Trade Networks and Diffusion of Regulatory Standards*

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Abstract

We document network effects in the diffusion of regulatory standards through international trade. Armed with data on standards imposed by countries on imports of commodities, we provide robust causal evidence that countries tend to domestically adopt regulations that they comply with while exporting. Leveraging the high dimensionality of our data, we show that the diffusion process is stronger in (*i*) regulations concerning attributes of the final product rather than production processes, (*ii*) countries more open to international trade, and (*iii*) final products rather than intermediate inputs. Our results imply that economic integration can strengthen regulatory standards, aiding international policy coordination.

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1 Introduction

Standardization is fundamental to modern economic production. On the one hand, adoption of standards can hinder competition, trade, product variety, and technology diffusion. On the other hand, regulatory standards not only address domestic market failures by ensuring quality and safety pertaining to consumers' health and the environment, but can also improve efficiency and consumer welfare especially when harmonized across countries (Costinot, 2008; Geng, 2019; Berlingieri, Breinlich and Dhingra, 2018; Grossman, McCalman and Staiger, 2021). A country's incentives to unilaterally adopt a regulation are limited when competing against unregulated foreign producers. However, when a country must comply with a regulation to export, the gains from domestic adoption can outweigh the costs imposed on producers. Thus, participation in trade can facilitate diffusion of regulations across countries (Vogel, 2000; Chen and Dar-Brodeur, 2020). International regulatory diffusion via market mechanisms demonstrates that economic incentives can align with social goals of countries.

We estimate the extent of diffusion in the domestic adoption of regulatory standards due to compliance requirements imposed by importing countries. To identify the impact of *importer pressure* on domestic adoption, we combine spatial econometric techniques with an instrument variables approach, which is based on interactions between geography and technological change (Feyrer, 2019*b*). Our sample of regulations comprises multiple Technical Barriers to Trade (TBT) imposed by countries on imports of a variety of products. Combining regulation data with product level bilateral trade flows, we construct a panel of over 125 million product-regulation-country-year observations that provide information on adoption of a regulation by each country's importers on a product. Our high-dimensional panel allows us to control for alternative channels of diffusion and economic indicators that are associated with regulatory adoption and to unravel factors that can intensify diffusion.

Our results show that countries tend to domestically adopt regulations that they comply with when exporting. In our strictest specification, we estimate that one standard deviation (s.d.), i.e., roughly 12.27 percentage point (p.p.), increase in the share of exports that comply with a regulation leads to a 3.96 basis point (b.p.) increase in the probability of domestic adoption of that regulation, which corresponds to 17.56% of average adoption. We devise two novel tests to show the robustness of the network effects. First, we impose different network structures when measuring network centrality of each country. This exercise reveals that connectedness via exports to countries *that have adopted a regulation*, rather than overall connectedness via exports, is the driver of regulatory diffusion. Second, we implement a placebo test by randomizing over adoption by countries for each product-regulation pair to show that our results are not driven by omitted variation. Our results are also robust to alternative treatment of the European Union countries, where regulations may diffuse faster due to mutual recognition of standards, and eliminating feedback effects from adoption of regulations to trade.

We exploit the high-dimensionality of our panel to show substantial heterogeneity in regulatory diffusion by standard type, product type, and country characteristics. Diffusion is stronger for *product* standards—regarding physical attributes of the final product—as opposed to *process* standards, which pertain to the manufacturing process. Product regulations, such as labelling and packaging requirements, are more cost-effective than regulations that involve adjustments to the production process. Further, regulatory bodies can test for conformity with product standards so they can discriminate against non-complying products, which confers a competitive advantage to complying exporters (Vogel, 2000; Greenhill, Mosley and Prakash, 2009). Compliance with process standards, such as amount of pesticides used during production, is harder to verify in the final product. Therefore, domestic adoption of such standards by exporting countries would confer little competitive advantage over other producers in the global market. In the same vein, we find stronger diffusion in final products, as opposed to intermediate inputs, reflecting easier verifiability of compliance by the consumer in the former. We also show that countries that are relatively open to international trade are the main drivers of regulatory diffusion while relatively closed countries face only modest incentives to match their trade partners' regulations. These findings demonstrate that economic openness and competition are key to regulatory diffusion.

A potential concern in the study of regulatory diffusion is that TBTs can serve as a substitutes for tariff reductions (Beverelli, Boffa and Keck, 2014; Orefice, 2017) and also hinder international trade (Fontagné and Orefice, 2018), especially when raised as Specific Trade Concerns (STCs) at the World Trade Organization (WTO) (Herghelegiu, 2018). Our instrumental variable approach, however, helps identify the impact of importer pressure on regulation adoption only via the geographic component of trade. Further, we control for average level of protection via tariffs in a product by a country with product-country-year effects in the second stage. Thus, we are able to alleviate the concern that our estimated importer pressure effect is contaminated by changes in tariffs.

As we move away from a world of protectionism via tariffs to a world where regulatory standards are implemented for preservation of consumers' health, safety, and values, a burgeoning literature explores the mechanisms behind the harmonization of standards.[1] Grossman, McCalman and Staiger (2021) show how harmonizing regulations forms part of an efficient trade agreement in the presence of negative consumption externalities. Whether harmonization is welfare-enhancing further depends on degree of consumption externality (Costinot, 2008), country preference heterogeneity (Geng, 2019), and interactions between political pressure and standard type (Maggi and Ossa, 2023). In contrast to international agreements where harmonization must be negotiated and is legally binding for member countries, we empirically show how economic incentives created via trade can facilitate regulatory coordination across countries even without the legal enforcement.

The diffusion of regulations via market mechanisms contrasts to a "race to the bottom" resulting from trade liberalization (Bagwell and Staiger, 2001). Due to the adverse effects of regulations on industry outcomes, as in (Greenstone, 2002), countries might tend to lower their standards over time to keep their products competitive in international markets. Instead, our paper provides empirical evidence in favor of Chen and Dar-Brodeur (2020), who analytically show that a trade policy designed to increase export market shares also improves labor standards. Likewise, Porter and van der Linde (1995) posit that well-designed

[1] Edgerington and Ruta (2016) provide an excellent discussion of the chief issues surrounding non-tariff measures.

regulation can trigger innovation that generates benefits greater than the compliance costs, leading to a competitive advantage over foreign firms not subject to similar regulations. Other work documents trade-induced propagation of liberal economic policies (Simmons and Elkins, 2004), labour laws (Greenhill, Mosley and Prakash, 2009), and automobile emission standards (Saikawa, 2013).

We are the first to causally estimate the extent of diffusion in domestic regulation adoption due to compliance requirements imposed by importing countries. To identify the effect, we construct an instrument for the spatial lag term measuring importer pressure in the style of Kelejian and Piras (2014). Upon estimating gravity regressions, we are able to construct an instrument that captures only the time-varying geographic component of trade (Frankel and Romer, 1999; Feyrer, 2019*b*). Besides establishing causality, our rich dataset allows us to ensure external validity across regulations and products, control for alternative diffusion channels, and assess heterogeneity across various dimensions in regulatory diffusion.

Our paper is also related to the literature that evaluates the impact of regulations on outcomes such as trade (Moenius, 2004; Disdier, Fontagné and Mimouni, 2008; An and Maskus, 2009; Bao and Qiu, 2012; Disdier, Fontagné and Cadot, 2014; Yue, 2021; Mattoo, Mulabdic and Ruta, 2022; Barattieri, 2022; Schmidt and Steingress, 2022; Zavala et al., 2023), export variety (Shepherd, 2007), costs and preferences (Maskus, Otsuki and Wilson, 2005; Ganslandt and Markusen, 2001), and pollution emissions (Duan et al., 2021). We demonstrate the effect of regulatory adoption on further adoption by exporting countries, showing how trade partners' decisions to adopt regulations are interdependent. Our findings highlight the importance of considering the network effect when estimating the overall effect of regulations on economic outcomes in the presence of international trade.

The rest of the paper is organized as follows: Section 2 provides details on Technical Barriers to Trade. Section 3 explains our empirical strategy. Section 4 describes the data and the summary statistics. Section 5 reports the results from the gravity regressions. Section 6 discusses the baseline diffusion results while Section 7 describes the robustness checks. Section 8 presents the heterogeneity analyses and Section 9 concludes.

2 Technical Barriers to Trade

We use data on the adoption of a diverse set of Technical Barriers to Trade (TBT), from the UNCTAD TRAINS database (United Nations Conference on Trade and Development, 2019*b*), as the foundation of our analysis. In this section, we describe the features of the TBT data that make it suitable for our analysis and the diffusion pattern observed in the TBTs. Our regulation adoption variable uses information on TBTs imposed by countries on their trading partners over the years. The data provide us with information on the type of regulation, the imposing country, exporting countries the regulation is imposed on, the regulated commodities, and the year of implementation.

As per the agreement on the Technical Barriers to Trade, World Trade Organization member countries can use TBT to achieve policy objectives such as protection of human health or environment, or prevention of deceptive practices. However, they must not employ TBT as unnecessary barriers to trade. Therefore, even though TBT can have economic effects by influencing traded quantities and prices, they are not supposed to be implemented with the objective of protectionism or restricting foreign competition. Moreover, the TBT should be non-discriminatory between like products regardless of country of origin (United Nations Conference on Trade and Development, 2018).

The data contain only regulatory standards adopted by countries at the national level, used as admissibility requirements for imports.[2] Countries adopt these regulations at will and have the liberty to choose the level of stringency to impose. The data, compiled by classifying legal documents into pre-defined Non-Tariff Measure (NTM) codes, comprise regulations coded in a standardized way. Therefore information on their stringency is limited (United Nations Conference on Trade and Development, 2018).

The NTM codes classify the TBTs based on requirements for compliance with product characteristics or production processes. We collect data on 19 NTMs: B21-Tolerance limits for residues of or contamination by certain substances, B22-Restricted use of certain

[2]It excludes voluntary measures imposed by private organizations and international standards issued by international organizations, such as the International Organization of Standards and CODEX Alimentarius.

substances, B31-Labelling requirements, B32-Marking requirements, B33-Packaging requirements, B41-TBT regulations on production processes, B42-TBT regulations on transport and storage, B49-Production or post-production requirements n.e.s, B6-Product identity requirements, B7-Product quality, safety or performance requirements, B81-Product registration/approval requirements, B82-Testing requirements, B83-Certification requirements, B84-Inspection requirements, B851-Origin of materials and parts, B852-Processing history, B853-Distribution and location of products after delivery, B859-Traceability requirements n.e.s, and B89-Conformity assessment related to TBT n.e.s.[3] Table 1 provides examples on regulations by NTM.

Being in principle non-discriminatory, a TBT imposes the standard on domestic production and all imports simultaneously. However, we drop about 2% of cases where the requirements were imposed on exports from only a subset of countries.[4] Further, for about 5% of product-ntm-country combinations, the particular NTM is adopted in more than one year. After keeping only the first year of adoption, we have data on the adoption of 19 NTMs by 92 countries in 5675 six-digit Harmonized System (HS) categories in the years 1995-2019.[5]

2.1 Evolution of Adoption

To begin, we look at the adoption pattern over the years across sixteen regulations in our sample for the most regulated commodity: HS6 300431-Medicaments; containing insulin, for therapeutic or prophylactic uses, packaged for retail sale. The literature on technology diffusion argues that the adoption of a diffusing technology, over time, resembles an S-shaped logistic curve (Bowen, Frésard and Taillard, 2017). This curve is marked by a period of slow adoption until a minimum threshold, commencing a period of rapid adoption before it slows down again due to widespread adoption, leaving only a few prospective adopters. To check

[3]As our focus is on non-discriminatory regulations imposed on domestic and imported goods alike, we exclude B1-Import Authorization and Licensing, which apply exclusively to imported goods. We further exclude B9-TBT measures n.e.s, which accounts for miscellaneous regulations.

[4]Examples of such exceptional cases include countries of origin belonging to the same regional trade agreement as the importing country exempted from certain additional taxes or certification requirements.

[5]Since the TBT data treats the European Union (EU) member countries as one entity, the EU is coded as a single country in the original data set.

Table 1: Technical Barriers to Trade

This table provides an example of a regulation under each NTM code in our data, obtained from United Nations Conference on Trade and Development (2019*a*).

