Economic Integration and Diffusion of Regulatory Standards: Evidence from Trade Networks*

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Abstract

We document network effects in the diffusion of regulatory standards through international trade. Using both an instrumental variables approach, based on the time-varying geographic component of trade, and a recentering approach, exploiting the timing of regulation adoption, we provide robust evidence that countries tend to domestically adopt the regulations of their key trade partners, especially when imposed by their export destinations. Leveraging the high dimensionality of our data, we show that the diffusion process is stronger for regulations and products with observable compliance. Our findings 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 market failures by ensuring quality and consumer and environmental safety but can also improve efficiency and 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 participate in global markets or has access to knowledge on product standardization, the gains from domestic adoption can outweigh costs imposed on producers. Thus, economic integration can facilitate regulatory diffusion (Vogel, 2000; Chen and Dar-Brodeur, 2020), demonstrating 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 by trade partners. Our sample of regulations comprises multiple Technical Barriers to Trade (TBT) imposed by countries on a variety of products. Combining regulation data with product-level bilateral trade flows, we construct a large panel of product-regulation-country-year observations that provide information on adoption of a regulation by each country's trade partners on a product. To identify the impact of economic integration, we implement an instrumental variables (IV) approach based on interactions between geography and technological advances in transport (Feyrer, 2019*b*), where we use the time-varying geographic component of trade to construct instruments for compliance intensity of export and import partners. We alternatively exploit the exogeneity in the timing of adoption of regulations to recenter compliance intensity of exports using its expected value, following the recent developments in the shift-share literature (Borusyak and Hull, 2023). Our empirical approach and the high dimensionality of our panel allow us to mitigate various threats to internal validity while controlling for alternative channels of regulatory diffusion and economic indicators.

Our results show that countries tend to domestically adopt the regulations implemented by their key trade partners, especially the compliance requirements imposed by their export destinations. Using the IV approach, we estimate that one standard deviation (s.d.) increase in the share of exports that comply with a regulation leads to an increase in the probability of domestic adoption, corresponding to 5.77-11.64% of average adoption. While we find consistent evidence of regulatory diffusion through export networks, the evidence on the impact of standard-complying imports is weaker and less robust. Therefore, our findings suggest that production adjustments necessary to export to standard-imposing countries, rather than exposure to standardized imports, is the primary channel through which globalization facilitates regulatory diffusion.

While important, trade may not fully capture the extent of economic integration through channels such as knowledge spillovers, technology transfers, and foreign direct investment, which contribute to the harmonization of standards (Frankel and Romer, 1999; Feyrer, 2019*b*). This measurement error would lead to an attenuation bias in the ordinary least squares (OLS) estimates. Our instrument, which is based on interactions between geography and technological advancement, plausibly affects adoption only through economic integration, thereby mitigating measurement error issues and other endogeneity concerns. In line with this argument, we find that our IV estimates of the impact of integration on diffusion are larger than the OLS estimates. The recentering approach not only results in stronger estimates—one s.d. increase in the share of compliant exports now accounts for 26.08-34.06% of average adoption—but also provides further evidence of a downward bias in OLS estimates.

We devise two novel placebo tests to demonstrate the robustness of our findings. First, we randomize over adoption by countries for each product-regulation to alleviate concerns that our true estimates capture omitted variation. Second, we impose different network structures when measuring a country's network centrality, revealing that connectedness via trade to countries that have adopted a regulation, rather than overall connectedness via trade, drives regulatory diffusion. We also show that our results are not driven by regional geography (Feyrer, 2019*b*) and robust to alternative treatment of European Union countries, where regulations may diffuse faster due to mutual recognition of standards.

We exploit the high dimensionality of our panel to show substantial heterogeneity in regulatory diffusion by standard and product type. Diffusion is stronger for product standards—regarding physical attributes of the product—than process standards, which pertain to the manufacturing process. Further, we find stronger diffusion in final products than intermediate inputs. These findings reflect stronger diffusion for standards and products where compliance is more easily verifiable.

Our paper contributes to the burgeoning literature that explores the mechanisms behind the harmonization of standards in an increasingly globalized world.[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 the 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 legal enforcement.

The diffusion of regulations via market mechanisms contrasts with a "race to the bottom", where countries might lower their standards over time to keep their products competitive in international markets (Bagwell and Staiger, 2001; Greenstone, 2002). 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 regulation can trigger innovation that generates benefits greater than compliance costs, granting a competitive advantage over foreign firms not subject to similar

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

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 by trade partners. Besides establishing causality, our rich dataset allows us to control for alternative diffusion channels and assess heterogeneity across various dimensions.

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), firm entry and terms of trade (Macedoni and Weinberger, 2024), and pollution emissions (Duan et al., 2021). We demonstrate the effect of regulatory adoption on further adoption by other countries, showing how trade partners' decisions to adopt regulations are interdependent. Our findings highlight the importance of considering network effects 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, the WTO 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 substances, B31-Labeling 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-

[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.

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 OA.5 provides specific examples on regulations under each 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 requirements were imposed on exports from only a subset of countries.[4] Further, for about 5% of product-ntm-country combinations, the 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 1995-2019.[5]

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. Figure OA.1 shows the fraction of countries that adopted over the years. 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 Transport and storage requirements, Certification, and Inspection requirements, process regulations with relatively fast adoption. Labeling requirements is the first regulation to reach the 5% adoption threshold. In fact, it reaches the threshold even before the sample period began in 1975. After labeling, regulations that reach the 5% threshold are Product identity, Registration, Testing, Certification, Packaging, Transport & storage, 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. The speed of adoption varies

[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.

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 1975 to 10% in 1977 to 20% in 1994. In contrast, process regulations diffuse much slower, with some not even crossing the 10% threshold by the end of the sample period. Figure OA.2 shows that the coverage ratio, defined as the fraction of within-sample trade in Medicaments affected by a regulation, grows with the share of countries that adopt each regulation and shows similar diffusion patterns across regulations.

3 Framework

To model regulatory diffusion due to globalization, we assume that the adoption of a regulation is dependent on the fraction of "neighbours" that adopted the same regulation by the previous year. Specifically, we estimate the following regression:[6]

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

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. We use two measures of a country's economic integration: AE_{prit-1} is the fraction of exports of country i in product p affected by the regulation r in year $t-1$, capturing importer pressure. AI_{prit-1}, is the fraction of imports of country i in product p that comply with regulation r in year $t-1$. The variables $\mathbf{X_{prit-1}}$ control for other channels of diffusion via competitor pressure and shared trade agreements. We introduce a time-lag to our variables of interest to allow time for a regulation to diffuse to a country after its adoption by the country's trade partners.

