Trade Networks and Diffusion of Regulatory Standards*

Sergio Rocha†
Monash University

Prakrati Thakur‡
Rensselaer Polytechnic Institute

Abstract

We study network effects in the diffusion of regulatory standards through international trade. Our results show that countries are more likely to domestically adopt regulations that they comply with while exporting. We find evidence of such diffusion primarily in regulations concerning attributes of the final product rather than production processes. Consistent with a network effect, we show that countries more open to international trade are the drivers of regulatory diffusion. In an analysis of diffusion in individual features *within* labelling regulations—the most prevalent regulations in our data—we find that labelling requirements ensuring the safety of use propagate the most, and countries tend to domestically adopt features similar to those imposed by their importing partners. Overall, our results support the argument that economic integration can facilitate the strengthening of regulatory standards, aiding international policy coordination.

Keywords: International Trade, Standards, Networks, Policy Diffusion
JEL Classification: F14, F68, C21, C23

*We thank Anil Bera, Dan Bernhardt, Andre Chagas, George Deltas, Tatyana Deryugina, Greg Howard, Johannes Moenius, Frédéric Robert-Nicoud, Vinicios Sant'Anna, Ben Shepherd, and seminar participants at the University of Illinois Urbana-Champaign, 2019 Mid-Continent Regional Science Association, 2020 North American Regional Science Council, and 2021 Midwest Economic Association.

†Department of Banking and Finance, Monash Business School, Monash University, 900 Dandenong Road, Caulfield East, VIC 3145, Australia. Email: sdrocha2@illinois.edu

‡Corresponding Author. Department of Economics, Rensselaer Polytechnic Institute, Russell Sage Laboratory, 110 8th Street, Troy, NY 12180. Email: thakup@rpi.edu

1 Introduction

The impact of regulation on economic outcomes is of central interest in policy-making. On the one hand, adoption of regulations by countries can hinder competition by adversely affecting trade (Disdier et al., 2008), technology diffusion (Conway et al., 2004), and production (Greenstone, 2002; Maskus et al., 2005). On the other hand, regulation is not only necessary to meet social goals such as protection of human health and the environment but can also achieve efficiency gains (Shapiro and Walker, 2020). A country's incentives for unilateral adoption of regulations that impose constraints on domestic producers are limited when competing against non-regulated foreign producers. However, when a country is pressured to comply with these regulations while exporting, the gains to domestic adoption can outweigh the costs imposed by such constraints. Thus, countries that adopt stricter standards can indirectly encourage further implementation in exporting countries, possibly enabling widespread adoption of these policies. The phenomenon of diffusion of regulations through market mechanisms, conceived as the "California effect" in Vogel (2000), demonstrates that economic incentives can align with the social goals of countries by stimulating regulatory coordination among them. Although limited empirical literature documents diffusion in standards, we still know little about the factors that facilitate regulatory propagation.

We estimate the extent of diffusion in the domestic adoption of regulations due to compliance requirements imposed by importing countries on their imports. Further, we are the first to shed light on factors that drive diffusion by studying regulation types and country characteristics that aid the propagation of regulatory standards through trade networks. To quantify the diffusion process, we employ spatial econometric techniques following the practice in related literature (Simmons and Elkins, 2004; Greenhill et al., 2009; Saikawa, 2013). Our sample of regulations consists of Technical Barriers to Trade (TBT) that offer information on various regulation types imposed by countries on imports of a broad class of organic chemicals. The class of organic chemicals, which comprises commodities ranging from the relatively safe (e.g. food additives) to the hazardous (e.g. pyrotechnics and pesticides), is the ninth most traded commodity globally.[1] In addition, it is also the most regulated class of commodities in our TBT data set. We combine regulation data with trade data on organic chemicals to construct a detailed panel comprising information on the adoption of eight regulations by each country's importers, which allows us to assess heterogeneity in diffusion *across* regulations.

Our results show that countries tend to domestically adopt regulations that they comply with when exporting internationally, suggesting that pressure from importers is a meaningful channel of diffusion. Controlling for other diffusion mechanisms (pressure from export competitors, knowledge spillover from other commodities, coercion, and cultural proximity (Simmons and Elkins, 2004; Saikawa, 2013)) and economic indicators, we estimate that one standard deviation (s.d.), i.e., roughly 30 percentage point (p.p.), increase in the share of exports that comply with a regulation is associated with a 1.06-1.92 p.p. increase in the probability of domestic adoption of that regulation. The size of these estimates is commensurate with 6.85-12.37% of average adoption. We find extensive variation in the diffusion by type of standard and countries' openness to international trade.

We show that 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 likely 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 et al., 2009).[2] However, since compliance with process standards, such as labour rights or amount of pesticides used during production, is harder to

[1] See Observatory of Economic Complexity, available at `https://oec.world/en/profile/hs92/organic-chemicals`

[2] The Environmental Protection Agency in the US cracked down on the automobile manufacturer Volkswagen Group on the discovery that several of their models were rigged to perform well during emissions testing but emitted up to 40 times NO_x in real-world driving. See BBC, December 10, 2015, "Volkswagen: The scandal explained". Available at `https://www.bbc.com/news/business-34324772`

verify in the final product, domestic adoption of such standards by exporting countries would confer little competitive advantage over other producers in the global market.

Importantly, our results show that countries that are relatively open to international trade are the drivers of regulatory diffusion. In addition, our estimated network effect is monotonically increasing in a country's level of openness to trade. These findings are consistent with Vogel's (2000) argument that economic openness and international competition are the drivers of policy diffusion because relatively closed countries face modest incentives to match trade partners' policy decisions. These results corroborate that our empirical approach captures a network effect rather than secular trends in regulation adoption.

One challenge in our study of processes of regulatory diffusion, which are endogenous to trade, is to verify that importer pressure is indeed a relevant channel. We address this concern through several novel robustness exercises. Notably, we impose alternative network structures while constructing measures of a country's centrality to show that connectedness in exports to countries *that have adopted a regulation* is more relevant for diffusion than connectedness in other types of networks. These measures of network centrality also allow us to assess indirect effects, i.e., from importer's importers, in regulatory diffusion thereby mitigating a known challenge with spatial econometric methods. We also implement a novel placebo test in the context of diffusion by randomizing adoption of regulations along different dimensions to show that our results are not picking omitted variation of different forms. While the inherent endogenous nature of diffusion forbids modeling it in a causal way (Greenhill et al., 2009; Simmons and Elkins, 2004; Saikawa, 2013; Bowen et al., 2017), our results provide compelling evidence of patterns consistent with regulatory diffusion via importer pressure and the factors that strongly influence this process.

To understand the diffusion of regulations further, we uncover which features of a regulation dominate during its propagation and whether diffusion in individual features also exists. To this end, we focus on labelling requirements—the most prevalent regulation in our sample—and utilize descriptions of measures necessary for the admissibility of products into regulation-imposing countries.[3] We use text analysis to break down each measure to its most salient features, henceforth, referred to as "functional roles". Our results suggest that requirements ensuring safety, such as warning symbols and directions for use, are most widely adopted as labelling regulations diffuse across countries. We also provide evidence that the adoption of each functional role responds strongly to importers' adoption of the same functional role but not to the adoption of other functional roles. Thus, our findings provide additional evidence in support of the network effect by demonstrating *within*-regulation diffusion in individual features.