B21: Tolerance limits

- ***Example:*** *The salt level in cement or sulphur level in gasoline must be below the specified amount.*

B22: Restricted use

- ***Example:*** *This measure refers to the restricted use of solvents in paints and the maximum level of lead allowed in consumer paint.*

B31: Labelling

- ***Example:*** *Refrigerators must carry a label indicating size, weight and level of electricity consumption.*

B32: Marking

- ***Example:*** *Handling or storage conditions according to the type of product must be specified; typically, indications such as "Fragile" or "This side up" must be marked on the transport container.*

B33: Packaging

- ***Example:*** *Palletized containers or special packages should be used for the protection of sensitive or fragile products.*

B41: Production processes

- ***Example:*** *Animal slaughtering requirements according to Islamic law must be followed.*

B42: Transport and Storage

- ***Example:*** *Medicines should be stored below a certain temperature.*

B6: Product identity

- ***Example****: For a product to be identified as chocolate, it must contain a minimum of 30 per cent cocoa.*

B7: Quality, Safety, and Performance

- ***Examples:*** *Doors must resist a certain minimum high temperature.*

B81: Product registration

- ***Example:*** *Drugs and medicines must be registered before they can be imported. They should prove to be safe and effective for their intended purpose in order to be registered.*

B82: Testing

- ***Example:*** *Testing of a sample of motor vehicle imports is required to show compliance with safety standards.*

B83: Certification

- ***Example:*** *A certificate of conformity is required for electric products.*

B84: Inspection

- ***Example:*** *Textile and clothing imports must be inspected for size and materials used before entry is allowed.*

B51: Origin of materials

- ***Example:*** *Manufactures of automobiles must keep the record of the origin of the original set of tyres for each vehicle.*

B852: Processing history

- ***Example:*** *For wool apparel products, disclosure of information on the origin of the sheep, location of the textile factory, as well as the identity of the final apparel producer, may be required.*

B853: Distribution and location after delivery

- ***Example:*** *Before placing imported cosmetic products on the European Union market, the person responsible must indicate to the competent authority of the member State where the products were initially imported, the address of the manufacturer or the address of the importer.*

whether the pattern holds in our sample, we plot the fraction of countries that adopted each regulation over the years. To formally estimate the speed and thresholds of adoption, we define p_{rit} as the probability of adoption of regulation r by country i in year t. Then, we fit a logistic diffusion model to the data by estimating the following equation:

$$p_{rit} = \frac{e^{\beta_0+\beta_1 t+\varepsilon_{rit}}}{1+e^{\beta_0+\beta_1 t+\varepsilon_{rit}}} \quad \forall r, \tag{1}$$

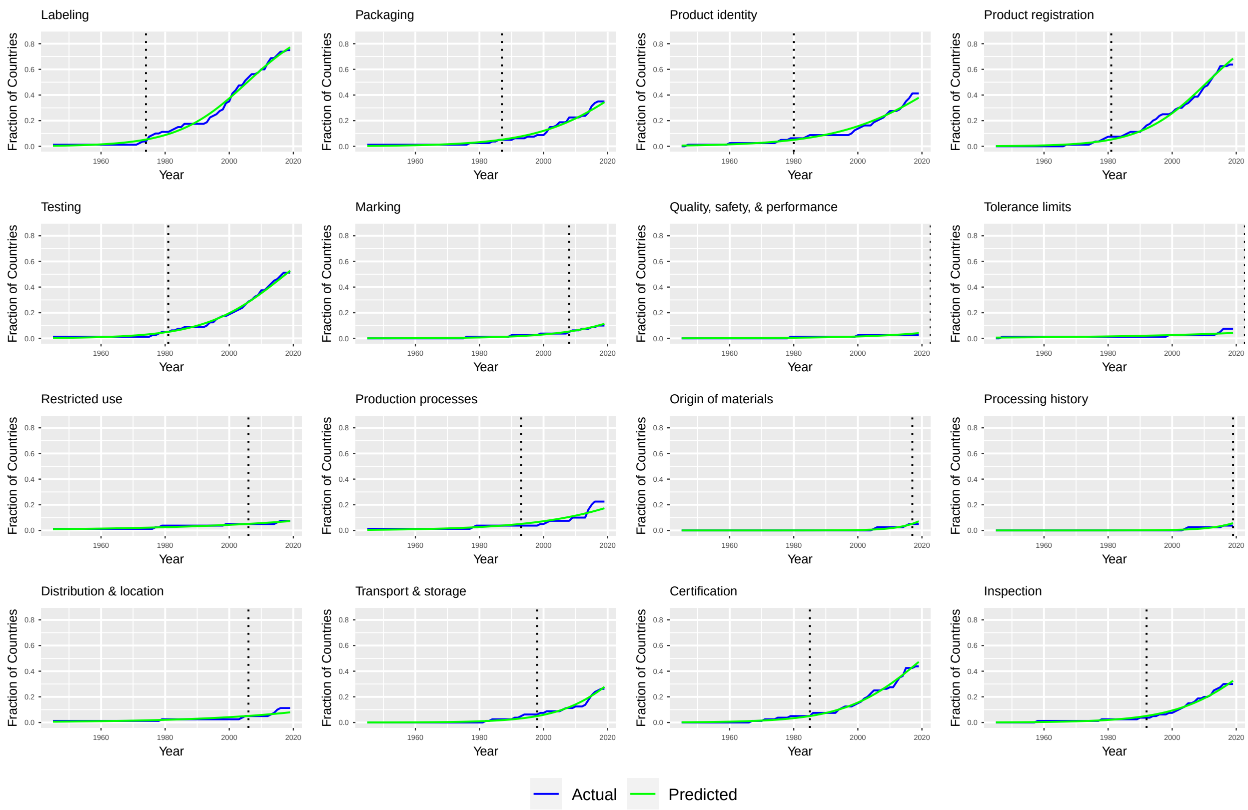
where β_0 and β_1 are parameters determining the location and scale of the logit curve, and ε_{rit} is a normally distributed error term. We compute the predicted fraction of countries that adopted by a year by averaging the fitted values from the estimation in that year.

Figure 1 shows that the actual fraction of countries that adopted closely follows the S-shaped pattern of the fitted logistic curve. In general, we find that *product* regulations (first 7 graphs) diffuse faster than *process* regulations (last 9 graphs). The exceptions are Quality-Safety-Performance, a product regulation with relatively slow adoption, and Certification and Inspection requirements, process regulations with relatively fast adoption. Labeling requirements is the first regulation to reach the conventional 5% adoption threshold used in technology diffusion literature (Bowen, Frésard and Taillard, 2017). In fact, it reaches the threshold even before the sample period began in 1974. After labeling, regulations that reach the 5% threshold are Product identity, Registration, Testing, Certification, Packaging, and Inspection in that order, in the 1980s and 1990s. The rest of the regulations reach the 5% threshold later in the 1990s or the 2000s. Table A.9 shows that the speed of adoption varies substantially across regulations. For example, at the beginning of the sample period, the adoption of labeling regulations doubles roughly every ten years, going from 5% in 1974 to 10% in 1982 to 20% in 1991. In contrast, process regulations diffuse much slower, with some not even crossing the 10% threshold by the end of the sample period.

We show association between the adoption of a regulation and the trade affected by that regulation by conducting a similar exercise with coverage ratio, defined as the fraction of within-sample trade in Medicaments affected by a regulation. Using beta regressions (Ferrari and Cribari-Neto, 2004), we show that the coverage ratio grows with the share of countries that adopt each regulation and shows similar diffusion patterns across regulations (See Appendix A).

Figure 1: Logit Fits for Adoption

Each panel in this figure represents adoption of a regulation, as specified by an NTM code, by countries over the years. The vertical axes represent the share of countries with the regulation in place by the corresponding year on horizontal axes. The blue lines depict the time series observed in data, whereas the green lines are the fitted values from Logit regressions specified in Equation (1). The dotted line represents the 5% threshold.



3 Framework

To model diffusion in the adoption of regulations, we employ a *pure-space recursive spatial lag* model, where adoption of a regulation is dependent on the fraction of "neighbours" that adopted by the previous year. Specifically, we estimate the following regression:

$$y_{prit} = \rho AE_{prit-1} + \boldsymbol{\beta}\mathbf{X_{prit-1}} + \mu_{pri} + \mu_{prt} + \mu_{rit} + \mu_{pit} + \varepsilon_{prit}, \tag{2}$$

where the dependent variable, y_{prit}, is a dummy indicating whether regulation r was in place in country i for product p in year t. Our variable of interest, AE_{prit-1}, is the fraction of exports of country i in product p affected by the regulation r in year $t-1$, a spatial lag capturing importer pressure. The variable X_{prit-1} controls for other channels of diffusion via competitor pressure. We introduce a time-lag to our variable of interest to allow time for a regulation to diffuse to a country after its adoption by the country's trade partners. Pure-space recursive spatial lag models with i.i.d. errors follow classical linear regression model assumptions and thus, can be estimated using ordinary least squares (OLS) (Anselin and Bera, 1998; Anselin, 2003).

We include product-regulation-country and product-regulation-year fixed effects, μ_{pri} and μ_{prt}, respectively. While the former absorbs time-invariant country characteristics specific to each product-regulation, the latter isolates the diffusion process that takes place over time from secular trends in the adoption of each product-regulation. We further control for diffusion channels that affect all products alike but vary across regulations, μ_{rit}, and channels that affect all regulations alike but vary across products, μ_{pit}. The former include institutional proximity across countries with similar colonial origins and culture, which spurs adoption of similar regulations, regardless of the product. The latter include specialization in production in different commodities across countries, regardless of the regulation. TBTs can serve as substitutes for tariff reductions (Beverelli, Boffa and Keck, 2014; Orefice, 2017) and also hinder international trade (Fontagné and Orefice, 2018), especially when raised as STCs at the WTO (Herghelegiu, 2018). The product-country-year effects also control for average level of protection on a product by a country, ensuring that our estimated effect is not contaminated by changes in tariffs.

Countries make an irrevocable decision to adopt a regulation for a particular product so we exclude the product-regulation-country observations after the year of adoption from the sample. Therefore, estimation of Equation (2) is a survival analysis that tells us which factors correlate with the *timing* of adoption and their relative importance. The coefficients of the independent variables can thus be interpreted in terms of probability of adoption. Although restricting observations until only first year of adoption and lagging the spatial lag terms alleviate reverse causality concerns, a diffusion channel that affects both regulation adoption and trade might still present threats to internal validity. To address this concern, we implement an instrumental variables approach that is based on interactions between geography and technological change. Before moving on to our identification strategy, however, we describe the construction of our spatial lag variables.

3.1 Affected Exports

For each product p and regulation r, we construct an indicator of country-year level adoption. This indicator is coded as 1 for all years after adoption is first observed in that country in the original data set, and it is zero in all prior years. Then, we construct a country-year level spatial lag term for each product-regulation that measures the fraction of exports of the product affected by that regulation (Saikawa, 2013; Simmons and Elkins, 2004; Greenhill, Mosley and Prakash, 2009). To construct the spatial lag for a product p and regulation r, we pre-multiply the adoption vector for a year, y_{prt}, by an exports weight matrix for that year, W_{pt}. The j-th element in the vector y_{prt} represents adoption by country j of regulation r in or before year t; and the ij-th element of matrix W_{pt} represents the fraction of country i's exports to country j in year t. This procedure yields the spatial lag vector:

$$AE_{prt} = W_{pt} y_{prt}.$$

The i-th element of AE_{prt} corresponds to regulation r, exporter i, and year t:

$$AE_{prit} = \sum_j w_{pijt} y_{prjt},$$

where w_{pijt} is the fraction of exports from country i to j in year t, and y_{prjt} is the adoption indicator for regulation r in importing country j in year t. The spatial lag term, interpreted as fraction of exports of country i that must comply with regulation r in year t, is used to capture importer pressure for each product p.

Another channel of regulatory diffusion in trade networks is via competitor pressure, in which countries match the standards of their closest export rivals to stay competitive in international markets. Since this mechanism can be as granular as importer pressure, it is not absorbed by the fixed effects and must be directly controlled for. We use a spatial lag term, based on Simmons and Elkins (2004), that captures the strength of competition in exports to control for competitor pressure. We build yearly matrices where the ij-th element is the correlation between exports of countries i and j in that year. The dyadic measure captures the strength of export competition between each pair of countries in each product. Next, we build the product-regulation-country-year level spatial lag by computing the average adoption of the top 10% competitors of a country:

$$CP_{prit} = \frac{\sum_j \mathbb{1}(c_{pijt} \in \text{9th Decile})y_{prjt}}{\sum_j \mathbb{1}(c_{pijt} \in \text{9th Decile})},$$

where c_{pijt} is the correlation between the exports of product p of countries i and j in year t. Thus, CP_{prit} is interpreted as the intensity of competitor pressure to adopt regulation r in product p experienced by country i in year t.