We include product-regulation-country, μ_{pri}, and product-regulation-year effects, μ_{prt}. While the former absorbs time-invariant country characteristics specific to each product-

[6]In the spatial econometrics literature, this model is known as the *pure-space recursive spatial lag* model. 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).

regulation, the latter isolates the temporal diffusion process from secular trends in adoption of each product-regulation. A potential omitted variable bias (OVB) concern arises when TBTs serve as substitutes for tariff reductions (Beverelli, Boffa and Keck, 2014; Orefice, 2017) and also hinder international trade (Fontagné and Orefice, 2018), which is especially the case for TBTs raised as Specific Trade Concerns at the WTO (Herghelegiu, 2018). To address this concern, we control for diffusion channels that affect all regulations alike but vary across products, μ_{pit}. These channels include country-specific product specialization and tariff protection levels, regardless of regulation. Further, we control for channels that affect all products alike but vary across regulations, μ_{rit}, which include institutional proximity across countries with similar colonial origins and culture, which spurs adoption of similar regulations, regardless of the product.

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 (1) 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 conditional on not having adopted by the previous year. Further, adoption by a country may affect its trade in later periods, leading to potential reverse causality concerns. Although restricting observations until only first year of adoption and lagging our measures of economic integration alleviate reverse causality concerns, a diffusion channel that affects both regulation adoption and trade might still present threats to internal validity.

Countries that are geographically close are often institutionally and culturally similar and exhibit higher levels of trade with one another. Consequently, geographical proximity can positively influence both the adoption of regulations and trade, potentially leading to an upward bias in the estimated coefficients of economic integration measures. Further, trade serves as an imperfect proxy for global economic integration through mechanisms such as knowledge spillovers and foreign direct investment, which also drive the harmonization of regulations across countries. This measurement error introduces attenuation bias in the OLS estimates. To address these concerns, we implement two identification strategies. First, we implement an instrumental variables approach that is based on interactions between geography and technological change (Feyrer, 2019*b*). Second, we exploit the shift-share like structure of our main regressor to purge OVB, following Borusyak and Hull's (2023) recentering approach. Before moving on to these identification strategies, however, we describe the construction of our main variables of interest.

3.1 Measures of Globalization and Controls

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. We combine this indicator with exports data to construct a product-regulation-country-year level variable that measures the fraction of exports of the product of a country affected by that regulation (Simmons and Elkins, 2004; Greenhill, Mosley and Prakash, 2009; Saikawa, 2013):

$$\mathit{Affected\ Exports}_{prit} = \sum_j w_{pijt} y_{prjt},$$

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. This variable, 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.

While *Affected Exports (AE)* captures the strength of economic integration of a country due to exports, diffusion of regulations may also occur due to strength of a country's import connections. Therefore, we similarly construct a variable that measures the fraction of imports of a country that comply with a regulation:

$$\mathit{Affected\ Imports}_{prit} = \sum_j w_{pjit} y_{prjt},$$

where w_{pjit} is the fraction of imports of country i from j in year t. *Affected Imports (AI)* captures the strength of economic integration due to imports.

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. Following Simmons and Elkins (2004), we use a term that captures the strength of competition in exports to control for competitor pressure. We first compute the correlation between exports of each country pair ij in each year. This 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 control by computing the average adoption of the top 10% competitors of a country:

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

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

Joint membership in trade agreements with other countries, especially the ones that include provisions on TBTs, can also drive regulation adoption by a country. We control for this channel by measuring the fraction of a country's trade agreement partners that adopted a regulation:

$$\textit{Affected Agreements}_{prit} = \frac{\sum_j A_{ijt} y_{prjt}}{\sum_j A_{ijt}},$$

where A_{ijt} is an indicator for whether countries i and j share a trade agreement in force in year t. Therefore, $\textit{Affected Agreements}_{prit}$ measures the strength of pressure from membership in trade agreements on country i to adopt regulation r in product p by year t. Since competitor pressure (CP) and affected agreements (AA) vary at product-regulation-country-year level, like affected exports and imports, they are not absorbed by the fixed effects and must be directly controlled for.

3.2 Instruments

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

$$(2) \qquad \ln trade_{pijt} = \beta_{air,t} \times \ln \text{airdist}_{ij} + \beta_{sea,t} \times \ln \text{seadist}_{ij} + \mu_{ij} + \mu_{pj} + \epsilon_{pijt}$$

where the dependent variable is trade flow in product p from country i to j in period t. The main predictors are the bilateral air distance, i.e., point to point great circle distance, and the bilateral sea distance, the coefficients of which are allowed to vary over time. The time-varying coefficients capture how the importance of air and sea transport changes with technological development during our sample period. The sensitivity of trade to air distance should grow while sensitivity to sea distance should decline over time as air transport becomes more and more feasible with technological change, especially for country pairs with no land routes (Feyrer, 2019*b*).

We further control for time-invariant bilateral effects, μ_{ij}, and the time-invariant product-importer effect, μ_{pj}. 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, any time effects idiosyncratic to a product or a country, such as income and average level of protection in a product via tariffs, are part of the error term. The time variation in trade predictions, therefore, come solely from changing sensitivity to air and sea distances. 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. The term, μ_{pj}, which measures the average trade by importer j in product p, scales the time-changing bilateral relationship with time-invariant partner specific information.

We produce an instrument for affected exports by estimating Equation (2) to get predictions of bilateral trade flows in each product and computing the fraction of predicted flows affected by a regulation as follows:

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

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

$$\widehat{\text{trade}}_{pijt} = \exp\left(\hat{\beta}_{air,t} \times \ln airdist_{ij} + \hat{\beta}_{sea,t} \times \ln seadist_{ij} + \hat{\mu}_{ij} + \hat{\mu}_{pj}\right). \tag{3}$$

These predictions consist of bilateral pair effects, time-invariant product-importer specific effects, and interactions between geography and technological development of transport.

The instrument for affected exports excludes information on the exporting country, such as μ_{pi}, thereby closing off a channel for adoption to feed back into exports. Likewise, an instrument for affected imports should not be contaminated with information specific to the importing country. Specifically, an analogous instrument for affected imports requires estimating the following gravity regression instead:

$$\ln trade_{pjit} = \beta_{air,t} \times \ln \text{airdist}_{ji} + \beta_{sea,t} \times \ln \text{seadist}_{ji} + \mu_{ji} + \mu_{pj} + \epsilon_{pjit}, \tag{4}$$

where the term, μ_{pj}, scales the time-changing bilateral relationship with time-invariant *exporter* specific information. Using the trade predictions from estimating Equation (4), the instrument for affected imports is constructed as follows:

$$AffectedImports\ IV_{prit} = \sum_j \hat{w}_{pjit} y_{prjt},$$

where $\hat{w}_{pijt}$ is the fraction of predicted trade flows from j to i in product p in year t.