Our paper closely relates to the literature on diffusion of policies. Simmons and Elkins (2004) study diffusion of liberal economic policies, namely liberalization of current account, capital account, and exchange rate regime. Greenhill et al. (2009) find evidence of trade-induced propagation of labour laws but not of labour rights practices. We expect such incongruity between legislation and actual enforcement for a hard-to-monitor *process* regulation. Finally, Saikawa (2013) shows that importer pressure is the primary driver of the diffusion of automobile emission standards. We are the first to examine heterogeneity in diffusion across various dimensions, which allows us to uncover regulation types and country characteristics associated with stronger diffusion. In addition, we provide direct empirical evidence for Vogel's (2000) assertion that economic integration and standards with observable compliance are the main drivers of regulatory diffusion. Since our data set allows us to study diffusion in individual features *within* a regulation, we develop an understanding of regulatory diffusion at an even more granular level, unveiling specific features of a regulation that prevail during the diffusion of the regulation itself. Further, our finding that countries tend to adopt regulations with features similar to those imposed by their export destinations provides additional evidence in favour of a network effect.

The ramping up of regulations via market mechanisms directly contrasts to a "race to the bottom". Due to the adverse effects of regulations on industry outcomes, as in (Green-

[3]These descriptions are available in the data for every instance of adoption of a labelling regulation by a country.

stone, 2002), countries might tend to lower their standards, over time, to keep their products competitive in international markets. In contrast, our paper supports Porter and van der Linde's (1995) contention that well-designed environmental regulation can trigger innovation that generates benefits greater than the compliance costs and lead to a competitive advantage over foreign firms not subject to similar regulations.

Our paper is also related to the standards and trade literature, which has focused primarily on the impact of regulation on agricultural trade (Disdier et al., 2008), export variety (Shepherd, 2007), and production costs (Maskus et al., 2005). Other studies examine the impact of harmonization of standards on exports (Czubala et al., 2009; Moenius, 2004; An and Maskus, 2009; Schmidt and Steingress, 2022), and stringency of regulation on agricultural trade (Winchester et al., 2012). Several of these papers explore heterogeneity in effects of regulation across different dimensions: by manufactured versus non-manufactured goods (Moenius, 2004), by type of harmonization—mutual recognition agreements versus international norms (An and Maskus, 2009), by high-income versus low-income countries (Shepherd, 2007; Disdier et al., 2008), by firm-size (Schmidt and Steingress, 2022), and by product quality (Yue, 2021). Finally, Ganslandt and Markusen (2001) theoretically examine the impact of an assortment of standards on costs and preferences of trading partners. In contrast, we study the effect of regulatory adoption on further adoption by exporting countries, showing how trade partners' decisions to adopt such policies are interdependent. Our findings suggest that the network effect should be accounted for when estimating the overall effects of regulations on economic outcomes in a trade network. By focusing on how the trade structure generates economic incentives for the diffusion of standards, we provide a novel perspective on the interaction between international trade and regulatory standards.

The rest of the paper is organized as follows: Section 2 presents the data, construction of the panel, and summary statistics. Section 3 discusses the baseline specification, followed by the main results in Section 4 and robustness checks in Section 5. In Section 6, we restrict the sample to labelling regulations and present the development, specifications, and results on the analysis of the functional roles. Finally, Section 7 concludes.

2 Data

We use data on the adoption of a diverse set of Technical Barriers to Trade (TBT), from the UNCTAD TRAINS database, as the foundation of our analysis. In sub-section 2.1, we describe the features of the TBT data that make it suitable for our analysis. Next, we describe the construction of the main variable of interest and the covariates that compose the final panel in sub-section 2.2. Finally, we describe the diffusion pattern observed in the TBTs in sub-section 2.3.

2.1 Background

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, its imposing country, exporting countries regulation is imposed on, the regulated commodities, and the year of implementation.

Several features of the TBT data set make it suitable for our analysis: 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 potentially 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 their country of origin.

The data set contains only regulatory standards adopted by countries at the national level and used as admissibility requirements on their imports.[4] Countries adopt these regulations at will and are at liberty to choose the level of stringency to impose. Further, the data, compiled by classifying legal documents into pre-defined Non-Tariff Measure (NTM) codes,

[4]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.

consist of regulations coded in a standardized way into types. Thus, information on their stringency is limited.

The NTM codes classify the TBTs based on requirements for compliance with product characteristics or production processes. We use adoption data on the following NTMs: B210-Tolerance limits for residues or contamination by certain substances, B220-Restricted use of certain substances, B310-Labelling requirements, B320-Marking requirements, B330-Packaging requirements, B410-TBT regulations on production processes, B420-TBT regulations on transport and storage, and B700-Product quality, safety or performance requirements.[5] Table A.1 provide examples on regulations under each NTM code.

Since our focus is on heterogeneity across regulations, we restrict the sample to 2-digit HS category 29: Organic Chemicals, the most heavily regulated commodity in the TBT data. Being in principle non-discriminatory, a TBT imposes the standard on domestic production and all imports simultaneously. However, for about 2% of cases, the requirements were imposed on exports from only a subset of countries.[6] For simplicity, we drop these observations. As a result of the above cleaning, we have data on the adoption of regulations by 80 countries across the 8 NTMs in the years 1970-2017.[7]

2.2 Panel Construction

In this section, we elaborate on the construction of our panel data set. First, we discuss the construction of our main variable of interest, Fraction of Affected Exports (AE), which captures the *importer pressure* channel of regulatory diffusion. Then, we describe the

[5]We exclude B1-Import Authorization and Licensing, and B8-Conformity Assessment Requirements, involving procedures ensuring compliance with TBT requirements. The two NTMs apply exclusively to imported goods, while our focus is on non-discriminatory regulations imposed on domestic and imported goods alike.

[6]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.

[7]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.

construction of variables used as controls for other channels of diffusion and country-year characteristics.

2.2.1 Fraction of Affected Exports

We obtain bilateral trade data for the 2-digit HS category 29—Organic Chemicals—from the UN Comtrade database for the years 1988-2017 in dollar value terms. As Figure A.1 shows, our sample is representative of the international market of organic chemicals. Specifically, trade among countries within our sample amounts to an average of 52% of the world trade in that commodity. Table A.2 reports the list of countries with their average share in the within-sample trade.

For each regulation r, we construct a country-year level adoption dummy. This dummy is coded as 1 for all years beginning the year 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 regulation that measures the fraction of exports affected by that regulation, following Saikawa (2013), Simmons and Elkins (2004), and Greenhill et al. (2009). To construct the spatial lag for a regulation r, we pre-multiply the adoption vector for any year, y_{rt}, by an exports weight matrix for that year, W_t. The j-th element in the vector y_{rt} represents adoption by country j of regulation r in or before year t; and the ij-th element of matrix W_t represents the fraction of country i's exports that go to country j in year t. This procedure yields the spatial lag vector:

$$AE_{rt} = W_t y_{rt}.$$

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

$$AE_{rit} = \sum_j w_{ijt} y_{rjt},$$

where w_{ijt} is the fraction of exports from country i to j in year t, and y_{rjt} 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 in our baseline analysis.

2.2.2 Controls

We construct several covariates to control for other diffusion mechanisms. Saikawa (2013) argues that *competitor pressure* is a potential channel of diffusion of regulations. She argues that countries adopt regulations in order to stay competitive against other exporters in the international market. To illustrate her point, consider a country C that imports from both A and B, where the former complies with C's regulations while the latter does not. Country C would, thus, favor imports from A, putting an indirect pressure on B to adopt as well. We control for the competitor pressure channel with two variables. For the first one, we follow Saikawa (2013) and build a Herfindahl-Hirschman Index (HHI) by taking sum of squares of the share of country i in imports of all other countries:

$$HHI_{it} = \sum_j s_{ijt}^2,$$

where s_{ijt} is the share of country i in the imports of country j in year t. The HHI is a country-year level variable that increases with the number of importers of a country and the share of that country in their imports. We interpret the HHI as a measure of a nation's status in global exports of organic chemicals, with higher values suggesting higher status, and consequently, lower competitor pressure (Saikawa, 2013). In our sample, the value of HHI ranges on the scale of 0 to 79. When a country holds no import share, its HHI is 0, while when it holds all the import share of all within-sample countries, its HHI is 79.