3.2 Instrument for Affected Exports

We use the geographic component of a country's trade with other countries that adopted a regulation as an instrument for affected exports. We build this instrument by combining predicted bilateral flows from gravity regressions, as in Frankel and Romer (1999) and Feyrer (2019*b*), with adoption of regulations. We estimate the following gravity regression:

$$\text{(3)} \qquad \ln \frac{trade_{pijt}}{s_{pt}GDP_{it}GDP_{jt}s_{pt}} = \beta_{air,t} \times \ln \text{airdist}_{ij} + \boldsymbol{\beta}\mathbf{X_{ij}} + \mu_{pi} + \mu_{pj} + \mu_{it} + \mu_{jt} + \epsilon_{pijt}$$

where the dependent variable is trade flow in product p from country i to j in period t, scaled by yearly share of the product in global trade, s_{pt}, and the trade partners' income levels. The main predictor is the bilateral air distance, i.e., point to point great circle distance, the coefficient of which is allowed to vary over time. The time-varying coefficient captures how the importance of air transport changes with technological development during our sample period. The sensitivity of trade to air distance should grow over time as air transport becomes more and more feasible with technological change. We control for several time-invariant bilateral characteristics, $\mathbf{X_{ij}}$.

We further control for time-invariant product-country effects, μ_{pi} and μ_{pj}, and time-varying country effects, μ_{it} and μ_{jt}. As our dependent variable in the second-stage varies at the product-regulation-country-year level, any fixed effects that account for time variation in product-country factors would contaminate the trade predictions. Therefore, while the country-year fixed effects account for time effects like changes in income and population that are common to all products in a country, any time effects idiosyncratic to a product within a country, such as average level of protection in a product via tariffs, are part of the error term. Although we exclude product-exporter-year and product-importer-year fixed effects for the purposes of prediction, our gravity regression results are robust to their inclusion.

We produce an instrument for affected exports by estimating Equation (3) to get predictions of bilateral trade flows in each product and constructing a spatial lag as follows:

$$AirDistance\ IV_{prit} = \sum_j \hat{w}_{pijt} y_{prjt}$$

where $\hat{w}_{pijt}$ is now the fraction of predicted trade flows from country i to j in year t in product p and the predicted bilateral trade flows are:

$$\widehat{\text{trade}}_{pijt} = \exp\left(\hat{\beta}_{air,t} \times \ln airdist_{ij} + \hat{\boldsymbol{\beta}}\mathbf{X_{ij}} + \hat{\mu}_{pi} + \hat{\mu}_{pj} + \hat{\mu}_{it} + \hat{\mu}_{jt}\right) \times s_{pt} GDP_{it} GDP_{jt} s_{pt} \tag{4}$$

Thus, the predictions are comprised of bilateral pair effects, time-invariant product-country specific effects, time-variant country effects, and interactions between geography and technological development in air transport.

3.3 Exclusion Restrictions

In the previous section, we make the case that no feedback effects exist from adoption to predicted trade. However, to further show the validity of the instrument, we must still determine whether it affects adoption solely through trade. Our instrument captures the time-varying geographic component of trade by allowing interactions between bilateral air distances and technological advances in air transport. Thus, we rely on changes in effective distances over time as a result of technological development, as in Feyrer (2019*b*), as opposed to a component that only accounts for time-invariant bilateral air distances, as in Frankel and Romer (1999).

Frankel and Romer (1999) study the causal impact of trade on income with an instrument based on the time-invariant geographic component of trade. If we were to base our instrument on Frankel and Romer's approach, it would violate the exclusion restriction because physical proximity to countries that have adopted a particular regulation may make for easier domestic adoption in a country through similar institutions, languages, and colonial origins (Kee, Nicita and Olarreaga, 2009). A separate issue in Frankel and Romer (1999) is not being able to control for country effects due to the time-invariant nature of their instrument. However, we don't share the same concern as in construction of our spatial lag terms, the time-variation also comes from the adoption vector and not solely through trade. Thus, we are able to include controls for other channels of diffusion like competitor pressure that vary over time.

Our instrumental variables approach also departs from the one in Feyrer (2019*b*), which captures time-variation in not just air distances but also sea distances. Feyrer (2019*b*) shows that the importance of air distance increases and the sea distance decreases with the development of air transport technology. Countries whose sea routes match their air routes see less benefit from the technological development than those whose air routes cross land masses. However, a challenge with using Feyrer's sea distances in our setting is that our sample comprises NTM-reporting countries. Given that Feyrer's original dataset comprises 55% country pairs with missing sea distances, we end up losing almost 27% of our observations in gravity regressions.[6] Nevertheless, we show that our estimates are qualitatively robust to including sea distances in Appendix B. Although the coefficients are smaller, we find that the size of even OLS and AirDistance IV estimates decrease if we restrict the sample to only the countries for which sea distance data are available. This finding suggests that the lower magnitudes result from loss in observations rather than the use of sea distances in constructing the instrument (See Appendix B for further discussion).

Further, excluding the impact of sea distance is less of a concern in our scenario. By the beginning of our sample period, in 1995, as opposed to Feyrer's in 1950, the air transport technology may have advanced to the extent that countries more reliant on air transport than sea transport hardly see a differentiated impact on trade with further development. Overall, during our sample period, we expect trade to be less sensitive to sea distances than air distances and also, for this sensitivity to change little over time.

Even so, our instrument may affect adoption through channels other than trade like economic integration that comes from improvements in air travel (Feyrer, 2019*b*). Diffusion in certain products or of certain regulations may occur due to increases in technology transfer and foreign direct investment that come from increased air travel by people. As such, our estimates can be interpreted as quantifying the effects of general globalization and therefore, as an upper bound on the causal impact of trade on adoption.

4 Data

We obtain data on yearly values of bilateral trade flows for each HS6 product from the BACI-CEPII database for the years 1995-2019 (Gaulier and Zignago, 2010). Out of the 92 countries in the TBT sample, trade flows on only 90 countries are available until the year 2000,[7] and out of the 5675 HS6 categories, trade flows on only 4255 are available. To balance the trade flow panel, we treat a missing trade flow in a product between a country pair as

[6]We obtain bilateral sea distance data from the replication package in Feyrer (2019*a*). The smaller sample size originates in the exclusion of landlocked countries and oil exporters in the calculation of bilateral sea distances in Feyrer's data.

[7]Botswana and Palestine only enter the sample in the year 2000.

a zero trade flow. As the European Union countries are coded as a single country in the TBT data, we first use bilateral trade flows for each EU country to get the predicted trade flows from the gravity regressions, and then, aggregate the predicted flows to the EU level.[8] Figure A.2 shows that countries within our sample represent over 87% of the world trade during our sample period.

To construct our instrument, we obtain data on great circle distances from Mayer and Zignago (2011), calculated from the latitude and longitude of the most important city or official capital of each country. We use indicators on contiguity, common language, and ever having had a colonial link between country pairs as additional bilateral controls in gravity regressions (Head and Mayer, 2013). In some specifications, we use data on population to control for the country-year effects. Data on both population and income, which is used to scale trade flows in gravity regressions, are from World Development Indicators Database (World Bank, n.d.*a*,n).

Table 2 reports the summary statistics. Overall, our sample has over 125 million product-regulation-country-year observations. For ease of exposition, all variables are in percentage points. Panel A reports the variables used in our main analysis. The dependent variable *Adopted (%)* has an average of only 0.23%. This small value is due to the survival format of the sample, where we exclude all observations of a product-regulation-country triple after the year of adoption by the country. Therefore, 0.23% is the unconditional probability of domestic adoption of a NTM in a product in our sample.

The independent variable of interest *AE*, shows that on average, 2.23% of a country's exports comply with a regulation imposed by its export destinations. *AirDistance IV* and *Air & Sea Distance IV* are the instrumental variables for *AE* where bilateral trade flows are predicted by air distances, using Equation (3), and air and sea distances, using Equation (6), respectively. The loss in sample size from using sea distances is clear: roughly 30% of the observations are missing for *Air & Sea Distance IV*.

In Table A.10, we observe a high correlation between our main independent variable and

[8]When estimating the OLS regressions, however, we simply aggregate the actual trade flows to the EU level.

Table 2: Summary Statistics

This table reports summary statistics of the variables used in our specifications. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. All variables in the table are in percentage points. Panel A describes the variables used in our main exercise. *Adopted* is an adoption indicator of the year a country domestically adopts a regulation on a product. We exclude from the sample product-regulation-country observations after the year of adoption. *AE* is the fraction of exports of a product that must comply with an NTM. *AirDistance IV* and *Air & Sea Distance IV* are the instruments for *AE*, where bilateral trade flows are predicted by countries' pairwise air distances, and air and sea distances, respectively. *CP* is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 and Appendix B for details on construction of the variables. Panel B describes the alternative network centrality measures that we use in Section 7.1. In the HS6-country-year networks, a link between countries A and B exists when country A exports the HS6 product to country B. In the HS6-NTM-country-year networks, a link between countries A and B exists when country A exports the HS6 product to country B and country B has the NTM on that product in place. In the weighted measures, the weight of the link is the inverse of the share of exports of country A to country B. For details on the construction of the network centrality measures, see Section 7.1 and Appendix C.

Panel A: Main Sample (%)	Mean	Median	Std. Deviation	Observations
Adopted	0.23	0.00	4.74	125,949,101
AE	2.23	0.00	12.27	125,949,101
AirDistance IV	2.03	0.00	11.44	118,047,211
Air & Sea Distance IV	1.07	0.00	9.15	83,758,783
CP	1.40	0.00	5.70	125,949,101
Panel B: Other Measures of Centrality (%)	Mean	Median	Std. Deviation	Observations
HS6-Country-Year Networks				
Degree	6.60	1.10	14.60	9,343,965
Harmonic	22.82	2.20	25.71	9,343,965
Weighted Harmonic	1.64	1.12	1.66	9,343,965
HS6-NTM-Country-Year Networks				
Degree	0.19	0.00	0.86	125,949,101
Harmonic	0.30	0.00	1.34	125,949,101
Weighted Harmonic	0.03	0.00	0.16	125,949,101

both instruments, thereby providing initial evidence that the instruments are not weak. We also observe a near perfect correlation between the two instruments, despite the non-negligible differences in the summary statistics.

5 Gravity Regression Results

Table 3 presents the results from various specifications of the gravity equation, including our preferred specification for prediction, Equation (3), in column (4). We estimate elasticity of product-level bilateral trade flows with respect to air distance in separate periods of five

Table 3: Gravity Regression Results

This table reports results from the estimation of Equation (3). Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are clustered at exporter-importer level.

	ln(trade)					
ln(airdist)	-0.89		-0.92	-0.82		-0.82
$\times\mathbb{1}(1995 \leq year \leq 2000)$	(-46.41)***		(-47.85)***	(-44.98)***		(-41.19)***
ln(airdist)	-0.93	-0.03	-0.94	-0.94	-0.12	-0.97
$\times\mathbb{1}(2001 \leq year \leq 2005)$	(-52.75)***	(-4.34)***	(-53.53)***	(-51.18)***	(-19.94)***	(-49.22)***
ln(airdist)	-0.95	-0.06	-0.95	-0.99	-0.18	-1.03
$\times\mathbb{1}(2006 \leq year \leq 2010)$	(-55.03)***	(-5.95)***	(-55.06)***	(-55.56)***	(-22.22)***	(-53.40)***
ln(airdist)	-1.05	-0.16	-1.04	-1.06	-0.25	-1.12
$\times\mathbb{1}(2011 \leq year \leq 2015)$	(-58.94)***	(-12.51)***	(-58.77)***	(-60.96)***	(-26.41)***	(-58.79)***
ln(airdist)	-1.09	-0.20	-1.07	-1.08	-0.27	-1.14
$\times\mathbb{1}(2016 \leq year \leq 2020)$	(-58.65)***	(-14.41)***	(-58.08)***	(-61.11)***	(-24.92)***	(-58.80)***
Bilateral controls	Y	N	Y	Y	N	Y
Partner-Year controls	N	N	Y	N	N	N
HS6-Partner FE	Y	Y	Y	Y	Y	N
Year FE	Y	Y	Y	N	N	N
Partner-Year FE	N	N	N	Y	Y	N
HS6-Partner-Year FE	N	N	N	N	N	Y
Exporter-Importer FE	N	Y	N	N	Y	N
Observations	166,080,730	166,080,730	166,080,730	166,080,730	166,080,730	166,080,730
Adjusted R^2	0.66	0.69	0.66	0.67	0.70	0.70

years each. Column (4) shows that between 1995 and 2000, the elasticity of trade with respect to air distance is -0.82. As time progresses and technology develops, this elasticity grows in magnitude, thereby making trade more sensitive to air distance. In the last period of our sample, 2016-2020, this elasticity rises above one in absolute value. A 1% increase in air distance is associated with a 0.82% decline in trade flows in 1995 and a 1.08% decline 20 years later. The change in elasticity from one time period to next is also highly statistically significant.