3.2.1 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 economic integration. Our instrument captures the time-varying geographic component of trade by allowing interactions between bilateral air and sea distances and technological advances in 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).

An instrument based on time-invariant distances 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). Our instrumental variables approach relies on 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.

Our instrument may affect adoption through channels other than trade like economic integration due to improved 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 from increased air travel by people. Moreover, trade itself is an imperfect measure of economic integration, potentially leading to attenuation bias in OLS estimates (Frankel and Romer, 1999; Feyrer, 2019*b*). As such, our IV 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.

Our instrumental variables, *AffectedExports IV* and *AffectedImports IV*, constructed as inner products between predicted export or import shares and adoption status of the trade partner, exhibit a structure akin to shift-share instruments. The consistency of estimates derived from shift-share instrumental variables estimation depends on either the exogeneity of the shares (Goldsmith-Pinkham, Sorkin and Swift, 2020) or the exogeneity of the shocks (Borusyak, Hull and Jaravel, 2022). While countries may strategically make adoption decisions (the shocks) for a particular product-regulation, the composition of trade (the shares)—which encapsulates variation due to geography and technological advancement—plausibly influences adoption only through economic integration, especially for regulations concerning economic interactions like the TBTs. Therefore, our shift-share instrument essentially captures differential exogenous exposure to common shocks. Goldsmith-Pinkham, Sorkin and Swift (2020) show that, in such a setting, the exogeneity of the shares is a sufficient condition for the validity of the instrument, eliminating the need for additional constraints requiring the exogeneity of the shocks.

A potential concern in this setting is that the shares may be codetermined with the level of the outcome of interest, i.e., the adoption status. However, keeping observations only until first year of adoption for each product-regulation-country implies that our outcome effectively captures *changes* in adoption rather than levels. This approach further enhances the plausibility of the exogeneity of shares assumption (Goldsmith-Pinkham, Sorkin and Swift, 2020). Nevertheless, concerns may persist regarding the presence of an omitted variable like differences across regions that simultaneously affects both the composition of trade and adoption. To alleviate this concern, we show the robustness of our results to including product-regulation-region-year fixed effects, following Goldsmith-Pinkham, Sorkin and Swift (2020) and Feyrer (2019*b*), in Appendix A. Next, we describe how we exploit the exogeneity in timing of the shocks to purge OVB arising with a shift-share like regressor, where the mapping from shocks to each unit's treatment is complex, by recentering affected exports, as recommended in Borusyak and Hull (2023).

3.3 Recentering Affected Exports

We saturate our baseline OLS model with a comprehensive set of fixed effects and covariates. However, such controls and fixed effects may not entirely mitigate the influence of alternative channels of diffusion without removing all variation in AE, particularly given the complex nature of each country's exposure to adoption by its import partners. Specifically, countries with greater economic integration with their regulation adopting trade partners may possess different institutional frameworks, which may also facilitate adoption of regulations. This institutional heterogeneity may confound the relationship between exposure to adoption and the propensity to adopt regulations. We use IVs based on time-varying geographic component of trade to address endogeneity in exposure to adoption. In this section, we alternatively adapt Borusyak and Hull (2023)'s approach for addressing non-random exposure to shocks in shift-share like treatments.

While the set of countries adopting a particular regulation may be subject to endogeneity concerns, the *timing* of adoption of each regulation by these countries is plausibly exogenous within a sufficiently narrow time window around the observed adoption year. Leveraging the timing of adoption of a regulation by countries as exogenous shocks, we recenter AE to address potential OVB concerns, following Borusyak and Hull (2023). For each product-regulation and a country that adopted this regulation, we randomly assign adoption year within a symmetric time window, spanning five years before and five years after the actual implementation. Then, we use this randomized adoption vector with the true trade flows to construct the variable, AE, as described in Section 3.1. In doing so, we keep the trade shares fixed at the first year of our sample period, 1995, as in Borusyak and Hull (2023).[7] We repeat this random assignment of adoption timing to each product-regulation-country in our sample 200 times. Then, for each observation, we average across the 200 constructions of randomized AE to obtain the *Expected* AE. Finally, we subtract the *Expected* AE from the actual AE to obtain the *Recentered* AE. Borusyak and Hull (2023) show that using the recentered treatment removes the bias from

[7] We also restrict to 1995 relationships in constructing our control variables, AI, CP, and AA.

non-random shock exposure. Even if OVB were not a concern, controlling for "expected treatment" nevertheless serves as an additional robustness check.

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,[8] 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 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.[9] Figure OA.3 shows that countries within our sample represent over 87% of the world trade during our sample period.

To construct our instruments, 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 obtain bilateral sea distance data from the replication package in Feyrer (2019*a*), which excludes landlocked countries and oil exporters.[10] 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.[11] Post-estimation, we sum the predicted flows for the two coasts to obtain the predicted flows for the US and Canada

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

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

[10] Feyrer's original dataset comprises 55% country pairs with missing sea distances.

[11] 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.

as a whole. We do the same for the EU countries: obtain the predictions for individual countries before aggregating to obtain the trade predictions for the EU as a whole.

We also 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, from World Development Indicators Database (World Bank, n.d.), to control for the country-year effects.

To construct the control for affected agreements, we use a comprehensive dataset covering 400 Preferential Trade Agreements (PTAs) notified at the WTO between 1958-2023 (Hofmann, Osnago and Ruta, 2017). This database provides granular information on each agreement, including its duration of enforcement for each country pair and whether the agreement includes provisions on TBTs. In instances where multiple agreements exist between country pairs, we use the earliest agreement's enforcement period as the effective enforcement years for the pair. We further treat the EU as a single entity, applying any agreement between an EU member and a non-member to the entire EU.