As an alternative to the HHI, 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. To construct the competitor pressure spatial lag term, we first build yearly matrices where the ij-th element of each matrix is the correlation between exports of countries i and j in that year. The dyadic measures capture the strength of exports competition between a pair of countries (Simmons and Elkins, 2004). Next, we build the regulation-country-year level spatial lag by taking the mean of the adoption dummy for the top 10% competitors of a country as identified by the matrix:

$$CP_{rit} = \frac{\sum_j \mathbb{1}(c_{ijt} \in \text{9th Decile}) y_{rjt}}{\sum_j \mathbb{1}(c_{ijt} \in \text{9th Decile})},$$

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

We also control for knowledge-spillovers from imports of other commodities. For example, firms in a country may learn the procedure of compliance with regulations imposed on organic chemicals by observing imported commodities that meet similar standards. We focus on two distinct commodities: HS2 85-Machinery and HS2 38-Other Chemicals, to capture knowledge-spillovers from products with different levels of closeness in production procedures to organic chemicals. To do this, we form two regulation-country-year level spatial lag terms, one for each commodity—machinery and other chemicals—measuring the fraction of imports of the commodity affected by a regulation. We denote the two spatial lag terms by:

$$KS^g_{rit} = \sum_j w^g_{jit} y^g_{rjt} \quad \forall g \in \{\text{Machinery}, \text{Other Chemicals}\},$$

where w^g_{jit} is the fraction of imports of good g in country i from j in year t, and y^g_{rjt} is the adoption dummy value for good g and regulation r in exporter j in year t. Thus, the KS variables measure the extent to which a country's imports of a good meet a certain standard.

Additionally, we control for diffusion via learning due to cultural proximity with other countries. While formulating regulations for its national setting, a country can draw information from regulations implemented in countries with similar cultural traits. To control for this, we construct three regulation-country-year spatial lags measuring the fraction of language partners that adopted, the fraction of colonial partners that adopted, and the fraction of dominant religion partners that adopted. These variables serve as a proxy for diffusion due to cultural or structural similarities among countries that share a common colonial heritage, language or religion (Simmons and Elkins, 2004). We use the following data to build the matrices relevant to each spatial lag: Bilateral data on common official language and colonial partners from Mayer and Zignago (2011), and Religious Composition by Country, 2010-2050 from Pew Research Center to derive dominant religion partners.

Finally, we include additional country-year level controls: Official Development Aid (ODA), measured as % of GNI, from the World Development Indicators Database, to control for coercion due to development aid received from rich countries. The Political Regime Score, compiled based on Wimmer and Min (2006) and Polity IV data from Center for Systemic Peace by Our World in Data, accounts for institutional characteristics of a country that might influence its incentives to adopt policies. The Political Regime Score varies on a scale of -10 to 10, with -10 being full autocracy and 10 being full democracy, and -20 being colonies or not yet sovereign states. We also control for country characteristics such as Foreign Direct Investment (FDI) as % of GDP and GDP per capita using data from the World Development Indicators Database. In the part of our analysis where we investigate heterogeneity in diffusion by openness to trade, we use data on Openness, measured as the trade value of a country scaled by its GDP, also from Our World in Data.

Lastly, we discuss our treatment of European Union (EU) member country observations. The TBT data provides the adoption of the 8 NTMs at the EU level. Hence, the spatial lag variables based on trade matrices—capturing importer pressure, competitor pressure, knowledge-spillover—and HHI, are constructed by aggregating trade flows to and from the European Union. We construct our other variables at the EU level as follows. If a country is a colonial or a language partner to any EU member, we consider that country to have that relationship with the EU as a whole. Since Christianity is the dominant religion in all major EU countries, the EU's religious partners are countries with Christianity as the dominant religion. We calculate the EU-level aggregate value for FDI by taking a GDP weighted average of FDI, as % of GDP, of EU countries across the years. Similarly, we obtain GDP per capita by taking a population-weighted average of GDP per capita of EU countries.

Political Regime Score for EU is the simple average of individual scores of EU countries, and since none of the EU countries received any ODA after they became members of the EU, the ODA assumes a value of 0 throughout the years.

For each of the 8 NTMs of interest, we have one country-year panel comprising 2,400 observations (80 countries × 30 years). We stack these panels to form our final sample with 19,200 regulation-country-year observations. Table 1 reports the summary statistics of the independent variables. Panel A, which breaks down the fraction of affected exports by NTM, shows substantial variation in compliance requirements across regulations. We find that labelling requirements represent the most widespread type of regulation, with an average of 48.8% of the sample countries' exports complying with labelling requirements imposed by within-sample importers. Packaging and Transport & Storage requirements account for 35.3% and 21.6% of countries' exports respectively, while Tolerance limits only affect 3.7% of exports. Panel B contains descriptive statistics of variables constructed at the regulation-country-year level, i.e., the spatial lag variables capturing various diffusion mechanisms. Finally, panel C describes other controls that vary at the country-year level.

— PLACE TABLE 1 ABOUT HERE —

2.3 Evolution of Regulation Adoption

To begin, we look at the adoption pattern over the years across the eight regulations in our sample.The literature on technology diffusion argues that the adoption of a diffusing technology, over time, resembles an S-shaped logistic curve (Bowen et al., 2017). This curve is marked by a period of slow adoption until a minimum threshold, which commences a period of rapid adoption before it slows down again due to the widespread adoption, leaving few potential new adopters. To check 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. The fitted values from the estimation are averaged by year to get the predicted fraction of countries that adopted by that year. Figure 1 shows that the actual fraction of countries that adopted closely follow the S-shaped pattern of the fitted logistic curve.

— Place Figure 1 About Here —

In general, we find that *product* regulations diffuse faster than *process* regulations. The exceptions are Marking requirements, a product regulation with relatively slow adoption, and Transport requirements, a process regulation with relatively fast adoption. Labelling requirements is the first regulation to reach the conventional 5% adoption threshold used in technology diffusion literature (Bowen et al., 2017). In fact, it reaches the threshold even before the sample period began in 1970. After labelling, regulations that reach the 5% threshold are Packaging, Quality-Safety-Performance, and Transport regulations, in that order, in late the 1970s or 1980s. The rest of the regulations reach the 5% threshold in the late 1990s, or the 2000s. Table (A.3) shows that the speed of adoption varies substantially across all eight regulations. For example, at the beginning of the sample period, the adoption of labelling regulations doubled roughly every ten years, going from 5% in 1970 to 10% in 1979 to 20% in 1989. In contrast, process regulations diffused much slower, including some that don't even cross the 10% threshold by the end of the sample period.

To complement the adoption curves, we conduct a similar exercise with each regulation's coverage ratios. The coverage ratio of a regulation is defined as the fraction of within-sample trade in organic chemicals 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).[8] The model is based on the assumption that coverage ratio is Beta-distributed, $y_t \sim \mathcal{B}(\mu_t, \phi),\ t = 1988, ..., 2017$; and the mean, μ_t, is related to the regressor, t, through a linear predictor and a link function:

$$g(\mu_{rt}) = \beta_0 + \beta_1 t, \quad \forall r, \tag{2}$$

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 2 shows that the coverage ratio of all regulations hit the 5% threshold by 1990, except Marking requirements and Tolerance limits, which were also among the slowest regulations in the logit fits of the fraction of countries that adopted. We observe similar patterns in the speeds of adoption, with product regulations being the fastest (See Table A.4).