The rest of the specifications deliver similar results both qualitatively and quantitatively. In columns (2) and (5), where we include pair fixed effects, only differentiated impacts over time are identified and all identification comes from within pair variations in trade. Column (6), where we control for country-year effects specific to a product via product-exporter-year and product-importer-year effects, is our most stringent specification. In all specifications, our results continue to hold—trade flows become more sensitive to air distance over time and these changes are significant.

Appendix B shows that even though our results are robust to including sea distances, we can make a case for their exclusion in the baseline. Further, product-country-year effects may contaminate our trade predictions with variation at the level of our dependent variable in the second stage. Therefore, we use estimates in column (4) in Table 3 for prediction of trade flows. These predictions are used to estimate the instrumental variable regression, the results of which are presented in the next section.

6 Regulatory Diffusion Results

We first estimate Equation (2) via OLS. Table 4 reveals a positive association between the fraction of a commodity's exports that comply with a certain regulation and the domestic adoption for that same product-regulation pair. The coefficient on our variable of interest, AE, ranges from 0.18 in our most saturated model, in column (3), to 0.42 and is statistically significant at the 0.1% level across specifications. The observed estimates imply that a one s.d. increase in affected exports of a country, i.e., roughly 12.27 percentage points (p.p.), is associated with a 2.26-5.10 basis points (b.p). increase in the probability of domestic adoption. Although the size of the effects is small, the economic magnitude is sizeable, corresponding to 10.02-22.61% of average adoption. We also find a positive and significant correlation between CP and the probability of adoption, suggesting that countries tend to match the standards of their closest export competitors (Simmons and Elkins, 2004).

While the results in Table 4 provide suggestive evidence of our proposed mechanism, a diffusion channel like physical proximity that influences both trade and regulation adoption would render AE endogenous. To establish causality, we instrument AE with $AirDistance\ IV$ constructed using trade flows predicted by time-varying air distances as described in Section 3.2. Our benchmark IV estimates of Equation (2) are in Table 5. Panel A reports the first stage, where we find that the instrument strongly correlates with AE across all specifications, with the F-statistics well above the threshold for weak IVs. A 1 p.p. increase in

Table 4: Estimation of Regulatory Diffusion - OLS

This table reports output from the estimation of our baseline specification described in Equation (2) via OLS. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, AE, is the fraction of exports of a product that must comply with a NTM. CP is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 for details on construction of variables. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

	Adopted (%)		
	(1)	(2)	(3)
AE	0.42	0.34	0.18
	(38.49)***	(47.33)***	(22.21)***
CP	1.19	1.26	0.42
	(49.60)***	(66.61)***	(22.00)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	125,949,101	125,949,101	125,949,101
Adjusted R^2	0.07	0.31	0.36

affected exports as predicted by time-varying air distances is associated with 0.86-0.87 p.p. increase in actual affected exports.

Panel B shows that the coefficient on AE in the second stage is positive and highly significant in all models. Based on the IV estimates, a one s.d. increase in affected exports leads to a 3.96-7.92 b.p increase in the probability of adoption, corresponding to a 17.56-35.11% increase relative to mean adoption. As a result of a separate diffusion channel that positively influences both regulation adoption and trade, we expect that the OLS estimates would be upward biased. On the contrary, we find that the IV coefficients on AE are larger than their OLS counterparts, suggesting a downward bias in the empirical correlation between AE and the probability of adoption. In fact, the IV point estimates are about 50% larger in magnitude than the OLS point estimates. Further, the Wu-Hausman test reveals that OLS

Table 5: Estimation of Regulatory Diffusion - AirDistance IV

This table reports output from the estimation of our baseline specification Equation (2) via IV regression. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, *AE*, is the fraction of exports of a product that must comply with a NTM. We instrument this variable with *AirDistance IV*, which uses predicted bilateral trade flows from gravity regressions that use countries' air distances. *CP* is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 for details on construction of variables. Panels A and B report the first and second stages of the estimation, respectively. The test for weak instruments yields robust F-statistics above the cutoff of 104 (Lee et al., 2022). Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

Panel A. First Stage

	AE (%)		
	(1)	(2)	(3)
AirDistance IV	86.24	87.15	85.82
	(1,207.15)***	(1,159.30)***	(1,294.72)***
CP	−0.51	0.19	−2.54
	(−7.99)***	(2.91)**	(−45.88)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	118,047,211	118,047,211	118,047,211
F-statistic	207,741,149	238,928,132	194,882,121
Adjusted R^2	0.75	0.77	0.80

Panel B. Second Stage

	Adopted (%)		
	(1)	(2)	(3)
AE (AirDistance IV)	0.65	0.49	0.32
	(44.08)***	(50.95)***	(28.50)***
CP	1.07	1.21	0.40
	(43.42)***	(62.28)***	(20.67)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	118,047,211	118,047,211	118,047,211
Wu-Hausman Statistic	6,919.80	3,879.90	1,872.60
Wu-Hausman test *p*-value	0.00	0.00	0.00
Adjusted R^2	0.08	0.31	0.37

and IV estimates are statistically significantly different.

Two possibilities explain the downward bias in the OLS estimates. First, trade is an imperfect measure of global economic integration via knowledge spillovers that also induce adoption of similar regulations across countries. This measurement error would lead to an attenuation bias in the OLS estimates. Second, adoption of NTMs may in practice hinder international trade (Bao and Qiu, 2012; Yue, 2021), thereby creating a downward bias in the OLS estimates.

Finally, we discuss how the interpretation of our results relies on the treatment of EU countries in our sample. The EU countries apply the principle of mutual recognition for TBT regulations, which ensures that goods in compliance with regulations of one country can also be sold in another even in the absence of perfect compliance with the regulations of the latter (Official Journal of the European Union, 2019). This application of mutual recognition leads the regulations to diffuse much faster within the EU. Therefore, results in Tables 4 and 5 are obtained by including European Union as one entity, implying that the reported estimates capture only extra-EU diffusion and not the unconstrained mechanical diffusion in regulations within the EU.[9]

Our baseline results confirm that importer pressure via compliance with a standard when exporting leads to higher internal adoption of a wide array of regulations and in a wide range of commodities. We show that our estimates are not contaminated by alternative diffusion channels like competitor pressure, institutional proximity, or specialization in certain products, tariff reductions, secular trends in adoption, and country characteristics specific to a product-regulation by controlling for various combinations of fixed effects and economic indicators. We are able to identify the impact of importer pressure off of the geographic

[9]In Appendix D, we provide further evidence that our results do not depend on the EU. Missing values of predicted trade flows upon estimating Equation (3) renders about 6% observations for *AirDistance IV* (used in Table 5) missing relative to the OLS (Table 4). However, this number is only at about 2% when we move from OLS to AirDistance IV estimation in Appendix D. This gap is explained by aggregation of trade flows at the EU level and treatment of a missing predicted trade flow for any EU country as a missing trade flow for the EU as a whole. Thus, when we perform the IV estimation including EU, the matrix in the spatial lag term would contain missing values when not just any EU country has missing exports to another country but also when any other country has missing exports to the EU. On excluding EU, however, these two forms of missingness disappear.

component of trade that varies with time.

7 Robustness

Given the spatial lag structure of our independent variable of interest, we devise two novel tests to assess the robustness of our results. In one, we switch the network employed and construct alternative measures of network centrality. In the other, we randomize over adoption by countries. The former is akin to manipulating the matrix while the latter is akin to manipulating the adoption vector in constructing the spatial lag, $AE = W_{pt}y_{prt}$, both with the goal to demonstrate that it's precisely importer pressure driving our results. In Appendices D and E, we report further robustness checks that alleviate concerns that our results are driven by the European Union or feedback effects from the adoption of a regulation to trade.

7.1 Alternative Measures of Network Centrality

We assess the soundness of our baseline results by estimating Equation (2) after replacing AE with other common measures of network centrality (Freeman, 1978; Agneessens, Opsahl and Skvoretz, 2010). In addition, by considering different kinds of networks when constructing these alternative measures, we are able to determine that it's the connectedness in exports to countries *that have adopted a regulation* that drives diffusion, rather than connectedess only via trade relations. Therefore, this exercise serves not only as a robustness check to alternative metrics, but also as a placebo test by showing that what matters for domestic adoption is not major export relations in a trade network, but rather leading export relations with countries that have a regulation in place.

Since the focus of our analysis is on regulatory diffusion from importers to exporters, we consider directed yearly trade networks where a connection from country i to country j exists when i exports to j. We use two measures of centrality that are common in the networks literature: degree and harmonic. Degree centrality simply counts the number of links originating at each node (country). Harmonic centrality is a measure of closeness that accommodates isolated nodes and groups of nodes (Latora and Marchiori, 2001; Saxena and Iyengar, 2020).[10] We provide details on these centrality measures in Appendix C.

We incorporate these measures in two ways. First, we focus solely on overall trade relationships, building yearly networks of exports across countries for each commodity. In this scenario, our measures will be at the product-country-year level and capture how well-connected, i.e., how *central*, a country is as an exporter of each product. Second, for each regulatory standard, we construct yearly networks of exports *only to countries with the regulation in place.* Here, for country i to be linked to country j, i must export to j and j must have the regulation of interest in place. Thus, the centrality score will be at the product-regulation-country-year level and gauge countries' centrality in exports of each product that comply with each regulation. Since our proposed channel of adoption is diffusion from importers with regulations in place, we expect to find sharper results in the latter networks.

Networks can also be unweighted or weighted, with the latter assigning weights that reflect the strength of the connection to each link. In our study, the weight of a link from i to j is j's share in i's total exports. We apply weighting only to the harmonic measure because a weighted degree measure sums the weights of a node's connections. Therefore, in our trade-based networks, this measure would simply add to one for each product-country-year with positive exports. In our adoption-based networks, a weighted degree measure would equal the share of exports that go to countries with the regulation in place, coinciding with our original importer pressure measure, AE.[11]

We report the results of this exercise in Table 6. In panel A, where the measures are constructed in trade-based networks, we cannot use product-country-year fixed effects as these would absorb the independent variables.[12] Although we find positive and significant coefficients in columns (1) and (4), these results no longer hold on controlling for confounders by

[10] Closeness scores measure how close each node is with all others in the network. We find cases of isolated nodes and groups of nodes in our data due to countries that do not export certain commodities.

[11] See Appendix C for details on the weighting of the harmonic centrality measure.

[12] Note that the sample is still at the product-regulation-country-year level because each trade-based centrality measure is matched to multiple NTMs.