Table 1 reports the summary statistics. Overall, our sample has over 126 million product-regulation-country-year observations. For ease of exposition, all variables are in percentages. 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 exclusion of all observations after the year of adoption for each product-regulation-country triple. Therefore, 0.23% is the unconditional probability of domestic adoption of a NTM in a product in our sample. The independent variables of interest, AE and AI, show that on average, 2.22% of a country's exports comply with a regulation imposed by its export destinations while 4.69% of its imports come from countries with a standard in place. *AffectedExports IV* and *AffectedImports IV* are the instruments for AE and AI, where bilateral trade flows are predicted by air and sea distances, using Equations (2) and (4). The loss in sample size from using sea distances is clear: roughly 33% and 53% of the observations are missing for *AffectedExports IV* and *AffectedImports IV*, respectively.[12]

[12]Even though the estimation of Equations (2) and (4) result in the same number of missing trade predictions, the asymmetry in the number of missing observations for $AE\ IV$ and $AIIV$ is due to un-

Table 1: Summary Statistics

This table reports summary statistics of the variables used in our main analysis. The sample consists of product-regulation-country-year observations where products and regulations are HS6 levels and NTMs, respectively. All variables are in percentages. *Adopted* is an indicator for 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. *Affected Exports* and *Affected Imports* are the export and import shares, respectively, of a product that must comply with a standard while *Affected Exports IV* and *Affected Imports IV* are their instruments, which use trade flows predicted by time-varying air and sea distances. *Affected Agreements* is the share of a country's trade agreement partners and *Competitor Pressure* is the share of the top 10 export competitors that have the regulation in place. See Section 3 for details on variable construction.

Main Sample (%)	Mean	Median	Std. Deviation	Observations
Adopted	0.23	0.00	4.75	126,534,427
Affected Exports	2.22	0.00	12.24	126,534,427
Affected Exports IV	1.09	0.00	9.15	84,520,421
Affected Imports	4.69	0.00	17.33	126,534,427
Affected Imports IV	2.91	0.00	14.09	59,110,131
Affected Agreements	2.26	0.00	9.21	126,534,427
Competitor Pressure	1.42	0.00	5.92	126,534,427

Table OA.6 shows a high correlation between our main independent variables and their respective instruments, thereby providing initial evidence against weak instruments.

5 Gravity Regression Results

Table 2 presents the results from various specifications of the gravity equation, including our preferred specification for prediction, Equations (2) and (4), in columns (1)-(2). We estimate elasticity of product-level bilateral trade flows with respect to air and sea distances in separate periods of five years each. Our most saturated specification, Column (5), shows that the size of elasticity of trade with respect to air distance increases while

balanced nature of the panel used in gravity regressions. To elaborate, consider a country i exporting to country j where the sea distance is unavailable while i doesn't import from j at all. Thus, the export matrix observation (i, j) would be missing while observation (j, i) would be zero. In contrast, the import matrix observation (i, j) would be zero and (j, i) would be missing. If the data comprised several instances of such js, with missing sea distances and j doesn't export to i at all, then several missing observations on the ith row on the export matrix would correspond to several missing observations on the ith column on the import matrix, thereby increasing missing observations on $AIIV$ manifold.

Table 2: Gravity Regression Results

This table reports the estimation of Equations (2) and (4). The sample consists of product-exporter-importer-year observations where $ln(trade)$ is the natural log of trade flows. The independent variables are the interactions of time-invariant logged air and sea distances with separate time indicators of five years each. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are clustered by exporter-importer.

	ln(trade)				
	(1)	(2)	(3)	(4)	(5)
ln(airdist) $\times \mathbb{1}(1995 \leq year \leq 2000)$			-0.66***		-0.59***
			(0.06)		(0.07)
ln(airdist) $\times \mathbb{1}(2001 \leq year \leq 2005)$	-0.03***	-0.02***	-0.78***	-0.11***	-0.74***
	(0.00)	(0.00)	(0.06)	(0.01)	(0.06)
ln(airdist) $\times \mathbb{1}(2006 \leq year \leq 2010)$	0.03***	0.04***	-0.79***	-0.14***	-0.78***
	(0.01)	(0.01)	(0.05)	(0.02)	(0.06)
ln(airdist) $\times \mathbb{1}(2011 \leq year \leq 2015)$	0.04***	0.05***	-0.72***	-0.19***	-0.86***
	(0.01)	(0.01)	(0.06)	(0.02)	(0.05)
ln(airdist) $\times \mathbb{1}(2016 \leq year \leq 2020)$	0.03***	0.04***	-0.74***	-0.16***	-0.85***
	(0.01)	(0.01)	(0.05)	(0.02)	(0.05)
ln(seadist) $\times \mathbb{1}(1995 \leq year \leq 2000)$	-1.01***	-1.02***	-0.34***	-1.05***	-0.34***
	(0.11)	(0.11)	(0.05)	(0.11)	(0.05)
ln(seadist) $\times \mathbb{1}(2001 \leq year \leq 2005)$	-1.02***	-1.03***	-0.28***	-1.06***	-0.34***
	(0.11)	(0.11)	(0.05)	(0.11)	(0.05)
ln(seadist) $\times \mathbb{1}(2006 \leq year \leq 2010)$	-1.11***	-1.11***	-0.29***	-1.08***	-0.35***
	(0.11)	(0.11)	(0.04)	(0.11)	(0.05)
ln(seadist) $\times \mathbb{1}(2011 \leq year \leq 2015)$	-1.14***	-1.13***	-0.36***	-1.09***	-0.35***
	(0.11)	(0.11)	(0.05)	(0.11)	(0.05)
ln(seadist) $\times \mathbb{1}(2016 \leq year \leq 2020)$	-1.12***	-1.12***	-0.33***	-1.11***	-0.38***
	(0.11)	(0.11)	(0.05)	(0.11)	(0.04)
X_{ij}			✓		✓
X_{it} and X_{jt}			✓		
μ_{pj}	✓		✓	✓	
μ_{pi}		✓	✓	✓	
μ_t			✓		
μ_{it} and μ_{jt}				✓	
μ_{pit} and μ_{pjt}					✓
μ_{ij}	✓	✓		✓	
N	120,607,225	120,607,225	120,607,225	120,607,225	120,607,225
$Adj R^2$	0.42	0.51	0.53	0.57	0.57

that for sea distance changes little over time. Between 1995 and 2000, the elasticity of trade with respect to air distance is -0.59. As time progresses and technology develops, this elasticity grows in magnitude, making trade more sensitive to air distance. In the last period of our sample, 2016-2020, this elasticity is -0.85. A 1% increase in air distance is associated with a 0.59% decline in trade flows in 1995 and a 0.85% decline 20 years later.

Although these findings 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 air transport technology may have advanced to the extent that countries more reliant on air transport relative to sea transport don't see a substantial impact from further development. Accordingly, we find that trade is about half as sensitive to sea distance than air distance throughout our sample period. Also, while the change in sensitivity of trade with respect to air distance is statistically significant from first period to last, this is not the case for sea distances.