— Place Figure 2 About Here —

3 Baseline Specification

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 had adopted by the previous year. Specifically, we estimate the following regression:

$$y_{rit} = \rho_r AE_{rit-1} + \boldsymbol{\beta_1} \mathbf{X_{rit-1}} + \boldsymbol{\beta_2} \mathbf{X_{it}} + \mu_{ri} + \mu_{rt} + \varepsilon_{rit}, \tag{3}$$

where the dependent variable, y_{rit}, is a dummy indicating whether regulation r was in place in country i in year t. Our main variable of interest, AE_{rit-1}, is the one-year lag of Fraction of Affected Exports, the spatial lag that serves as a proxy for importer pressure. We introduce

[8] 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).

a time-lag to our main variable of interest to allow time for a regulation to diffuse to a country after its adoption by the country's trading partners.[9] Pure-space recursive spatial lag models with i.i.d. errors follow classical linear regression model assumptions and thus, can be estimated using OLS (Anselin and Bera, 1998; Anselin, 2003). By allowing ρ to vary by type of regulation, as indicated by the subscript r, we capture heterogeneity in the strength of diffusion across regulations through the importer pressure channel.

Since the spatial lag term, AE_{rit}, is based on time-varying exports weight matrices, it might capture omitted variables correlated with adoption. Thus, it is imperative to specify the model as completely as possible to control for other channels of diffusion. In Equation (3), $\mathbf{X_{rit}}$ is a vector that includes regulation-country-year specific variables, such as KS^g_{rit}, for knowledge-spillover, and the spatial lags based on colonial partners, language partners, and dominant religion partners. Further, the vector $\mathbf{X_{it}}$ includes country-year specific variables, such as HHI_{it}, ODA_{it}, PR_{it}, $GDP/capita_{it}$, and FDI_{it} for competitor pressure, official development aid, political regime, income per capita, and foreign direct investment respectively.

In addition to the described control variables, we include two different sets of fixed effects to account for unobserved heterogeneity along various dimensions. In our main specification, we include regulation-country and regulation-year level fixed effects, μ_{ri} and μ_{rt} respectively. While the former absorbs time-invariant country characteristics specific to each regulation, the latter isolates the diffusion process that takes place over time from secular trends in the adoption of each regulation. To further reduce the possibility that our results reflect omitted variation, we also estimate specifications where we control for country-year level unobservables by including the fixed effects μ_{it}. Because the inclusion of country-year fixed effects absorbs

[9] Although lagged variables might alleviate endogeneity concerns in some instances, it does not address reverse causality between regulation adoption and trade due to the correlation in trade flows over time. Further, to tackle the endogeneity, we could use 2SLS by instrumenting Wy with $\hat{W}X$, where $\hat{W}$ is a matrix of fitted values from gravity equation regressions of w_{ijt} (Kelejian and Piras, 2014). However, the explanatory variables in the gravity equation used as instruments, such as income levels, colonial relationship, and language relationship, are correlated with adoption in ways other than the trade channel, violating the exclusion restriction. Instead, we include such variables as controls.

any variation at that level, coefficients on variables part of the vector $\mathbf{X_{it}}$ can no longer be estimated. Thus, in these cases, we control for competitor pressure with the spatial lag CP_{rit-1} instead of HHI_{it}. Due to the potential correlation between observations within a country and a year for any regulation, we cluster standard errors at regulation-country and regulation-year level in our specifications.

Presumably, several networks of diffusion we control for overlap with each other. Thus, multicollinearity becomes a potential concern. For instance, culturally close countries are also likely to be major trading partners. However, the correlation matrix in Table A.5 shows that correlation between our main variable of interest, AE, and other explanatory variables is moderate mainly in the range -0.12 to 0.6, suggesting multicollinearity is not a significant issue in our estimation.[10]

To test whether more open countries are associated with greater diffusion through the importer pressure channel, we explore heterogeneity by openness of a country to international trade. For countries that are close to autarky or relatively closed to trade, the adoption decision would be driven by secular trends rather than the strength of the importer pressure. To test our hypothesis, we modify our main specification as follows:

$$y_{rit} = \rho AE_{rit-1} + \rho_c[AE_{rit-1} \times \text{Closed}_{it}] + \boldsymbol{\beta_1}\mathbf{X_{rit-1}} + \boldsymbol{\beta_2}\mathbf{X_{it}} + \mu_{ri} + \mu_{rt} + \varepsilon_{rit}, \tag{4}$$

where we interact our main variable of interest AE_{rit-1}, with a dummy indicating whether the country is relatively closed to trade, defined as:

$$\text{Closed}_{it} = \mathbb{1}(\text{Openness}_{it} < 0.4 \text{ quantile})$$

To assess the robustness of our results to different classifications of countries into the "Closed"

[10] We could correct for multicollinearity by dropping a few of a set of strongly correlated variables. However, we find that none of the variance inflation factors (VIFs) for each of our independent variables crosses the rule of thumb threshold of 5, suggesting multicollinearity is not a significant issue (Kutner et al., 2004). Hence, we regress the model with the explanatory variables as specified to prevent the omitted variable bias.

category, we also use 0.6 quantile as the cut-off threshold. In the estimation of Equation (4), ρ captures the effect of the importer pressure on adoption by open countries, while ρ_c captures the differentiated impact on relatively closed ones.

4 Results

As highlighted in Section 3, various factors determine the propagation of regulations in a trade network. Hence, we begin by estimating the effect on regulatory adoption of different diffusion mechanisms. To quantify overall diffusion due to the influence of adoption by importers on their exporters, we estimate specification (3) keeping the coefficient on the main variable of interest, AE, constant in Section 4.1. Next, we study whether certain types of regulation or country characteristics—particularly openness to trade—are associated with stronger diffusion due to importer pressure. To this end, we estimate specification (3) allowing ρ to vary by type of regulation in Section 4.2, and by level of openness in Section 4.3.

4.1 Diffusion Mechanisms

Table 2 presents the results for our main specification described in Equation (3). Our estimation reveals a positive relationship between adoption probability and the fraction of exports affected by a regulation. We find that the coefficient on our main variable of interest, AE, is in the range 0.036-0.065 and statistically significant at the 5% level across specifications. The observed estimates imply that a 10 p.p. increase in affected exports of a country is associated with a 0.36-0.65 p.p. increase in the adoption probability of any regulation by that country. These findings provide evidence that countries are more likely to adopt a regulation when their exports already comply with it, suggesting that *importer pressure* is an important factor driving the propagation of regulations across countries. These results support the findings on diffusion of automobile emission standards (Saikawa, 2013) and labour rights (Greenhill et al., 2009) in a trade network.

— PLACE TABLE 2 ABOUT HERE —

Next, we consider knowledge-spillovers from importing other commodities that are regulated. Table 2 shows that the signs on the coefficients to the variable $KS^{\text{other chemicals}}$ depend on the set of fixed effects at use. Similarly, the coefficient for knowledge-spillovers from Machinery, $KS^{\text{machinery}}$, is positive but not significant across models. Thus, we find inconclusive evidence for knowledge-spillovers from importing regulation-complying Other Chemicals and Machinery on a country's domestic adoption of regulations for Organic Chemicals.