Table 6: Alternative Measures of Network Centrality

This table reports output from the estimation of Equation (2) replacing *AE* with alternative measures of network centrality. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. *CP* is the fraction of the top 10 export competitors that has that NTM in place. See Section 3 and Section 7.1 for details on construction of variables. Panel A uses centrality scores at the product-country-year level, which measure countries' centrality in the overall export networks of the products in the sample. Panel B uses centrality scores at the product-regulation-country-year level, which, for each regulation-product pair, measure centrality in exports to countries with the regulation in place. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

Panel A. Trade-based Networks

	Adopted (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Degree	2.41	−0.01	−0.40						
	(55.91)***	(−0.63)	(−10.28)***						
Harmonic				0.03	−0.01	−0.05			
				(3.83)***	(−1.85)	(−8.04)***			
Weighted Harmonic							−1.88	−0.38	−0.51
							(−25.72)***	(−7.91)***	(−8.16)***
CP	1.14	1.58	0.55	1.26	1.58	0.56	1.33	1.60	0.56
	(46.88)***	(74.60)***	(26.28)***	(51.18)***	(74.72)***	(26.67)***	(53.81)***	(75.21)***	(26.70)***
HS6-NTM-Country FE	Y	N	Y	Y	N	Y	Y	N	Y
HS6-NTM-Year FE	Y	N	Y	Y	N	Y	Y	N	Y
NTM-Country-Year FE	N	Y	Y	N	Y	Y	N	Y	Y
HS6-Country-Year FE	N	N	N	N	N	N	N	N	N
Observations	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101
Adjusted R^2	0.07	0.20	0.26	0.07	0.20	0.26	0.07	0.20	0.26

Panel B. Adoption-based Networks

	Adopted (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Degree	23.81	12.32	8.64						
	(74.26)***	(61.09)***	(34.30)***						
Harmonic				14.68	8.36	5.31			
				(82.49)***	(71.31)***	(38.26)***			
Weighted Harmonic							38.77	33.80	18.83
							(41.11)***	(52.62)***	(25.62)***
CP	0.83	1.01	0.37	0.76	0.83	0.33	1.15	1.20	0.40
	(34.04)***	(54.02)***	(19.37)***	(31.71)***	(45.46)***	(17.60)***	(48.45)***	(64.16)***	(21.35)***
HS6-NTM-Country FE	Y	N	Y	Y	N	Y	Y	N	Y
HS6-NTM-Year FE	Y	N	Y	Y	N	Y	Y	N	Y
NTM-Country-Year FE	N	Y	Y	N	Y	Y	N	Y	Y
HS6-Country-Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Observations	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101	125,949,101
Adjusted R^2	0.07	0.31	0.36	0.07	0.31	0.36	0.07	0.31	0.36

adding additional fixed effects in columns (2), (3), (5), and (6). In contrast, all the estimates are consistently positive and significant in panel B, where the measures are constructed in adoption-based networks. Based on our strictest models, we estimate that a one s.d. increase in *Degree*, *Harmonic*, and *Weighted Harmonic* is associated with 7.43, 7.10, and 3.03 b.p. increase in probability of domestic adoption, which corresponds to 34.33%, 32.85%, and 14.00% of average adoption, respectively. Thus, while we find lack of evidence in the trade networks, we find consistent evidence for diffusion in adoption networks regardless of how we measure importer pressure.

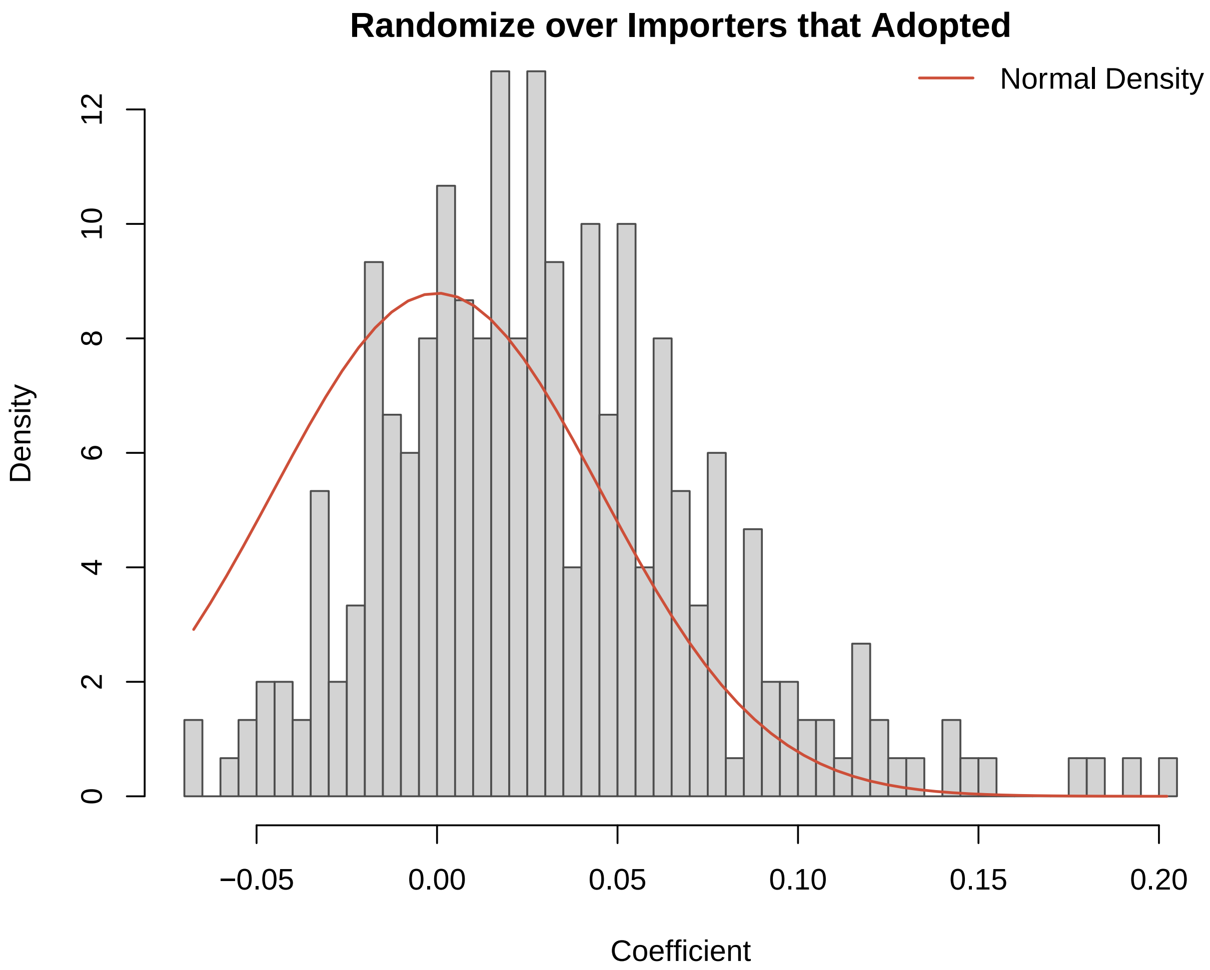
7.2 Random Assignment of Adoption

We conduct a placebo test to verify that the positive and significant effect of affected exports on domestic adoption is indeed driven by importer pressure rather than an omitted variable. For each product-regulation combination, we randomize over which countries adopt the regulation in each year while keeping the overall *proportion* of countries that adopted each year at the true level. Then, we use this randomized adoption vector with the true trade matrices to construct the spatial lag variable, AE, as described in Section 3.1. In this way, we break the importer pressure channel of diffusion by allowing countries to randomly adopt a regulation while preserving the overall level of adoption, and thereby omitted variation, at the product-regulation-year level. We control for omitted variation at this level by estimating our baseline specification controlling for all possible fixed effects including product-regulation-year effects (Equation (2)). We repeat this random assignment of adoption to the 92 countries in our sample 300 times. Figure 2 shows the distribution of coefficients from the 300 trials.

We find that the distribution of coefficients is centered around a value close to zero and the mean of these coefficients is significantly different from the coefficient from true adoption, 0.18, at the 0.1% level. Even this partial randomization in adoption, along only the country dimension, reduces the size of the mean coefficient to only about 17% of the true estimate, thereby alleviating the concern that our true estimate picks omitted variation.

Figure 2: Random Assignment of Adoption

This figure presents the distribution of coefficients from estimation of the baseline specification after randomizing over importers that adopted each regulation in each product in a year. See Section 7.2 for details. The mean over 300 iterations is 0.0307 ($s.d. = 0.0454$)



8 Heterogeneity in Regulatory Diffusion

In Section 6 we show that countries are more likely to domestically adopt regulations that they largely comply with when exporting. Naturally, many factors can modulate the intensity of this diffusion process. In this section, we exploit the multidimensional nature of our dataset to test heterogeneity in regulatory diffusion as a function of regulation, country, and product characteristics. To do so, we interact AE with each cross-sectional variable of interest in Equation (2). The coefficients on the interaction terms inform us whether and how regulatory diffusion responds to the factors of interest.[13]

8.1 By Regulation Type

We expect regulatory diffusion induced by exports to be stronger for regulations for which compliance is easier to verify. We posit that this is the case for product standards—regarding physical attributes of the final product—as opposed to process standards, which pertain to manufacturing processes. We classify NTM codes into product or process regulations based on the description of the measures, available in United Nations Conference on Trade and Development (2019*a*) and summarized in Table 1. We classify as product regulations those NTMs for which compliance is verifiable in the final product and at the destination country. Out of the 19 TBTs in our sample, we consider 7 as clear product regulations: B310, B320, B330, B600, B700, B810, and B820, while the rest as process regulations. Therefore, *Product Regulation* is an NTM-level indicator that equals one for NTMs that belong to the aforementioned group, and zero otherwise.

In Columns (1)-(3) of Table 7, the coefficient on AE alone suggests that process regulations also diffuse through export networks. Nevertheless, the positive, significant coefficients on the interaction term imply that diffusion of product regulations occurs 59.78%-124.14% faster than process regulations. Since compliance with product regulations is observable, manufacturers gain a competitive advantage by differentiating their products by meeting product standards (Greenhill, Mosley and Prakash, 2009). In contrast, process regulations are harder to monitor, so adoption by a country's importers provides only a weak incentive for domestic adoption.

Although we assign all NTMs in our sample into product or process standards in the main analysis, some regulations are, in fact, quite ambiguous to classify. In particular, the categories B83, B84, B85, and B89 may be interpreted as product standards *about* processes. For instance, it may be easy to verify conformity with traceability requirements on the final

[13] In all of our heterogeneity tests, the coefficients on the cross-sectional variables cannot be estimated as they are absorbed by the fixed effects.

product, as required by the B85 standards, without being able to determine if the listed locations are reported accurately. Similarly, certification or inspection of the product, as required by B83-84, is allowed even in the exporting country, thereby making the verification of compliance with the underlying processes essentially ineffective. After excluding these categories entirely, our results are qualitatively similar, albeit with slightly smaller coefficients (See Table A.11).

Table 7: Heterogeneity in Regulation Adoption

This table reports output from the estimation of Equation (2) via IV regression interacting *AE* with cross-sectional variables. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, *AE*, is the fraction of exports of a product that must comply with a NTM. We instrument this variable with *AirDistance IV*, which uses predicted bilateral trade flows from gravity regressions that use countries' air distances. *Product Regulation* is an indicator of the NTM belonging to the group of product standards. *Open Country* is an indicator of the country being above median openness as of 1995. *Final Product* is an indicator of the HS6 category being classified as a final product instead of an intermediate input. *CP* is the fraction of the top 10 export competitors that have that NTM in place. See Sections 3 and 8 for details on construction of variables. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at HS6-country and HS6-year level.

	Adopted (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AE (AirDistance IV)	0.45	0.29	0.24	0.45	0.41	0.21	0.56	0.20	0.16
	(31.50)***	(26.14)***	(18.87)***	(30.78)***	(40.88)***	(19.23)***	(29.39)***	(16.25)***	(11.53)***
AE (AirDistance IV) × *Product Regulation*	0.34	0.36	0.14						
	(18.96)***	(26.55)***	(9.06)***						
AE (AirDistance IV) × *Open Country*				0.42	0.19	0.26			
				(14.21)***	(9.14)***	(11.32)***			
AE (AirDistance IV) × *Final Product*							0.23	0.73	0.38
							(6.61)***	(30.82)***	(14.25)***
CP	1.06	1.19	0.40	1.05	1.21	0.40	1.03	1.19	0.40
	(42.94)***	(61.22)***	(20.37)***	(42.48)***	(62.39)***	(20.70)***	(38.31)***	(56.45)***	(18.68)***
HS6-NTM-Country FE	Y	N	Y	Y	N	Y	Y	N	Y
HS6-NTM-Year FE	Y	N	Y	Y	N	Y	Y	N	Y
NTM-Country-Year FE	N	Y	Y	N	Y	Y	N	Y	Y
HS6-Country-Year FE	N	Y	Y	N	Y	Y	N	Y	Y
Observations	118,047,211	118,047,211	118,047,211	117,549,067	117,549,067	117,549,067	95,329,716	95,329,716	95,329,716
Wu-Hausman Statistic	3,632.50	2,138.80	960.30	3,664.70	2,047.60	1,110.00	3,162.60	2,535.20	1,057.50
Wu-Hausman test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Adjusted R^2	0.08	0.31	0.37	0.08	0.31	0.37	0.08	0.32	0.38

8.2 By Openness of Countries

Adoption of regulations through importer pressure can also depend on the openness of a country to international trade. Arguably, a country with minor international trade flows relative to its size will have lower incentives to match the regulations of its export partners. To test this notion, we construct a country-level indicator, *Open Country*, that equals one if a country was above the median openness as of 1995. Data on openness, measured as the total trade value of a country scaled by its GDP, are from World Bank and OECD – processed by Our World in Data. We use this time-invariant indicator based on the first year of our sample to alleviate concerns that openness can endogenously respond to the evolution of a country's regulatory stringency over the years. Columns (4)-(6) in Table 7 show that the coefficients for both *AE* and its interaction with *Open Country* are positive and significant. Although our evidence suggests regulatory diffusion in both relatively closed and open countries, the diffusion is significantly stronger in the latter, where the increase in the probability of internal adoption due to increase in compliance in exports is 45.94%-123.81% higher.