Columns (3)-(4), where we include product-country and year effects as well as bilateral and country-year level controls or fixed effects, deliver similar results both qualitatively and quantitatively. In column (4) where we include pair fixed effects, only differentiated impacts over time are identified and all identification comes from within pair variations in trade. Therefore, in the most saturated specifications, our results continue to hold—trade flows become more sensitive to air distance, while staying less sensitive to sea distance, and these changes over time are statistically significant.[13]

In our trade predictions that are used for instrumental variables regressions, however, we allow all time-variation to come solely from interactions between geography and technology. Therefore, we use estimates in columns (1)-(2) in Table 2 for prediction of trade flows. The predictions using estimates in column (1), which exclude any exporter-specific information while scaling the bilateral relationships with product-importer specific information, as in Equation (2), are used to construct *AffectedExports IV*. Analogously, the predictions using estimates in column (2), which exclude any importer-specific information while scaling the bilateral relationships with product-exporter specific information, as in Equation (4), are used to construct *AffectedImports IV*.[14] The next section presents

[13] In Table OA.7, we report estimates from gravity regressions on a balanced panel, which includes only those product-exporter-importer combinations with observed trade across all sample years. While this approach introduces a selection bias toward wealthier countries—similar to the sample differences in Feyrer (2019*b*)—our key findings continue to hold. Specifically, although air distance sensitivities are more stable over time, the qualitative patterns, regarding the changing importance of air and sea distances, in Table OA.7 are similar to those in Table 2.

[14] Using sea distances as a predictor, however, limits our observations in gravity regressions as almost 29% of the sea distance observations are missing.

the results from IV regressions using these instruments.

6 Regulatory Diffusion Results

6.1 Instrumental Variables Approach

We first estimate Equation (1) via OLS, restricting the sample to observations with nonmissing IV values to facilitate comparison with IV estimates.[15] Table 3 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 AE, which ranges from 0.08, in our most saturated model, to 0.18, is statistically significant at the 0.1% level across specifications. In contrast, the coefficient on our import-based measure of economic integration, AI, although positive across specifications, is only statistically significant in our least saturated model, in column (1). The two control variables, CP and AA, also show a positive, significant correlation with the probability of adoption, suggesting that countries tend to match the standards of both their partners in agreements that include TBT provisions and their closest export competitors (Simmons and Elkins, 2004).

In addition to AE and AI serving as imperfect measures of economic integration, a diffusion channel like physical proximity that influences both trade and regulation adoption would render AE and AI endogenous. To address these concerns, we instrument these variables with $AE\ IV$ and $AI\ IV$, constructed using trade flows predicted by time-varying air and sea distances, as described in Section 3.2. Our benchmark IV estimates of Equation (1) are in Table 4, with the first stages for AE and AI in Panel A. We find that the instruments strongly correlate with the endogenous variables across all specifications, with the F-statistics well above the threshold of 104 for weak IVs (Lee et al., 2022). A 1 p.p. increase in affected exports (imports) as predicted by time-varying air and sea distances is associated with 0.94 (0.88) p.p. increase in actual affected exports (imports).

[15] We include only countries for which we observe both sea and air distances to other countries.

Table 3: Estimation of Regulatory Diffusion - OLS

This table reports the estimation of Equation (1) via OLS. The sample consists of product-regulation-country-year observations where *Adopted (%)* is an indicator of the year a country domestically adopts a regulation on a product, in percentages. We exclude product-regulation-country observations after the year of adoption. The main independent variables, *Affected Exports* and *Affected Imports*, are the export and import shares, respectively, of a product that comply with a standard. See Section 3 for details on variable construction. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered by product-country and product-year.

	Adopted (%)		
	(1)	(2)	(3)
Affected Exports	0.18***	0.09***	0.08***
	(0.01)	(0.01)	(0.01)
Affected Imports	0.06***	0.00	0.00
	(0.01)	(0.01)	(0.01)
Affected Agreements			0.09***
			(0.02)
Competitor Pressure			0.16***
			(0.03)
μ_{pri}	✓	✓	✓
μ_{prt}	✓	✓	✓
μ_{rit}		✓	✓
μ_{pit}		✓	✓
N	52,533,916	52,533,916	52,533,916
$Adj R^2$	0.12	0.40	0.40

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., i.e., roughly 12.24 percentage points (p.p.), increase in affected exports leads to a 1.30-2.63 basis points (b.p.) increase in the probability of adoption. Although the size of the effects is small, the economic magnitude is sizeable, corresponding to 5.77-11.64% of average adoption. Similar to our OLS results, we find positive coefficients on instrumented AI across all models, but statistical significance vanishes as we tighten the specification. These estimates imply that one s.d., roughly 17.33 p.p., increase in affected imports causes a 0.30-1.72 b.p.

Table 4: Estimation of Regulatory Diffusion - Air and Sea Distance IV

This table reports the estimation of Equation (1) via IV regression. The sample consists of product-regulation-country-year observations where *Adopted (%)* is an indicator of the year a country domestically adopts a regulation on a product, in percentages. We exclude product-regulation-country observations after the year of adoption. The main independent variables, *Affected Exports* and *Affected Imports*, are the export and import shares, respectively, of a product that comply with a standard while *Affected Exports IV* and *Affected Imports IV* are their instruments, which use trade flows predicted by time-varying air and sea distances. See Section 3 for details on variable construction. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered by product-country and product-year.

Panel A. First Stage

	Affected Exports (%)			*Affected Imports (%)*		
	(1)	(2)	(3)	(1)	(2)	(3)
Affected Exports IV	94.01***	93.64***	93.66***	0.98***	0.76***	0.73***
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)
Affected Imports IV	0.15***	0.11***	0.12***	88.08***	87.44***	87.44***
	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)	(0.08)
Affected Agreements			−0.04			−0.66***
			(0.02)			(0.06)
Competitor Pressure			−0.66***			1.20***
			(0.06)			(0.09)
μ_{pri}	✓	✓	✓	✓	✓	✓
μ_{prt}	✓	✓	✓	✓	✓	✓
μ_{rit}		✓	✓		✓	✓
μ_{pit}		✓	✓		✓	✓
F-statistic	648,627	729,323	729,323	60,144	111,672	111,672
N	52,533,916	52,533,916	52,533,916	52,533,916	52,533,916	52,533,916
$Adj R^2$	0.86	0.88	0.88	0.80	0.83	0.83

Panel B. Second Stage

		Adopted (%)	
	(1)	(2)	(3)
Affected Exports	0.21***	0.11***	0.11***
	(0.02)	(0.01)	(0.01)
Affected Imports	0.10***	0.02*	0.02
	(0.01)	(0.01)	(0.01)
Affected Agreements			0.09***
			(0.02)
Competitor Pressure			0.16***
			(0.03)
μ_{pri}	✓	✓	✓
μ_{prt}	✓	✓	✓
μ_{rit}		✓	✓
μ_{pit}		✓	✓
N	52,533,916	52,533,916	52,533,916
$Adj R^2$	0.12	0.40	0.40

increase in the probability of adoption, corresponding to 1.34-7.61% of average adoption.