Turning to pressure due to exports competition, we find that in model (1), the variable capturing competitor pressure, HHI, is negatively associated with adoption probability at the 5% significance level. A country with high HHI holds a substantial market share in exports of Organic Chemicals, and thus, faces less pressure to match the standards of export competitors. The estimated coefficient on HHI implies that a one s.d. increase in HHI is associated with a 1.32 p.p. decrease in adoption probability. Further, in model (2), where we include country-year fixed effects, our alternative measure of competitor pressure, CP, has a positive coefficient, which is significant at the 1% level. Since CP measures the prevalence of a regulation across a country's major export competitors, countries with higher CP experience more competitive pressure to adopt the regulation. Consistent with this reasoning, we find that a 10 p.p. increase in adoption by a country's major competitors is associated with a 1.56 p.p. increase in the probability of adoption by that country. Regardless of the variable we use, our findings suggest that competitor pressure is an important driver of policy diffusion, consistent with Simmons and Elkins (2004) and Saikawa (2013).

Finally, among the variables capturing adoption by cultural partners, only the coefficient on adoption by dominant religion partners is significant across specifications. We find that the coefficient on RA is positive and significant at 1% level in model (2). Here, the coefficient is 0.449, implying that a 10 p.p. increase in dominant religion partners that adopted is associated with a 4.49 p.p. increase in adoption probability. However, our results present weak evidence, if any at all, in support of adoption due to the influence of colonial and language partners.

4.2 Heterogeneity by Type of Regulation

Now, we explore whether certain types of regulation are associated with stronger diffusion due to influence from importers on their exporting countries in a trade network. To wit, we run the specification in Equation (3), allowing the coefficient on the fraction of affected exports AE to vary by type of regulation: first, by whether it is a product or a process regulation, and then at the more granular NTM code level.[11] To do so, we estimate specification (3), allowing the coefficient on AE to vary by type of regulation r, which entails including interactions of AE with all possible categories—product and process regulation dummies or the 8 NTM code dummies.[12] Thus, the coefficients of each interaction amount to total slopes rather than differentiated effects relative to a base category.

Table 3 shows that the coefficient on AE interacted with the indicator of product regulation is positive and significant at the 5% level across all models (1)-(2). The estimates vary from 0.045-0.099, implying that a 10 p.p. increase in exports affected by product regulations is associated with a 0.45-0.99 p.p. increase in adoption probability. Notably, the magnitude of the point estimates for the diffusion of product standards is 25-52% higher than the 0.036-0.065 obtained in Table 2. In contrast, we find no evidence of diffusion in process regulations via the importer pressure channel. Since compliance with product regulations can be directly observed, manufacturers gain a competitive advantage by differentiating their products by meeting product standards (Greenhill et al., 2009). However, process regulations are harder to monitor, so adoption by a country's importers provides only a weak incentive for the country's internal adoption.

— PLACE TABLE 3 ABOUT HERE —

To disentangle further the observed relationship between adoption of regulations and

[11] Out of the 8 NTMs in our sample, we classify B310-Labelling requirements, B320-Marking requirements, B330-Packaging requirements, and B700-Product quality, safety or performance requirements as product regulations, while the rest as process regulations.

[12] By interacting with a complete set of possible categories, the original variable must be excluded to avoid perfect collinearity.

importer pressure by type of regulation, we estimate our specification in Equation (3), now allowing the coefficient on AE to vary by NTM. Table 3 reveals that labelling regulations, and to a certain degree, packaging regulations, are driving the positive association between the adoption of product regulations and importer pressure. The coefficient on interaction of AE with the labelling regulation indicator is in the range 0.087-0.168 and significant at least at 5% level across models. Comparison between these point estimates and those reported in models (1)-(2) of Table 3 suggest that labelling standards diffuse 70-93% faster than overall product regulations.

4.3 Heterogeneity by Openness

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 will have little incentives to match the policies of its trade partners. To test heterogeneity in adoption by openness, we estimate the regression in Equation (4) and report the results in Table 4. We find that the coefficient on the fraction of affected exports, AE, is positive and significant at least at 10% level across thresholds and models, indicating that importer pressure is a relevant channel of diffusion in *relatively open* countries. Also, moving from models (1) and (2) to (3) and (4)—as the average level of openness of the relatively open countries increases—so does the magnitude of the point estimates. The estimates range from 0.037-0.140, higher than the estimates of 0.036-0.065 in Table 2.

— PLACE TABLE 4 ABOUT HERE —

In contrast, the coefficient on the fraction of affected exports interacted with "Closed" dummy is consistently negative and significant at 5% level in models (2) and (4). The slope on the fraction of affected exports for closed countries is lower by 0.003-0.141 units than the slope for relatively open countries. Further, row 3 in Table 4 shows that not only do these countries experience less diffusion but also do not experience any significant diffusion due to importer pressure. Consistent with a network effect, our findings suggest that countries that are open to international trade are the main drivers of the observed international regulatory diffusion.

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, the main results in Tables 2-4 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.

5 Robustness Checks

In this section, we assess the robustness of our results to different assumptions. In Section 5.1, we construct alternative measures of network centrality of countries to verify that our results are driven by importer pressure. In Section 5.2, we conduct placebo tests to show that our results do not pick unobserved variation of different forms. In Section 5.3, we show that our main results hold even on excluding the European Union from the sample entirely. Finally, in Section 5.4, we show that our results are robust to an alternative construction of our main independent variable, AE, alleviating the concern that our results capture feedback effects from the adoption of a regulation to trade.

5.1 Alternative Measures of Network Centrality

In this section, we assess the soundness of our results by estimating Equation (3) after replacing AE with other common measures of network centrality that also capture importer pressure (Freeman, 1978; Agneessens et al., 2010). Besides serving as a robustness check, the following exercises are informative in two ways. Since the measures of network centrality allow us to impose different kinds of networks in their construction, these measures demonstrate that connectedness in exports to countries *that have adopted a regulation* is more relevant for diffusion than connectedness in other types of networks such as that in a trade network. Further, the measures allow us to assess indirect network effects, i.e., how adoption by a country's importers' importers influence domestic adoption, which is challenging in a spatial structure as higher-order spatial lag operators yield circular and redundant relations (Anselin and Bera, 1998).

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 four measures of network centrality that are common in the networks literature: degree, closeness (harmonic), eigenvector, and betweenness (Freeman, 1978; Saxena and Iyengar, 2020). Degree centrality simply counts the number of links originating at each node (country). Harmonic centrality is a closeness score suitable to accommodate isolated nodes and groups of nodes (Latora and Marchiori, 2001; Saxena and Iyengar, 2020).[13] For each year, the variable $Harmonic$ is defined as:

$$Harmonic_i = \sum_{j \neq i} \frac{1}{d(i,j)} \tag{5}$$

where $d(i,j)$ is the number of countries in the shortest path between i and j.[14] If there's no path between i and j, then $\frac{1}{d(i,j)} = 0$. The third measure is eigenvector centrality, an extension of degree centrality that accounts for indirect links. Specifically, if $A = (a_{i,j})$ is an adjacency matrix that describes pairwise connections, i.e., $a_{i,j} = 1$ if and only if i is directly

[13] Closeness scores measure how close each node is from all others in the network. We find cases of isolated nodes and groups of nodes in our data especially in early years of regulation networks where only exports to countries with the regulation in place count as links.