8.3 By Product Type

Product characteristics like end-use can also play a role in the intensity of regulatory diffusion through export networks. We conjecture that diffusion is stronger for final products than for intermediate inputs. Compliance with a regulation is easier to verify in the final product by a consumer than in an intermediate input to manufacturing. Therefore, while manufacturers can gain a competitive advantage by complying with a regulation in the final product, the incentives to comply are weaker for intermediate inputs, which are to some extent protected from complete verifiability.

We obtain data on end-use for each HS6 category from the Fifth Revision of Broad Economic Categories (United Nations Statistical Division, 2016), which classifies products either for final consumption, as intermediate inputs, or as capital goods. We exclude ambiguous product categories for which the end-use was assigned as both final consumption and intermediate inputs from our sample. We further exclude products for which end-use is not assigned and capital goods from our sample. Thus, the product-level indicator *Final Product* assumes a value of one if the product's end-use is final consumption, otherwise zero. Columns (7)-(9) of Table 7 show that the coefficients on both *AE* and its interaction with *Final Product* are positive and significant. While we find evidence of regulatory diffusion in both intermediate and final products, the diffusion is 41.67-357.87% stronger in the latter.

9 Conclusion

Although imposing regulations on domestic producers can adversely affect economic outcomes, regulations are necessary to meet the health and environmental protection goals of a country. Potentially, when a country is pressured to comply with a regulation imposed at its export destinations, the gains to domestic adoption can outweigh the compliance costs, encouraging further adoption in the exporting country. Thus, economic integration and international competition can strengthen the adoption of regulations by facilitating diffusion from importing to exporting countries in an international trade network.

We quantify the diffusion in Technical Barriers to Trade, required for admissibility of imports, through international trade networks. We show that an increase in the extent to which a country complies with a standard while exporting significantly increases the probability of adoption of that standard domestically. Exploiting our high-dimensional data, we establish that this diffusion process is stronger for standards and products with observable compliance and countries that are relatively more open to international trade.

The richness of our data and our identification strategy allow us to go well beyond previous studies, significantly expanding our understanding of trade-based regulatory diffusion. Our collective evidence lends support to economic integration as a device to incentivize an international regulatory "race to the top", highlighting the role of major importers in triggering this process. We believe that this is a promising line of research with the potential to assist policy coordination among countries in an increasingly globalized world.

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Online Appendix to "Trade Networks and Diffusion of Regulatory Standards"

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A Beta Regressions

The coverage ratio of a regulation is defined as the fraction of within-sample trade in Medicaments affected by that regulation, thus taking values on the standard unit scale $[0, 1]$. We use coverage ratios as the dependent variable and apply the beta regression technique for modelling rates and proportions from Ferrari and Cribari-Neto (2004).[14] The model is based on the assumption that coverage ratio is Beta-distributed, $y_t \sim \mathcal{B}(\mu_t, \phi),\ t = 1995, ..., 2019$; and the mean, μ_t, is related to the regressor, t, through a linear predictor and a link function:

$$g(\mu_{rt}) = \beta_0 + \beta_1 t, \quad \forall r, \tag{5}$$

where t stands for Year, and $g(.) : (0, 1) \mapsto \mathbb{R}$ is the logit link function for the mean, μ_{rt}. For simplicity, we assume an identity link function for the precision parameter, ϕ. Figure A.1 shows that the coverage ratio of most regulations hit the 5% threshold by 1995. The regulations to reach this threshold the latest are Tolerance limits, Transport and storage requirements, and Origin of materials, which are also among the slowest regulations when considering only the fraction of countries that adopted over time. We observe similar patterns in the speeds of evolution of coverage ratios across regulations, with product regulations being the fastest (See Table A.1).

[14] Actually, beta regression is used in modelling continuous variable y that lies in the open standard unit interval $(0, 1)$. In our sample, since some observations lie at the extremes 0 and 1, we apply the standard transformation $(y(n - 1) + 0.5)/n$, with sample size n, following Smithson and Verkulien (2006) and Cribari-Neto and Zeileis (2010).

Figure A.1: Beta Fits for Coverage Ratio

Each panel in this figure shows of the evolution of Coverage Ratio of each regulation, as specified by NTM code, over the years. Coverage ratio is defined as the fraction of within-sample trade that is affected by a regulation. The blue lines depict the time series observed in data, whereas the green lines are the fitted values from Beta regressions specified in Equation (5). The dotted line represents the 5% threshold.

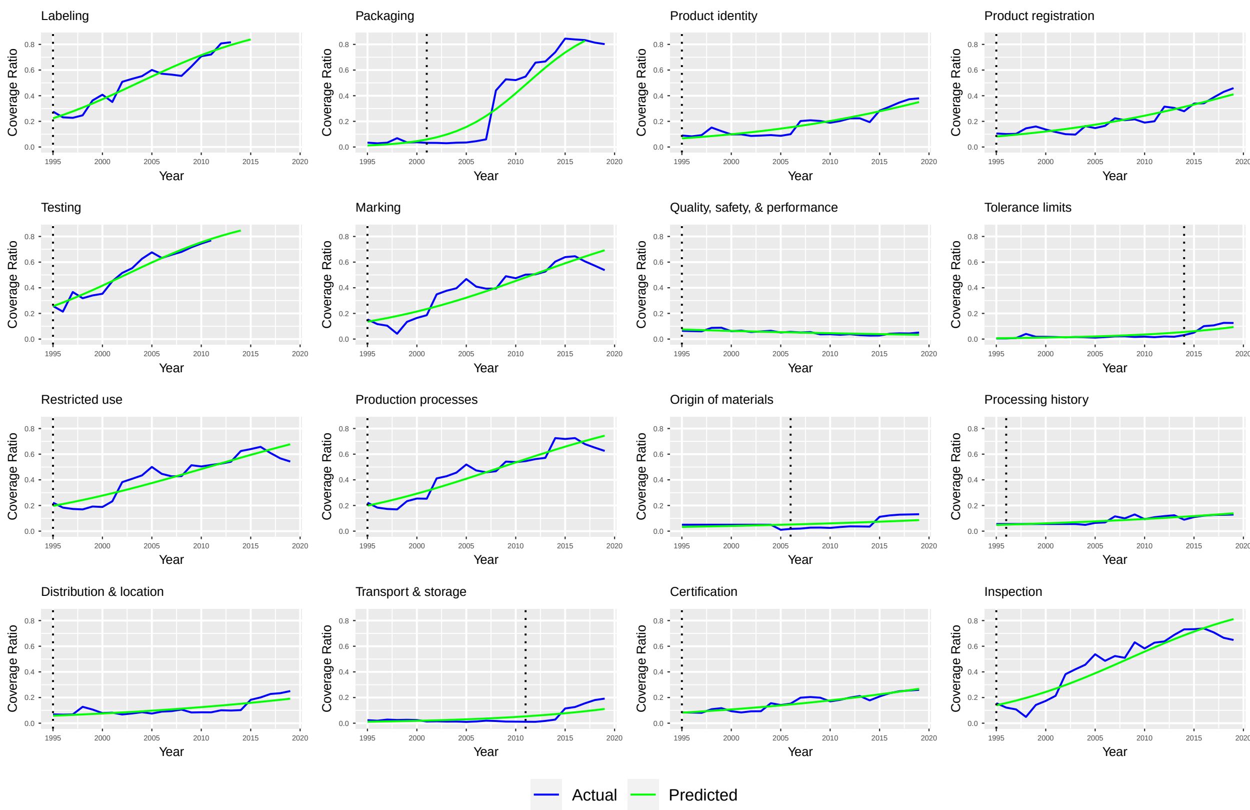

Table A.1: Beta Regressions for Coverage Ratio

This table reports the output of Beta regressions specified in Equation (5), where each column represents a type of regulation, as specified by NTM code. The dependent variable is the coverage ratio of the regulation that varies by year. We define coverage ratio as the fraction of within-sample trade that is affected by a regulation. The independent variable is year. Significance levels are indicated by * p<0.05; ** p<0.01; *** p<0.001.

	Adopted							
	Tolerance limits	Restricted use	Labeling	Marking	Packaging	Production processes	Transport/Storage	Quality/Safety/Performance
Year	0.15	0.04	0.11	0.07	0.27	0.06	0.13	−0.02
	(9.40)***	(6.05)***	(12.53)***	(6.64)***	(18.48)***	(8.30)***	(6.61)***	(−2.98)**
Constant	−297.43	−88.26	−225.94	−144.84	−545.19	−121.03	−265.70	35.98
	(−9.48)***	(−6.12)***	(−12.53)***	(−6.69)***	(−18.50)***	(−8.35)***	(−6.67)***	(2.78)**
Observations	25	25	25	25	25	25	25	25
Log Likelihood	68.79	40.04	32.81	34.21	42.77	38.19	54.07	71.57
$\hat{p} \geq 5\%$	2011	1995	1995	1995	2003	1995	2009	1995
$\hat{p} \geq 10\%$	2016	1995	1995	1995	2006	1995	2015	-
$\hat{p} \geq 20\%$	-	1999	1995	2006	2009	1998	-	-
$\hat{p} \geq 40\%$	-	-	2004	-	2012	2014	-	-

	Product identity	Registration	Testing	Certification	Inspection	Origin of materials	Processing history	Distribution/Location
Year	0.12	0.13	0.12	0.09	0.10	0.08	0.07	0.08
	12.82***	15.80***	21.02***	10.18***	11.58***	5.48***	7.95***	10.29***
Constant	−241.76	−257.90	−237.51	−175.29	−199.43	−163.58	−151.99	−162.99
	−12.87***	−15.84***	−21.00***	−10.25***	−11.62***	−5.56***	−8.04***	−10.40***
Observations	25	25	25	25	25	25	25	25
Log Likelihood	39.47	40.90	45.37	41.41	36.18	49.57	49.43	50.95
$\hat{p} \geq 5\%$	1995	1995	1995	1995	1995	2003	1995	1995
$\hat{p} \geq 10\%$	1999	1998	1995	1997	1995	2012	2005	2003
$\hat{p} \geq 20\%$	2006	2004	1995	2006	2001	-	2016	2013
$\hat{p} \geq 40\%$	2014	2012	2001	2018	2011	-	-	-

B Air and Sea Distances

We produce an alternative instrument for affected exports by allowing not just effective air distances but also the effective sea distances to change with time. As air transport technology develops, we expect trade to become more sensitive to air distances and less sensitive to sea distances, especially for country pairs with no land routes (Feyrer, 2019*b*). To obtain predicted trade flows, we estimate the following gravity equation, found by extending Equation (3) with sea distances, the coefficient of which varies over time:

$$\ln \frac{trade_{pijt}}{s_{pt} GDP_{it} GDP_{jt} s_{pt}} = \beta_{air,t} \times \ln \text{airdist}_{ij} + \beta_{sea,t} \times \ln \text{seadist}_{ij} + \boldsymbol{\beta}\mathbf{X_{ij}} + \mu_{pi} + \mu_{pj} + \mu_{it} + \mu_{jt} + \epsilon_{pijt} \tag{6}$$

We use the sea distance data constructed by Feyrer (2019*b*), which excludes landlocked countries and oil exporters. Further, for large countries, the United States and Canada, two sea distances, one for the east coast and one for the west coast, are available with each of their trade partners. In estimating the gravity regressions, we tackle this by splitting the bilateral trade flows of the US and Canada into two, with 80% of the trade attributed to the east coast and the rest to the west coast, following Feyrer's baseline strategy.[15] Post-estimation, we sum the predicted flows for the two coasts to obtain the predicted flows for the US and Canada as a whole. We do the same for the European Union countries: obtain the predictions for individual EU countries before aggregating those to obtain the predictions for trade flows of the EU as a whole. For a cleaner comparison between the number of observations used in estimating Equation (3) and Equation (6), we keep the split between the two coasts for the US and Canada and the individual EU countries when estimating the former even though it does not involve using the sea distance data.