As a result of a separate diffusion channel that positively influences both regulation adoption and trade, we would expect that the OLS estimates would be upward biased. Instead, we find that the IV coefficients on AE and AI are larger than their OLS counterparts, suggesting a downward bias in the empirical correlation between economic integration and regulation adoption. Further, our results suggest that the OLS and IV estimates are statistically different from the each other, as the Wu-Hausman test p-values are virtually zero in all models.[16] 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 3 and 4 are obtained by including European Union as one entity, implying that the reported estimates capture only extra-EU diffusion rather than the unconstrained mechanical diffusion in regulations within the EU.[17]

Our baseline results confirm that economic integration with standard-compliant countries via trade leads to higher internal adoption of a wide array of regulations, in a wide range of commodities. Our estimates further suggest that the export-based measure of integration better explains regulatory diffusion. Arguably, adjustments that producers

[16]The lowest Wu-Hausman statistic that we obtain in Table 4 is 46.10 in column (3). We omit these results from the table due to space constraints.

[17]In Appendix OA.2, we exclude the EU from the sample altogether to provide further evidence that our results do not depend on the EU.

must implement to export a commodity to standard-imposing locations facilitate subsequent domestic adoption, implying regulatory diffusion from countries to their exporters. Finally, we show that our estimates are not contaminated by alternative diffusion channels like competitor pressure, trade agreements that enforce TBTs, and 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 globalization off of the geographic component of trade that varies with time.

6.2 Recentering Approach

Recentering removes the variation due to institutional heterogeneity in *AE*. Specifically, moving from a regression of *AE* on *Expected AE* to a regression of *Recentered AE* on *Expected AE*, the coefficient and the Adjusted R^2 fall dramatically from 1.06 (s.e. = 0.0007) to 0.06 (s.e. = 0.0007) and 0.90 to 0.03, respectively. Columns (1)-(2) in Table 5 show that using *Recentered AE* increases the size of coefficient from 0.19-0.64 (without controls) and from 0.09-0.49 (with controls).[18] The coefficients on *Recentered AE* are estimated by comparing countries with larger than expected *AE* against those with lower than expected *AE* because countries adopted regulations in different years, not because of their institutional differences. Thus, even after removing the OVB where some countries may be receiving systematically higher values of *AE*, our results continue to hold. The increase in size of estimate with *Recentered AE* provides further evidence of a downward bias in the OLS estimates. Our results are also strengthened after recentering *AE* in the full sample: A one s.d. increase in *AE* increases domestic adoption probability by 6-7.83 b.p., which accounts for 26.08-34.06% of average adoption.

Another solution to the OVB concerns proposed by Borusyak and Hull (2023) is to use *Expected AE* as a control in the regression of regulation adoption on *Recentered AE*,

[18] These comparisons use the full sample of observations, since we no longer need to restrict the sample to countries with observable air and sea distances to other countries, as required for comparison between Tables 3 and 4.

Table 5: Estimation of Regulatory Diffusion with 1995 Bilateral Trade - Unadjusted and Recentered OLS

This table reports the estimation of Equation (1) via OLS. The sample consists of product-regulation-country-year observations where *Adopted (%)* is an indicator of the year a country domestically adopts a regulation on a product, in percentages. We exclude product-regulation-country observations after the year of adoption. The main independent variables, *Affected Exports* and *Affected Imports*, are the 1995 export and import shares, respectively, of a product that comply with a standard. We follow Borusyak and Hull (2023) to create *Expected AE*, *Recentered AE*, and 95% randomization inference confidence intervals (RICI) (in square brackets). See Section 3 and Appendix B for details on construction of variables and RICI. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered by product-country and product-year.

	Adopted (%)		
	Unadjusted	Recentered	Controlled
	Panel A: Without Controls		
Affected Exports	0.19***	0.64***	0.64***
	(0.01)	(0.02)	(0.02)
		[0.58, 0.70]	[0.58, 0.71]
Affected Imports	0.08***	0.07***	0.08***
	(0.01)	(0.01)	(0.01)
Expected Affected Exports			-0.01
			(0.01)
Adj R^2	0.36	0.36	0.36
	Panel B: With Controls		
Affected Exports	0.09***	0.49***	0.53***
	(0.01)	(0.02)	(0.02)
		[0.43, 0.56]	[0.46, 0.59]
Affected Imports	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Affected Agreements	3.10***	3.09***	3.10***
	(0.06)	(0.06)	(0.06)
Competitor Pressure	0.19***	0.20***	0.20***
	(0.02)	(0.02)	(0.02)
Expected Affected Exports			-0.10***
			(0.01)
Adj R^2	0.36	0.36	0.36
μ_{pri}	✓	✓	✓
μ_{prt}	✓	✓	✓
μ_{rit}	✓	✓	✓
μ_{pit}	✓	✓	✓
N	126,521,609	126,521,609	126,521,609

an approach which increases efficiency in large samples by removing residual variation in the outcome. Column (3) in Table 5 shows that controlling for *Expected AE* yields a coefficient that is similar in size to the coefficient on *Recentered AE* in column (2). The negative coefficient on *Expected AE* shows that countries more exposed to potential adoption by their import partners via trade seem less likely to adopt a regulation domestically, whether or not adoption by their import partners actually occurred. The fact that we obtain similar coefficient estimates with and without controls shows that these controls do not isolate the same variation as *Expected AE*. Therefore, *Expected AE* may be sufficient to purge the OVB in *AE*. Further, dependencies across observations can render inference based on conventional clustered standard errors invalid, so we construct randomization inference confidence intervals (RICI) following Borusyak and Hull (2023) (See Appendix B for details). The coefficient on *Recentered AE* across columns (2)-(3) is statistically different from zero under both clustered standard errors and the wider RICI.