[14] The shortest path between any two nodes i and j in the network is the path from i to j crossing the least number of nodes.

connected to j and $a_{i,j} = 0$ otherwise. Then:

$$Eigenvector_i = \frac{1}{|\lambda|} \sum_{j \neq i} a_{i,j} \times Eigenvector_j \tag{6}$$

where $\lambda \neq 0$ is the largest eigenvalue of A in absolute terms and $Eigenvector_i$ is the i-th element of the eigenvector of matrix A associated with λ. Note that Equation (6) defines the score of a node as a function of the score of its neighbors. Succinctly put, eigenvector centrality builds on the notion that a central node is one connected to other central nodes. Thus, this measure is regarded as an extension of degree centrality that accounts for indirect links instead of focusing solely on direct ones. Finally, our fourth measure is betweenness centrality, which is based on how often a particular node serves as a pivot between all other pairs of nodes. Specifically,

$$Betweenness_i = \sum_{j \neq s \neq i} \frac{\sigma_{js}(i)}{\sigma_{js}} \tag{7}$$

where σ_{js} is the number of shortest paths between j and s and $\sigma_{js}(i)$ is the number of such shortest paths that pass through i. Loosely speaking, this score captures the importance of each node for the flow of information through the network (Saxena and Iyengar, 2020).

For ease of interpretation, all centrality measures resulting from the definitions above are normalized. Specifically, degree and harmonic scores are divided by the maximum number of links a node may have. *Betweenness* is divided by the total number of possible bilateral links between all other nodes excluding i. Finally, *Eigenvector* scores are scaled by their maximum component such that the resulting highest score is always one.

We incorporate these measures in our framework in multiple ways. First, we focus solely on overall trade relationships, building yearly networks of exports between countries. In this scenario, our measures of interest will be at the country-year level, and will capture how well-connected, i.e., how *central*, each country is as an exporter of organic chemicals. Alternatively, for each regulatory standard, we construct yearly networks of exports *only to* *countries with the regulation in place*. Here, for country A to be linked to country B, A must export to B and B must have the regulation of interest in place. Thus, the centrality score will be at the country-year-regulation level and will gauge countries' centrality in exports 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 such networks. This would mean that what matters for internal adoption is not being a major exporter, but rather being a leading exporter to countries with the regulation in place.

Additionally, networks can 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. Here, the shortest path between i and j is computed based on 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. Since we have directed trade networks that can be weighted or unweighted and that might account or not for regulations in export destinations, we perform four tests for each node centrality measure.

5.1.1 Unweighted Centrality Measures

Table 5 reports results of the estimation of Equation (3) using each of the centrality measures as the main independent variable. Panel A considers networks of overall exports, where the scores are defined at the country-year level. Hence, we only use NTM-Country and NTM-Year fixed effects in these specifications. The results show that only degree centrality positively predicts domestic adoption of regulations. This estimate is statistically significant at the 5% level, and implies that a one s.d. increase in degree centrality is associated with a 3.3 p.p. increase in average adoption. Overall, the results in panel A offer no consistent evidence of a positive association between export centrality and domestic adoption of regulations.

— PLACE TABLE 5 ABOUT HERE —

Panel B uses networks of exports to countries with each regulation in place, allowing us to also include country-year fixed effects in our estimations. In stark contrast with panel A, it reports positive coefficients of the centrality scores across the board. All the estimates are statistically significant at least at the 5% level. In particular, column (1) shows that an one s.d. increase in degree centrality is associated with a 3.7 p.p. increase in average adoption. In addition, the results in columns (5)–(8) provide evidence of strong indirect diffusion: a one s.d. increase in eigenvector and betweenness centrality imply 16–36 p.p. and 8–12 p.p. higher probability of domestic adoption, respectively.

5.1.2 Weighted Centrality Measures

In this section we repeat our previous exercise using networks weighted by export shares.

— PLACE TABLE 6 ABOUT HERE —

Table 6 report results of regressions with harmonic, eigenvector and betweenness centrality as main independent variables.[15] In panel A, one can see that none of the three measures are significantly correlated with internal adoption when only overall export links are considered. In panel B, where we also include country-year fixed effects, one can see that all specifications deliver a positive and statistically significant relationship between adoption and centrality, barring one. Again, the estimates are suggestive of strong indirect effects of adoption. Altogether, we consider our results with multiple measures of network centrality as compelling evidence of policy diffusion via importer pressure. To wit, these results suggest that what matters for internal adoption is not a country's export network *per se*. Instead, a country is more likely to adopt a regulatory standard when it is pivotal in an export network that complies with that standard specifically.

5.2 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 and not an omitted

[15] We don't use a weighted degree measure because in an export network this measure always sums up to one. In networks of exports only to countries with the regulations in place, it is the sum of weights to export destinations, coinciding with our original measure of importer pressure, AE (Barrat et al., 2004).

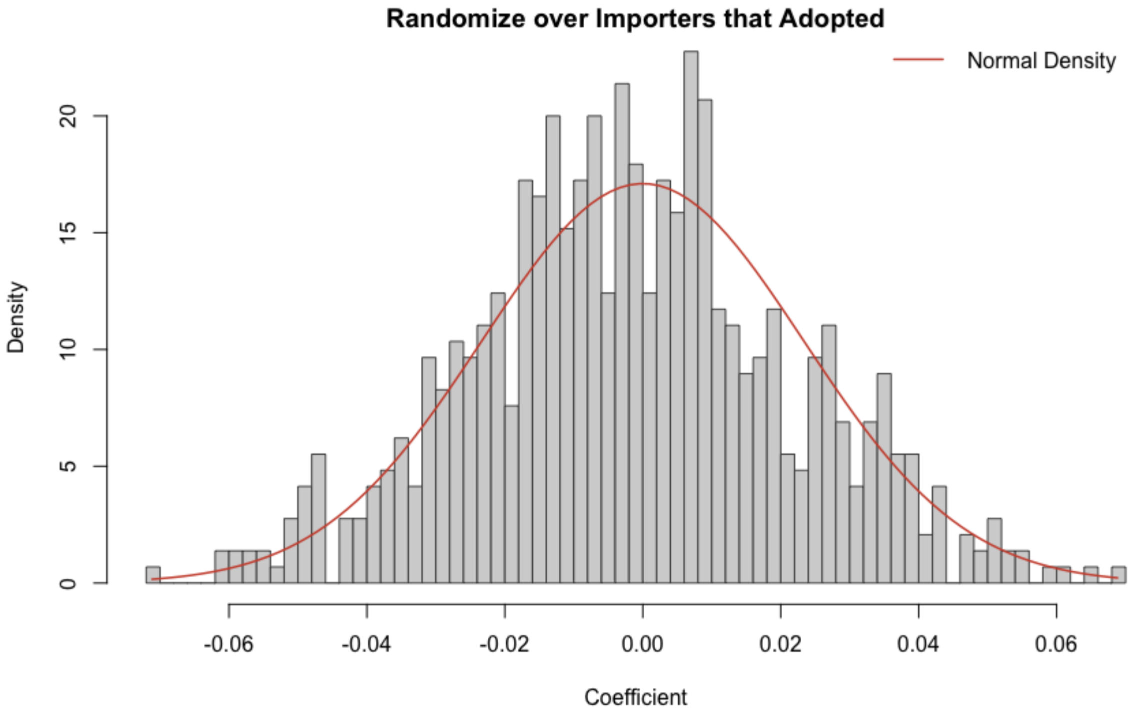
variable. For each NTM, we randomize over which countries adopt the regulation in each year while keeping the overall *proportion* of countries that adopted each year at the true level. Then, we use this randomized adoption vector with the true trade matrices to construct the spatial lag variable, AE, as described in Section 2.2.1. 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 NTM-Year level. We control for omitted variation at this level by estimating our baseline specification (3) with NTM-Country and NTM-Year fixed effects. We repeat this random assignment of adoption to the eighty countries in our sample 25 times for each year. Top panel in Figure 3 shows the distribution of coefficients from the 725 trials. We find that the distribution of coefficients is centered around zero and significantly different from the coefficient from true adoption, 0.036, at the 5% level.[16]