Table A.2 shows that across all specifications, the size of elasticity of trade with respect to air distance increases while that for sea distance decreases over time. Although these findings

[15] Feyrer (2019*b*)'s results are robust to using only east coast sea distances, changing the weights between the two coasts, and removing US and Canada altogether.

qualitatively conform with Feyrer's, quantitatively trade is less sensitive to sea distance for our sample period, 1995-2020, which is later than Feyrer's in 1950-1997. By the beginning of our sample period, in 1995, air transport technology may have advanced to the extent that, with further development, countries more reliant on air transport relative to sea transport don't see a differentiated impact. In support of this argument, we find that trade is about half as sensitive to sea distance than air distance throughout our sample period. Also, while the changes in sensitivity of trade with respect to air distance is statistically significant from one time period to the next, this is not always the case for sea distances. As air transport develops, explanatory power of sea distance falls.

Unlike Feyrer (2019*b*), where the rise in elasticity with respect to air distance is half as large on including sea distances, we find that this rise is almost the same, if not larger, in magnitude regardless of whether we include or exclude sea distances. Importantly, including sea distances also severely limits our observations in gravity regressions as almost 27% of the sea distance observations are missing.

As discussed in Section 3.3 and Section 4, the use of sea distances to predict bilateral trade flows as part of our IV strategy significantly limits our sample by excluding landlocked countries and oil exporters. We nevertheless estimate Equation (2) by instrumenting AE with *Air & Sea Distance IV*, which is constructed using trade flow predictions found by estimating Equation (6), thus following Feyrer (2019*b*) more closely.

Panel A in Table A.3 shows a very good fit in the first stage, with the instrument strongly predicting the actual values of AE. The second stage, in panel B, further lends support to our baseline results. Across all specifications, the coefficient on instrumented AE is positive and significant at the 0.1% level. The size of the estimated effects, however, are smaller than our baseline IV results. Specifically, the estimates in Table A.3 imply that a one s.d. increase in AE leads to 1.24-2.88 b.p. higher probability of domestic adoption by exporting countries, which corresponds to 5.49%-12.78% of average adoption.

However, this fall in magnitude of the impact of affected exports is due to differences in the samples rather than differences in the predictive power of the instruments. To show this, we

Table A.2: Gravity Regression Results including Air and Sea Distances

This table reports results from the estimation of Equation (6). Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are clustered at exporter-importer level.

	ln(trade)					
ln(airdist) $\times\mathbb{1}(1995 \leq year \leq 2000)$	-0.64 (-12.62)***		-0.68 (-14.15)***	-0.64 (-11.90)***		-0.64 (-10.73)***
ln(airdist) $\times\mathbb{1}(2001 \leq year \leq 2005)$	-0.70 (-13.41)***	-0.06 (-3.22)**	-0.72 (-13.97)***	-0.77 (-13.88)***	-0.13 (-10.10)***	-0.79 (-14.31)***
ln(airdist) $\times\mathbb{1}(2006 \leq year \leq 2010)$	-0.77 (-15.00)***	-0.13 (-5.46)***	-0.76 (-14.88)***	-0.80 (-15.89)***	-0.17 (-10.31)***	-0.84 (-16.44)***
ln(airdist) $\times\mathbb{1}(2011 \leq year \leq 2015)$	-0.88 (-17.68)***	-0.25 (-8.53)***	-0.87 (-17.09)***	-0.87 (-18.84)***	-0.24 (-10.97)***	-0.91 (-19.75)***
ln(airdist) $\times\mathbb{1}(2016 \leq year \leq 2020)$	-0.95 (-19.40)***	-0.33 (-9.83)***	-0.91 (-17.97)***	-0.85 (-18.53)***	-0.23 (-9.72)***	-0.90 (-20.15)***
ln(seadist) $\times\mathbb{1}(1995 \leq year \leq 2000)$	-0.35 (-7.58)***	-0.76 (-6.30)***	-0.34 (-7.64)***	-0.26 (-5.60)***	-0.66 (-5.35)***	-0.27 (-5.31)***
ln(seadist) $\times\mathbb{1}(2001 \leq year \leq 2005)$	-0.32 (-6.83)***	-0.72 (-5.90)***	-0.31 (-6.79)***	-0.26 (-5.40)***	-0.66 (-5.48)***	-0.27 (-5.62)***
ln(seadist) $\times\mathbb{1}(2006 \leq year \leq 2010)$	-0.27 (-6.02)***	-0.67 (-5.64)***	-0.28 (-6.08)***	-0.27 (-5.99)***	-0.67 (-5.77)***	-0.28 (-6.16)***
ln(seadist) - $\times\mathbb{1}(2011 \leq year \leq 2015)$	-0.24 (-5.35)***	-0.64 (-5.49)***	-0.25 (-5.58)***	-0.27 (-6.58)***	-0.69 (-6.06)***	-0.29 (-6.87)***
ln(seadist) $\times\mathbb{1}(2016 \leq year \leq 2020)$	-0.20 (-4.37)***	-0.59 (-5.13)***	-0.22 (-4.80)***	-0.30 (-7.09)***	-0.70 (-6.17)***	-0.32 (-7.67)***
Bilateral controls	Y	N	Y	Y	N	Y
Partner-Year controls	N	N	Y	N	N	N
HS6-Partner FE	Y	Y	Y	Y	Y	N
Year FE	Y	Y	Y	N	N	N
Partner-Year FE	N	N	N	Y	Y	N
HS6-Partner-Year FE	N	N	N	N	N	Y
Exporter-Importer FE	N	Y	N	N	Y	N
Observations	120,429,398	120,429,398	120,429,398	120,429,398	120,429,398	120,429,398
Adjusted R^2	0.67	0.69	0.67	0.68	0.70	0.71

re-estimate OLS and AirDistance IV regressions after restricting the sample to observations with non-missing sea distances. The results in Tables A.4 and A.5, which are estimated on the sample of Table A.3, are analogous to Tables 4 and 5, respectively. Again, we find positive and significant coefficients on AE across all specifications, but with estimates that are smaller in size. Notably, estimates in Tables A.5 and A.3 hardly differ in size, confirming that the instruments perform similarly within our sample period. Moreover, the OLS estimates in Table A.4 are consistently smaller than their IV counterparts in Tables A.5 and A.3,

Table A.3: Estimation of Regulatory Diffusion - Air and Sea Distance IV

This table reports output from the estimation of our baseline specification Equation (2) via IV regression. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, *AE*, is the fraction of exports of a product that must comply with a NTM. We instrument this variable with *Air & Sea Distance IV*, which uses predicted bilateral trade flows from gravity regressions that use countries' air and sea distances. *CP* is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 and Appendix B for details on construction of variables. Panels A and B report the first and second stages of the estimation, respectively. The test for weak instruments yields robust F-statistics above the cutoff of 104 (Lee et al., 2022). Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

Panel A. First Stage

	AE (%)		
	(1)	(2)	(3)
Air & Sea Distance IV	90.20	90.03	89.69
	(1,204.50)***	(1,108.52)***	(1,270.30)***
CP	1.11	0.72	−0.91
	(16.06)***	(10.19)***	(−14.63)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	83,758,783	83,758,783	83,758,783
F-statistic	238,632,430	257,112,104	225,749,362
Adjusted R^2	0.80	0.82	0.84

Panel B. Second Stage

	Adopted (%)		
	(1)	(2)	(3)
AE (Air & Sea Distance IV)	0.18	0.24	0.10
	(14.50)***	(24.51)***	(9.92)***
CP	0.41	0.84	0.15
	(14.28)***	(34.36)***	(6.07)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	83,758,783	83,758,783	83,758,783
Wu-Hausman Statistic	215.90	339.60	93.20
Wu-Hausman test p-value	0.00	0.00	0.00
Adjusted R^2	0.10	0.32	0.39

reassuring the downward bias in our baseline results.

Table A.4: Estimation of Regulatory Diffusion - OLS. Non-missing Sea Distances.

This table reports output from the estimation of our baseline specification described in Equation (2) via OLS. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. We exclude the observations where *Air & Sea Distance IV* is missing. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, AE, is the fraction of exports of a product that must comply with a NTM. CP is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 and Appendix B for details on construction of variables. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

	Adopted (%)		
	(1)	(2)	(3)
AE	0.13	0.19	0.07
	(12.76)***	(22.38)***	(8.13)***
CP	0.42	0.85	0.15
	(14.62)***	(34.73)***	(6.20)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	83,758,783	83,758,783	83,758,783
Adjusted R^2	0.10	0.32	0.39

Table A.5: Estimation of Regulatory Diffusion - AirDistance IV. Non-missing Sea Distances.

This table reports output from the estimation of our baseline specification Equation (2) via IV regression. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. We exclude the observations where *Air & Sea Distance IV* is missing. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, *AE*, is the fraction of exports of a product that must comply with a NTM. We instrument this variable with *AirDistance IV*, which uses predicted bilateral trade flows from gravity regressions that use countries' air and sea distances. *CP* is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 and Appendix B for details on construction of variables. Panels A and B report the first and second stages of the estimation, respectively. The test for weak instruments yields robust F-statistics above the cutoff of 104 (Lee et al., 2022). Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

Panel A. First Stage

	AE (%)		
	(1)	(2)	(3)
Air & Sea Distance IV	90.24	90.10	89.75
	(1,204.52)***	(1,111.90)***	(1,274.98)***
CP	1.09	0.66	−0.93
	(15.76)***	(9.41)***	(−15.06)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	83,758,783	83,758,783	83,758,783
F-statistic	239,566,874	258,471,154	226,839,090
Adjusted R^2	0.80	0.82	0.84

Panel B. Second Stage

	Adopted (%)		
	(1)	(2)	(3)
AE (Air & Sea Distance IV)	0.18	0.23	0.10
	(14.37)***	(24.51)***	(9.91)***
CP	0.41	0.84	0.15
	(14.30)***	(34.37)***	(6.08)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	83,758,783	83,758,783	83,758,783
Wu-Hausman Statistic	192.30	337.30	90.90
Wu-Hausman test p-value	0.00	0.00	0.00
Adjusted R^2	0.10	0.32	0.39

C Construction of Centrality Measures

We provide more details on the construction of the two centrality measures used in Section 7.1. Degree centrality simply counts the number of links originating at each node. Hence, in the trade-based networks, a country's degree centrality is the number of export partners for each commodity. In the adoption-based networks, for each commodity-regulation pair, a country's degree centrality is the number of export partners with the regulation in place.

Harmonic centrality is a measure of closeness that accommodates isolated nodes and groups of nodes. According to this metric, a node will be more central the shorter the distances from it to all other nodes in a network. The measure *Harmonic* for node i is:

$$Harmonic_i = \sum_{j \neq i} \frac{1}{d(i,j)}, \tag{7}$$

where $d(i,j)$ is the number of nodes in the shortest path between i and j. The shortest path between any two nodes i and j in the network is the path from i to j crossing the fewest number of nodes. If there's no path between i and j, then $\frac{1}{d(i,j)} = 0$. To construct a weighted harmonic centrality measure, the shortest path between i and j minimizes the sum of weights rather than the number of links along all paths leading from i to j, and $d(i,j)$ becomes the sum of the weights along the shortest path. Therefore, the weights are interpreted as distances between two nodes. Since a country's share of exports to another measures the strength of the link, we use its inverse as weights for harmonic centrality.

For ease of interpretation, our centrality measures are normalized by the number of possible links that a node might have. In our framework, this is the number of countries in the network minus one. We divide the raw degree and harmonic centrality score by this number so that both measures take values between zero and one.

Panel B in Table 2 reports summary statistics on the centrality measures. Our trade-based centrality measures show that, on average, a country exports each product to 6.60% of the other countries in the sample and has a mean inverse path length of 22.85% to other countries in the unweighted measure and 1.64% in the weighted version. Unsurprisingly, these figures are much smaller in sparser adoption-based networks, at 0.19%, 0.30%, and 0.03%, respectively.

D Extra-EU Diffusion

In a spatial econometric structure, the inclusion of major players can substantially alter results via the spatial lag. In our framework, the EU as a whole is a key importer of multiple commodities, accounting for a share of over 17% of within-sample total imports between 1995 and 2020. Thus, the adoption of a regulation by the EU has a large impact on other countries' fraction of exports of the commodities affected by the regulation. To ensure that our findings are not heavily dependent on regulatory diffusion from the EU to the rest of the world, we redo our main exercises excluding the EU from our sample altogether.

The results from the OLS estimation of Equation (2) are in Table A.6 and the IV estimation using *AirDistance IV* are in Table A.7. Overall, the point estimates of diffusion via importer pressure are larger than those in Tables 4 and 5 but follow similar patterns across specifications. Based on the IV estimates, a one s.d. increase in *AE*, roughly 9.69 p.p, leads to a 5.07-9.41 b.p. increase in the probability of domestic adoption, which corresponds to 23.47-43.56% of average adoption. As the exclusion of the EU leads to qualitatively similar and quantitatively stronger estimates, we conclude that our results are robust to the exclusion of a major importer and provide further evidence of substantial extra-EU regulatory diffusion.

