industries	Clean industries
	(1)	(2)	(3)	(4)	(5)	(6)
Panel D. Add 1996-2015 changes in institutions						
Pacific Ocean	1.9	0.0	*0.8%*	0.2%	0.1%	-0.3%
Western Europe	1.3	0.0	*0.9%*	0.2%	0.0%	-0.2%
Eastern Europe	0.2	0.5	*-1.6%*	-0.3%	0.0%	0.4%
Latin America	-0.6	0.1	*-0.1%*	0.0%	0.0%	0.0%
North America	2.4	0.0	*0.7%*	0.1%	0.1%	-0.2%
China	0.7	0.8	*-4.8%*	-0.5%	-0.3%	0.8%
Southern Europe	0.7	-0.1	*1.2%*	0.3%	0.1%	-0.3%
Northern Europe	2.2	0.6	*-4.0%*	-0.6%	-0.2%	0.8%
Indian Ocean	-0.3	-0.2	*1.3%*	0.3%	0.2%	-0.5%
Rest of World	0.2	0.1	*0.4%*	0.1%	0.0%	-0.1%
Global	—	—	*-1.4%*	—	—	—

Notes: institutional quality is first principal component for each country. Dirty, moderate, and clean industries are based on dividing global industries into thirds based on global log emissions rate, measured as the first principal component of the log emissions rate across pollutants, and calculated as a weighted average across all countries. Data from Exiobase.