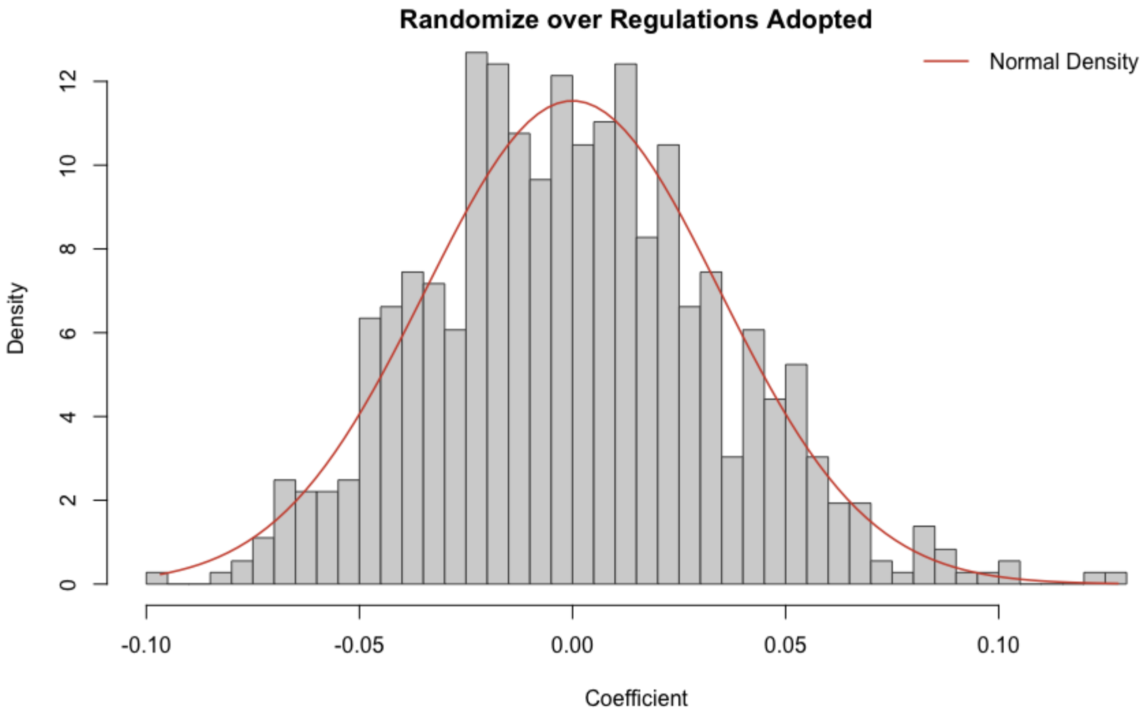
The NTM-Country and NTM-Year level fixed effects control for the omitted variation at the NTM-Year level that we are still preserving in our randomizations while breaking the importer pressure channel of adoption. However, our baseline results could be driven by omitted variation at the Country-Year level and not importer pressure. To ensure this is not the case, we also implement a randomization strategy to preserve the variation at Country-Year level while breaking the importer pressure. For each Country-Year pair, we randomize over which regulations are adopted while keeping the *proportion* of adopted regulations at the true level. Thus, we preserve the overall level of adoption for each country in a particular year but allow the country to randomly choose *which* regulations to adopt.[17] Bottom panel in Figure 3 shows the distribution of coefficients from the estimation of the baseline specification with Country-Year fixed effects in 725 trials. Again, we find that the distribution of coefficients

[16] With this form of randomization, we still expect and do find a positive and significant coefficient, on average, with only Country-Year fixed effects as they don't control for the relevant omitted variation at the NTM-Year level even though importer pressure is broken.

[17] In the first strategy, the importer pressure channel is broken by withholding major importing countries from adoption of a particular regulation whereas in the second strategy, major importers randomly adopt different regulations thereby creating importer pressure to adopt a different set of regulations altogether.

is centered around zero and significantly different from the coefficient from true adoption, 0.065, at the 5% level. Our placebo test provides additional evidence in favor of importer pressure driving diffusion.





5.3 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 organic chemicals, accounting for an average share of 23% of within-sample trade. Thus, the adoption of a regulation by the EU has a large impact on other countries' fraction of exports affected by the regulation. We test the robustness of our results to the exclusion of the EU from our data set altogether.

The results of estimation of Equation (3) without the EU are reported in Table 7. Overall, the point estimates of diffusion via importer pressure are larger than those reported in sub-section 4.1 but follow similar patterns across specifications. The coefficient of AE ranges between 0.042-0.087 and is statistically significant at the 1% level across specifications. As before, diffusion in labelling regulations (Table A.6) and adoption by countries open to international trade (Table A.7) drive these results. As the exclusion of the EU leads to qualitatively similar and quantitatively stronger results, our results are robust to the exclusion of a major importer and provide further evidence of substantial extra-EU diffusion.

— PLACE TABLE 7 ABOUT HERE —

5.4 Feedback Effects

Another potential concern in our 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 results. To address this issue, we test the robustness of our results to an alternative characterization of the fraction of affected exports, AE. Specifically, we re-define AE_{rit-1} as $[W_{t-2}y_{rt-1}]_i$, which is the product of the exports weight matrix lagged by an extra year and an adoption dummy lagged as before by one year. The adoption of a regulation by a country is less likely to affect its trade with other countries the year before the adoption, thus mitigating this particular reverse causality concern. As Table A.8 shows our results are robust to this change. The point estimates in models (1)-(2) range between 0.036-0.064, which are very close to our original estimates in Table 2. Again, we find that product standards and, more specifically, labelling regulations are more strongly associated with diffusion due to importer pressure.

6 Functional Roles Analysis

To delve deeper into the propagation of regulations in a trade network, we study the spread of the most salient features of a regulation as the regulation itself diffuses across countries. We restrict our analysis to NTM B310-Labelling requirements, which are the most widely adopted regulations in our sample. To conduct our analysis, we exploit "measure descriptions" containing detailed information on measures necessary for the admissibility of products into the regulation-imposing country. These descriptions are available for each time the NTM B310 is imposed. This section first describes the data and the procedure we follow to break down each measure to its salient features, which we refer to as Functional Roles. Then, we state the regression specifications we employ to elicit which functional roles dominate during regulatory diffusion and whether diffusion exists *within* a regulation, i.e., in each functional role individually. Finally, we present and discuss the results.

6.1 Data and Classification

We use data on 447 measure descriptions for labelling requirements on HS2 29-Organic Chemicals imposed by a subset of 52 countries available in UNCTAD TRAINS for years 1988-2017. To assign the information in measure descriptions to functional roles, we first break the descriptions down into keywords such as "Name", "Ingredients", "Composition", "Language", and "Color", which describe the information that must be contained on the labels of imported organic chemicals. Then, we classify the keywords into functional roles—a keyword's purpose—in two distinct ways, Generous and Parsimonious.

In the Generous classification, we assign one of three functional roles—Safety Assurance, Quality Assurance, or Other—to each keyword. For example, “Directions for use” and “Warning” are classified as Safety Assurance, while “Rating” and “Weight” are part of Quality Assurance. Some keywords may fall under both Safety and Quality Assurance, and all other keywords become a part of Other. Figure 4 summarizes this procedure. In the Parsimonious classification, we drop ambiguous keywords, such as “Name of Seller”, that fall under both Safety and Quality Assurance in the Generous classification. To further reduce ambiguity, we drop the Other category altogether and retain only Safety and Quality Assurance in the Parsimonious classification. We follow the two classification procedures, with Parsimonious being the more rigorous of the two, to ensure the robustness of our results to different treatments of keywords that may have multiple functional roles. To enhance integrity and accuracy, the two authors worked independently to assign functional roles to each keyword. In case of diverging assignments, the authors debated each case separately until an agreement was reached. The complete list of keywords with their corresponding functional roles under both classifications is given in Table A.9.