E Feedback Effects

A potential concern in our OLS baseline specification is feedback effects from the adoption of regulation in year $t-1$ into trade in the same year. The adoption of a regulation by a country's importers can affect its trade with those partners, posing an endogeneity threat to our OLS results. While our IV approach is designed to deal with this issue, we use an alternative approach in this section by characterizing the independent variables differently.

Table A.6: Estimation of Regulatory Diffusion Without EU - OLS

This table reports output from the estimation of our baseline specification Equation (2) via OLS, with the European Union excluded from the sample. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, AE, is the fraction of exports of a product that must comply with a NTM. CP is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 for details on construction of variables. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

	Adopted (%)		
	(1)	(2)	(3)
AE	0.64	0.49	0.32
	(39.44)***	(47.38)***	(27.23)***
CP	1.06	1.29	0.44
	(43.55)***	(65.55)***	(22.35)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	124,673,888	124,673,888	124,673,888
Adjusted R^2	0.08	0.31	0.36

Table A.7: Estimation of Regulatory Diffusion Without EU - AirDistance IV

This table reports output from the estimation of our baseline specification Equation (2) via IV regression, with the European Union excluded from the sample. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, AE, is the fraction of exports of a product that must comply with a NTM. We instrument this variable with *AirDistance IV*, which uses predicted bilateral trade flows from gravity regressions that use countries' air distances. CP is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 for details on construction of variables. Panels A and B report the first and second stages of the estimation, respectively. The test for weak instruments yields robust F-statistics above the cutoff of 104 (Lee et al., 2022). Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

Panel A. First Stage

	Adopted (%)		
	(1)	(2)	(3)
AirDistance IV	84.33	85.38	84.36
	(931.46)***	(915.70)***	(1,057.18)***
CP	0.20	0.59	−1.53
	(3.45)***	(9.25)***	(−29.46)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	122,382,953	122,382,953	122,382,953
F-statistic	189,920,331	216,717,586	182,158,103
Adjusted R^2	0.72	0.73	0.77

Panel B. Second Stage

	AE (%)		
	(1)	(2)	(3)
AE (AirDistance IV)	0.97	0.71	0.52
	(43.54)***	(51.85)***	(32.09)***
CP	0.99	1.25	0.43
	(40.50)***	(62.96)***	(21.48)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	122,382,953	122,382,953	122,382,953
Wu-Hausman Statistic	7,308.30	4,515.60	2,472.70
Wu-Hausman test p-value	0.00	0.00	0.00
Adjusted R^2	0.08	0.31	0.36

Specifically, we re-define AE_{prt} as $W_{p,1995}y_{prt}$, which is the product of the exports weight matrix in 1995, the first year in our sample, and the time-varying adoption vector. The underlying rationale is that bilateral trade is less likely to respond several years in advance of regulation adoption by countries. Therefore, we effectively discard any changes to bilateral trade after 1995. For consistency in the construction of the variables, we also restrict to 1995 trade flows in constructing CP.

We report the OLS estimates of Equation (2) using the 1995 trade matrix in Table A.8. Across all specifications, the estimates are qualitatively and quantitatively similar to our baseline results. We find that a s.d. increase in AE, roughly 11.44 p.p., is associated with an increase in the probability of domestic adoption of 2.29-6.75 b.p., which corresponds to 10.39-30.66% of average adoption. These results further alleviate endogeneity concerns that our main findings are simply capturing countries' trade responses to the implementation of TBTs by export partners.

Table A.8: Estimation of Regulatory Diffusion with 1995 Bilateral Trade - OLS

This table reports output from the estimation of our baseline specification Equation (2) via OLS. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, AE, is the fraction of exports of a product that must comply with a NTM, computed using bilateral trade in 1995. CP is the fraction of the top 10 export competitors that have that NTM in place, also based on bilateral trade in 1995. See Section 3 and Appendix E for details on construction of variables. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at the HS6-country and HS6-year levels.

	Adopted (%)		
	(1)	(2)	(3)
AE	0.59	0.31	0.20
	(36.27)***	(39.09)***	(18.14)***
CP	1.22	0.88	0.31
	(40.22)***	(49.76)***	(13.15)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	123,799,732	123,799,732	123,799,732
Adjusted R^2	0.07	0.31	0.36

F Additional Figures and Tables

Table A.9: Logit Regressions for Adoption

This table reports the output of Logit regressions specified in Equation (1), where each column represents a type of regulation, as specified by the NTM code. The dependent variable is a dummy indicating adoption of the regulation by a country by a particular year. The independent variable is year. Significance levels are indicated by * p<0.05; ** p<0.01; *** p<0.001.

	Adopted							
	Tolerance limits	Restricted use	Labeling	Marking	Packaging	Production processes	Transport/Storage	Quality/Safety/Performance
Year	0.03	0.03	0.09	0.07	0.07	0.05	0.09	0.06
	(5.55)***	(7.49)***	(33.60)***	(10.83)***	(20.16)***	(13.91)***	(16.48)***	(6.61)***
Constant	−57.11	−59.73	−183.10	−152.14	−143.13	−107.12	−192.26	−114.79
	(−5.95)***	(−7.92)***	(−33.72)***	(−11.05)***	(−20.42)***	(−14.25)***	(−16.66)***	(−6.85)***
Observations	6000	6000	6000	6000	6000	6000	6000	6000
Log Likelihood	−543.86	−808.48	−2,118.85	−543.69	−1,371.74	−1,033.93	−879.92	−310.03
$\hat{p} \geq 5\%$	-	2006	1974	2008	1987	1993	1998	-
$\hat{p} \geq 10\%$	-	-	1982	2018	1998	2007	2006	-
$\hat{p} \geq 20\%$	-	-	1991	-	2009	-	2015	-
$\hat{p} \geq 40\%$	-	-	2002	-	-	-	-	-
	Product identity	Registration	Testing	Certification	Inspection	Origin of materials	Processing history	Distribution/Location
Year	0.06	0.10	0.08	0.08	0.08	0.17	0.14	0.04
	21.60***	29.81***	25.81***	23.74***	18.95***	6.16***	5.91***	8.61***
Constant	−126.76	−193.65	−161.11	−168.08	−164.62	−342.11	−292.06	−74.92
	(−21.88)***	(−29.94)***	(−26.01)***	(−23.95)***	(−19.17)***	(−6.22)***	(−5.98)***	(−9.00)***
Observations	6000	6000	6000	6000	6000	6000	6000	6000
Log Likelihood	−1,645.96	−1,809.95	−1,728.67	−1,521.11	−1,153.96	−172.08	−166.96	−744.06
$\hat{p} \geq 5\%$	1980	1981	1981	1985	1992	2017	2019	2006
$\hat{p} \geq 10\%$	1992	1989	1991	1994	2001	-	-	-
$\hat{p} \geq 20\%$	2005	1997	2001	2004	2011	-	-	-
$\hat{p} \geq 40\%$	-	2007	2013	2016	-	-	-	-

Figure A.2: Share of World Trade among Countries within Sample

This figure depicts the share of total world trade among the countries in our sample. For each year, we compute the ratio of total trade flows among the countries within our sample to total world trade in the HS6 commodities for which we have TBT information. The figure plots the evolution of this ratio over the sample period.

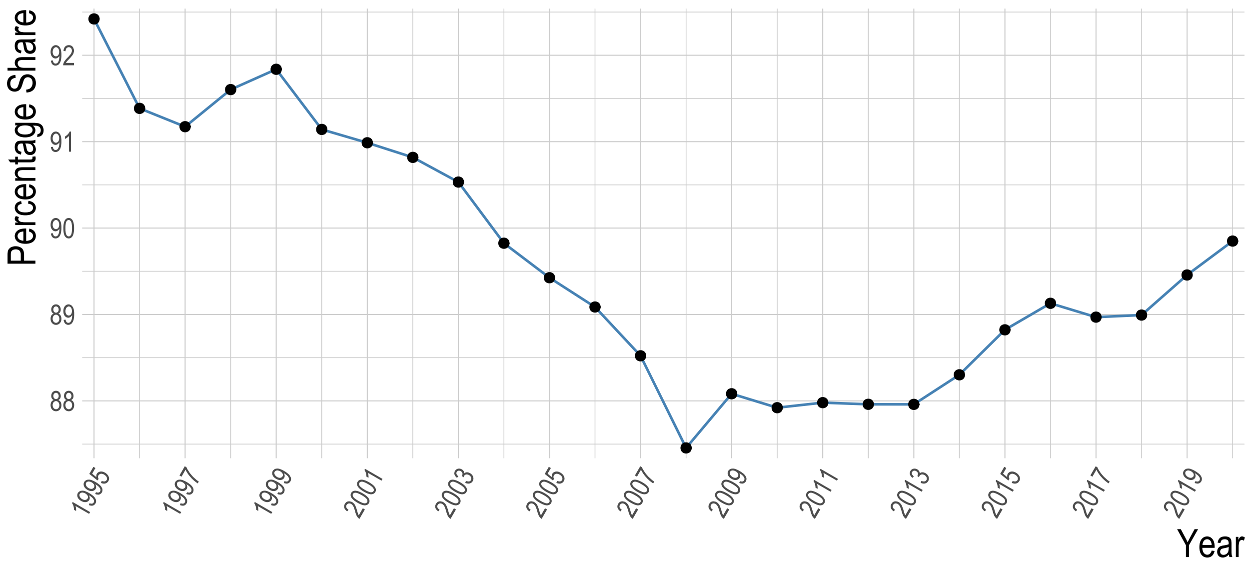

Table A.10: Correlation Matrix

This table reports pairwise correlations between the variables used in the estimation of Equation (2) in our baseline analysis. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. *Adopted* is an adoption indicator of the year a country domestically adopts a regulation on a product. We exclude from the sample product-regulation-country observations after the year of adoption. *AE* is the fraction of exports of a product that must comply with a NTM. *AirDistance IV* and *Air & Sea Distance IV* are the instruments for *AE*, where bilateral trade flows are predicted by countries pairwise air distances, and air and sea distances, respectively. *CP* is the fraction of the top 10 export competitors that have that NTM in place. See Section 3 and Appendix B for details on construction of the variables.

	Adopted	*AE*	*AirDistance IV*	*Air & Sea Distance IV*	*CP*
Adopted	1.00	0.02	0.03	0.01	0.03
AE	-	1.00	0.84	0.88	0.24
AirDistance IV	-	-	1.00	0.99	0.26
Air & Sea Distance IV	-	-	-	1.00	0.22
CP	-	-	-	-	1.00

Table A.11: Heterogeneity in Regulation Adoption: Alternative NTM Classification

This table reports output from the estimation of Equation (2) via IV regression interacting AE with cross-sectional variables. The sample consists of product-regulation-country-year observations where products and regulations are represented by HS6 levels and NTMs, respectively. The dependent variable, *Adopted (%)*, is an adoption indicator of the year a country domestically adopts a regulation on a product, in percentage points. We exclude from the sample product-regulation-country observations after the year of adoption. The main independent variable, AE, is the fraction of exports of a product that must comply with a NTM. We instrument this variable with *AirDistance IV*, which uses predicted bilateral trade flows from gravity regressions that use countries' air distances. *Product Regulation* is an indicator of the NTM belonging to the group of product standards. We discard the NTM categories B83, B84, B85, and B89. CP is the fraction of the top 10 export competitors that have that NTM in place. See Sections 3 and 8 for details on construction of variables. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered at HS6-country and HS6-year level.

	Adopted (%)		
	(1)	(2)	(3)
AE (AirDistance IV)	0.49	0.34	0.29
	(22.98)***	(21.19)***	(15.35)***
AE (AirDistance IV) × *Product Regulation*	0.30	0.29	0.08
	(12.46)***	(16.20)***	(3.90)***
CP	1.22	1.47	0.47
	(41.41)***	(61.59)***	(19.44)***
HS6-NTM-Country FE	Y	N	Y
HS6-NTM-Year FE	Y	N	Y
NTM-Country-Year FE	N	Y	Y
HS6-Country-Year FE	N	Y	Y
Observations	78,285,339	78,285,339	78,285,339
Wu-Hausman Statistic	2,783.50	1,536.90	652.00
Wu-Hausman test p-value	0.00	0.00	0.00
Adjusted R^2	0.08	0.33	0.38