7 Robustness

The appendices contain extensive robustness checks that strongly support our main conclusions—production adjustments necessary to export to standard-imposing countries is the primary channel through which globalization facilitates regulatory diffusion. Correlations in instruments between adjacent countries might contaminate our IV estimates with trends that result from regional geography (Feyrer, 2019*b*). Specifically, comparisons across regions could potentially confound our estimates with local geographic factors that drive both economic integration and standardization. In Appendix A, we include product-regulation-region-year fixed effects to show that our results are not driven by comparisons across regions. In Appendix C, we randomize over adoption by countries for each product-regulation to alleviate concerns that our true estimates capture omitted variation. In Section OA.1, we impose different network structures when measuring a country's network centrality, revealing that connectedness via trade to countries that have adopted a regulation, rather than overall connectedness via trade, drives regulatory diffusion. In Section OA.2, we assess the robustness of our results to the exclusion of EU countries, where regulations may diffuse faster due to mutual recognition of standards.

8 Heterogeneity in Regulatory Diffusion

In Section 6 we show that countries are more likely to domestically adopt regulations enforced by their main trade partners. Moreover, our results suggest that this diffusion is largely driven by exposure via exports. Naturally, many factors can modulate the intensity of regulatory convergence. In this section, we exploit the multidimensionality of our data to test heterogeneity in diffusion by regulation and product characteristics. To do so, we interact AE with cross-sectional variables of interest in Equation (1). The coefficients on the interaction terms inform us whether and how regulatory diffusion via exports responds to the factors of interest.[19]

First, 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 OA.5. 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 6, the coefficient on instrumented AE alone suggests that process regulations also diffuse through export networks. Nevertheless, the positive,

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

Table 6: Heterogeneity in Regulation Adoption

This table reports the estimation of Equation (1) via IV regression after interacting *Affected Exports* with cross-sectional variables. The sample consists of product-regulation-country-year observations where *Adopted (%)* is an indicator of the year a country domestically adopts a regulation on a product, in percentages. We exclude product-regulation-country observations after the year of adoption. The main independent variables, *Affected Exports* and *Affected Imports*, are the export and import shares, respectively, of a product that comply with a standard while *Affected Exports IV* and *Affected Imports IV* are their instruments, which use trade flows predicted by time-varying air and sea distances. *Product Regulation* is an indicator of the NTM belonging to product standards while *Final Product* is an indicator of the HS6 being a final product. See Sections 3 and 8 for details on variable construction. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered by product-country and product-year.

	Adopted (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Affected Exports	0.14***	0.06***	0.06***	0.17***	0.04*	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Affected Exports × *Product Regulation*	0.13***	0.09***	0.08***			
	(0.03)	(0.02)	(0.02)			
Affected Exports × *Final Product*				0.18***	0.19***	0.19***
				(0.04)	(0.04)	(0.04)
Affected Imports	0.10***	0.02*	0.02	0.10***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Affected Agreements			0.09***			0.04*
			(0.02)			(0.02)
Competitor Pressure			0.15***			0.16***
			(0.03)			(0.03)
μ_{pri}	✓	✓	✓	✓	✓	✓
μ_{prt}	✓	✓	✓	✓	✓	✓
μ_{rit}		✓	✓		✓	✓
μ_{pit}		✓	✓		✓	✓
N	52,533,916	52,533,916	52,533,916	43,504,202	43,504,202	43,504,202
$Adj\,R^2$	0.12	0.40	0.40	0.12	0.42	0.42

significant coefficients on the interaction term imply that diffusion of product regulations occurs 92.13%-139.59% 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), which may also be more cost-effective than requirements that involve adjustments to the production process. 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 quite ambiguous to classify. In particular, 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 product, as required by the B85 standards, without being able to determine if the 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 (See Table OA.8).

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 on 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 for final consumption, as intermediate inputs, or as capital goods. We exclude from sample the products for which the end-use is both final consumption and intermediate input, the end-use is missing, and capital goods.[20] Thus, the product-level indicator *Final Product* assumes a value of one if the product's end-use is final consumption, zero otherwise. Columns (4)-(6) of Table 6 show that the coefficients on the interaction of AE and *Final Product* are positive and significant. While we find evidence of regulatory diffusion in intermediate products, the diffusion is 104.90-515.03% stronger in final products.

[20]We experiment with an alternative where we categorize ambiguous products based on compliance observability—final goods take precedence over intermediate or capital goods, and capital goods over intermediate goods—and retain products classified solely as capital goods. Table OA.8 shows that regulations spread similarly for capital goods and intermediate inputs, reflecting compliance unobservability.

9 Conclusion

Although imposing regulations on domestic producers can adversely affect economic outcomes, regulatory standards are necessary to meet the health and environmental protection goals of a country. Potentially, when a country actively participates in global markets of standardized products, the gains to domestic adoption can outweigh the compliance costs. Thus, globalization and economic integration can facilitate regulatory diffusion from complying countries to their trade partners.

We estimate the diffusion in Technical Barriers to Trade through international trade networks. Using an instrumental variables approach based on interactions between geography and technological advances in transport, we show that countries are more likely to domestically adopt standards that their major trade partners adopt. Notably, our results are primarily driven by export relationships, arguably reflecting how production adjustments required to export to standard-imposing countries encourage subsequent domestic implementation. We substantiate these findings through a recentering approach which exploits the exogeneity of the timing of regulation adoption by export destinations to address endogeneity concerns. Exploiting our high-dimensional data, we also establish that the diffusion process is stronger for standards and products with observable compliance.

The richness of our data combined with our identification strategies allow us to go well beyond previous studies, significantly expanding our understanding of trade-based regulatory diffusion. Our collective evidence supports economic integration as a device for the international regulatory "race to the top", highlighting the role of major importers in triggering this process. We believe 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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Appendix

A Within-Region Diffusion

A key advantage in relying on the time-varying geographic component of trade as the instrument is to eliminate time-invariant sources of variation across countries. Still, correlations in instruments between adjacent countries might contaminate estimates with trends that result from regional geography (Feyrer, 2019*b*). In our framework, comparisons across regions could potentially confound our estimates with local geographic factors that drive both economic integration and standardization, even for particular commodity-standard pairs. To alleviate this concern, we include fixed effects interacting indicators for each region z with product, regulation, and time, following Feyrer (2019*b*). Therefore, our estimates would capture diffusion due to integration *within* a product-regulation-region-time combination.

Table A.1 shows that the estimates are largely similar to our baseline IV estimates in Table 4, providing evidence that our results are not driven by differences across regions. Panel A shows a strong first stage for both endogenous variables. The second stage in panel B shows that the coefficient on AE is positive and significant at the 0.1% level, although slightly smaller in magnitude. The estimated effect in column (3) implies that a one s.d. increase in AE leads to a 1.27 p.p. higher probability of domestic adoption, which corresponds to an increase of 5.64% relative to the mean. In contrast, the coefficient of AI is positive only in the model in column (1). Interestingly, the estimated coefficient for AA flips sign but remains statistically significant with the inclusion of regional fixed effects. Finally, the coefficient estimate for CP is similar to that in baseline analysis, although with a smaller magnitude.

Table A.1: Estimation of Regulatory Diffusion Within Regions - Air and Sea Distance IV

This table reports the estimation of Equation (1) via IV regression. The sample consists of product-regulation-country-year observations where *Adopted (%)* is an indicator of the year a country domestically adopts a regulation on a product, in percentages. We exclude product-regulation-country observations after the year of adoption. The main independent variables, *Affected Exports* and *Affected Imports*, are the export and import shares, respectively, of a product that comply with a standard while *Affected Exports IV* and *Affected Imports IV* are their instruments, which use trade flows predicted by time-varying air and sea distances. See Section 3 for details on variable construction. Significance levels are indicated by *, **, and *** at the 5%, 1%, and 0.1% level, respectively. Standard errors are two-way clustered by product-country and product-year.

Panel A. First Stage

	Affected Exports (%)			*Affected Imports (%)*		
	(1)	(2)	(3)	(1)	(2)	(3)
Affected Exports IV	94.12***	93.76***	93.78***	0.78***	0.59***	0.59***
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
Affected Imports IV	0.14***	0.10***	0.10***	88.08***	87.96***	87.97***
	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)	(0.08)
Affected Agreements			−0.16***			−1.12***
			(0.03)			(0.08)
Competitor Pressure			−0.64***			0.05***
			(0.06)			(0.09)
μ_{pri}	✓	✓	✓	✓	✓	✓
μ_{rit}		✓	✓		✓	✓
μ_{pit}		✓	✓		✓	✓
μ_{przt}	✓	✓	✓	✓	✓	✓
F-statistic	657,893	723,131	723,131	125,174	178,390	178,390
N	52,533,916	52,533,916	52,533,916	52,533,916	52,533,916	52,533,916
Adj R^2	0.86	0.88	0.88	0.81	0.83	0.84

Panel B. Second Stage

		Adopted (%)	
	(1)	(2)	(3)
Affected Exports	0.19***	0.11***	0.10***
	(0.02)	(0.01)	(0.01)
Affected Imports	0.09***	−0.01	−0.01
	(0.01)	(0.01)	(0.01)
Affected Agreements			−0.12***
			(0.02)
Competitor Pressure			0.13***
			(0.03)
μ_{pri}	✓	✓	✓
μ_{rit}		✓	✓
μ_{pit}		✓	✓
μ_{przt}	✓	✓	✓
N	52,533,916	52,533,916	52,533,916
Adj R^2	0.15	0.41	0.41

B Randomization Inference Confidence Intervals

Dependencies across observations due to observed and unobserved shocks can render inference based on conventional clustered standard errors invalid. To alleviate this concern, we construct randomization inference confidence intervals (RICI), which guarantee correct coverage in finite samples of observations or shocks, based on the discussion in Borusyak and Hull (2023). We first create a grid of hypothesized values for the parameter of interest, ρ_E, and consider a scalar test statistic T. For each hypothesized value $\rho_E = b$, we follow the steps below:

1. We compute the original value of the test statistic, $T(b)$.
2. We simulate the distribution of the test statistic under the null by exploiting the permutations of the shock. Specifically, we compute the test statistic value for each randomization of the adoption vector, denoted by $T^*(b)$, described in Section 3.3.
3. Under the simulated distribution, we compute the p-value for the original test statistic.[21]
4. A p-value $< \alpha$ provides evidence against the null. Since the simulated distribution is discrete, a rejection criterion of p-value $< \alpha$ is conservative, meaning the Type I error rate will be smaller than the significance level of α.[22]

The confidence interval is constructed by inverting these tests, i.e., it consists of all those b that are not rejected. Building on Borusyak and Hull (2023), we choose a test statistic such that the recentered OLS estimate $\hat{\rho}_E$ is typical under the null $\rho_E = \hat{\rho}_E$, meaning that $T(\hat{\rho}_E) = \mathbb{E}[T^*(\hat{\rho_E})]$. Specifically, the test statistic is $T = \frac{1}{N}\sum_i \tilde{AE}_i(y_i - b\tilde{AE}_i)$

[21] For a two-sided hypothesis test, the p-value is the proportion of simulated test statistics whose absolute values exceed the absolute value of the observed test statistic.

[22] Consider the absolute values of the 200 simulated test statistics arranged in descending order, with $T^*_{(i)}$ denoting the value in the ith position. With the rejection criterion of p-value $\leq \alpha$, if $T = T^*_{(10)}$, we find evidence against the null (p-value $= \alpha$) while if $T = T^*_{(11)}$, we fail to reject the null (p-value $= \alpha$). We adopt the conservative rejection criterion of p-value $< \alpha$ instead for instances like $T_{(11)} < T < T_{(10)}$ which also provides evidence against rejecting the null even though the computed p-value is α.

where $\tilde{AE}$ is the *Recentered AE*, N denotes the sample size and i the observation.[23] When the recentered OLS regression includes covariates or fixed effects, the test statistic is $T = \frac{1}{N}\sum_i \tilde{AE}_i(y_i^{\perp} - b\tilde{AE}_i^{\perp})$, where $x^{\perp}$ denotes the residualized variable x.[24]

C 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 flows to construct the 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 (1)). We repeat this random assignment of adoption to the 92 countries in our sample 300 times.

Figure A.1 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, 0.17, at the 0.1% level (See Table OA.9 for OLS with full sample). Even this partial randomization in adoption, along only the country dimension, reduces the size of the mean coefficient to only about 22% of the true OLS estimate, thereby alleviating the concern that our true estimate picks omitted variation.

[23]Equivalently, recentered OLS estimator is the Hodges-Lehmann estimator associated with this T.

[24]Note that the simulated test statistic, $T^* = \frac{1}{N}\sum_i \tilde{AE}_i^*(y_i^{\perp} - b\tilde{AE}_i^{\perp})$, is centered around zero. Therefore, under the null $\rho_E = \hat{\rho}_E$, $T \approx 0$.

Figure A.1: Random Assignment of Adoption

This figure presents the distribution of coefficients from estimation of the baseline specification Equation (1) after randomizing over importers that adopted each regulation in each product in a year. See Appendix C for details. The mean over 300 iterations is 0.0364 ($s.d. = 0.0489$)