Finally, we assign scores to Safety Assurance, Quality Assurance, and Other based on the total number of keywords that fall under each functional role following both types of classification for each measure description. The scores serve as a proxy for how much of a description fulfils a particular purpose, which we call a functional role. Table A.10 presents the summary statistics for each functional role. Row 3 shows that, regardless of the classification, on average, Safety Assurance appears the most as part of a measure description. It also has the highest variance within a description and is imposed the most times in our sample, as shown in lines 4 and 5, respectively. Out of the 447 measure descriptions, Safety Assurance appears at least once in 264 under the Generous classification and 209 descriptions under the Parsimonious classification. Quality Assurance and Other are imposed less than Safety Assurance. A similar pattern of dominance of Safety Assurance plays out in the graphs of the evolution of the three functional roles in Figure A.2.

For each functional role, our procedure yields a country-year panel with 1560 observations (52 countries $\times$ 30 years). Finally, we stack the country-year panels of 3 functional roles for

Generous classification and 2 functional roles for Parsimonious classification to yield our final data sets comprising 4680 and 3120 observations, respectively.

6.2 Specifications

We seek to understand which features of labelling regulation dominate during the diffusion of the regulation itself. In addition, we test whether the adoption of functional roles by a country is driven by the adoption of the same functional roles by its importers. That is, we investigate whether the diffusion phenomenon, observed for individual NTMs, also exists for individual functional roles *within* labelling regulations. To answer our first question, we model the relationship between $Score$ and the percentage of affected exports, AE, as follows:

$$\text{(8)} \qquad \text{PPML:} \quad Score_{itf} = exp(\rho_f log(AE_{it-1} + 1) + \mu_{it}) \times \epsilon_{itf}$$

where $Score_{itf}$ is the Score by year t for country i of functional role f, and ϵ_{itf} is the error term with $E[\epsilon_{itf}|AE_{it-1}, \mu_{it}] = 1$. Here, we allow the coefficient on AE_{it-1} to vary by functional role, as indicated by subscript f on ρ. Such a formulation allows us to get the total marginal effect of AE for each functional role. We include country-year fixed effects, μ_{it}, to control for unobserved confounders at the country-year level. We estimate the equation using the Poisson Pseudo-Maximum Likelihood (PPML) technique, which yields consistent and efficient estimates of elasticities (Santos Silva and Tenreyro, 2006). We prefer the PPML method for two reasons. First, the presence of heteroscedasticity implies that the mean of the log of the error term, which depends on higher-order moments of the error term, is not independent of the covariates, leading to inconsistent estimates while estimating the log-linearized version of Equation (8) via OLS. In contrast, the PPML estimator has been shown to perform well under different specifications of heteroscedasticity. Second, we have many zeros in the dependent variable, which severely limits the sample while estimating the log-linearized version of Equation (8). The PPML estimator, however, is shown to be robust to the presence of excessive zeros in the dependent variable. For comparison and validation, we also estimate the equivalent log-log OLS model below:

$$\text{(9)} \qquad \text{OLS:} \quad log(Score_{itf}) = \rho_f log(AE_{it-1} + 1) + \mu_{it} + \epsilon_{itf}$$

where ϵ_{itf} is the error term with $E[\epsilon_{itf}|AE_{it-1}, \mu_{it}] = 0$.

To test for diffusion in functional roles, we split the percentage of affected exports in proportion to functional roles adopted by importers and estimate the following two specifications:

$$\text{(10)} \qquad \text{PPML:} \quad Score_{itf} = exp(\rho log(AE_{i,t-1,f} + 1) + \alpha log(AE_{i,t-1,-f} + 1) + \mu_{it}) \times \epsilon_{itf}$$

$$\text{(11)} \qquad \text{OLS:} \quad log(Score_{itf}) = \rho log(AE_{i,t-1,f} + 1) + \alpha log(AE_{i,t-1,-f} + 1) + \mu_{it} + \epsilon_{itf}$$

where $AE_{i,t-1,f}$ is the percentage of exports affected by the same functional role, f, as the dependent variable, while $AE_{i,t-1,-f}$ is the percentage of exports affected by all other functional roles, denoted by $-f$. By construction, these two variables add up to total percentage of affected exports: $AE_{i,t-1,f}$+$AE_{i,t-1,-f}$=AE_{it-1}. The parameter ρ in equations (10) and (11) captures diffusion in a functional role due to adoption of the same functional role, while α captures diffusion due to adoption of all other functional roles by a country's importers.

6.3 Results

Table 8 presents the results of the estimation of specifications (8) and (9). The first row reveals that the interaction between the log of percentage of affected exports and the Safety Assurance indicator is consistently positive and significant across all models and classifications. Focusing on our preferred PPML estimates, we find that a 1% increase in the percentage of affected exports is associated with an increase of 0.593-0.692% in Safety Assurance Scores. In contrast, *Score* is less elastic with respect to the percentage of affected exports interacted with either Quality Assurance or with Other. Under the Generous classification, Scores are less elastic with respect to the interaction with Quality Assurance than with Other. However, this result reverses in OLS estimates. Under the Parsimonious classification, the PPML estimate of the elasticity with respect to interaction with Quality Assurance is positive but not statistically significant, while the OLS estimate is negative. Thus, the slope coefficient for Safety Assurance is the most robust under different models and classifications. We conclude that, on average, Safety Assurance features diffuse the most among the three functional roles and that the gap between Scores of Safety Assurance and Quality Assurance widens as the percentage of exports affected by labelling regulations increase.

— PLACE TABLE 8 ABOUT HERE —

We present results for diffusion in functional roles in Table 9. The first row shows that the coefficient on percentage of exports affected by own functional roles is consistently positive and significant across models and classifications. Again, our preferred PPML estimates show that a 1% increase in a country's percentage of exports affected by a functional role is associated with a 0.608-0.698% increase in the country's Score of the same functional role. Thus, a country adopts regulatory measures with functional roles similar to those of its importers' regulations. The coefficient on the percentage of exports affected by all other functional roles is negative and significant across all models, except for PPML with Generous classification. The estimates imply that a 1% increase in a country's percentage of exports affected by other functional roles is associated with a 0.103-0.199% decrease in that country's Score of a functional role.

— PLACE TABLE 9 ABOUT HERE —

In summary, our results show that Safety Assurance features dominate when labelling regulations diffuse in a trade network via importer pressure. Additionally, we document diffusion in individual functional roles within a regulation—the adoption of certain features of a regulation by a country responds strongly to the adoption of similar features by its importers. In contrast, we do not find evidence of complementarities in diffusion across functional roles—a country's adoption of regulations with a particular feature, if anything, responds negatively to importers' implementation of features of a different nature.

7 Conclusion

Although imposing regulations on domestic producers adversely affects economic outcomes (Disdier et al., 2008; Conway et al., 2004; Greenstone, 2002; Maskus et al., 2005), 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 by its importing country, the gains to domestic adoption can outweigh the 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 (Vogel, 2000).

We document the extent of diffusion in domestic adoption of Technical Barriers to Trade, required for admissibility of imported organic chemicals. Controlling for other diffusion mechanisms and economic indicators, we find a positive association between domestic adoption by a country and the extent to which the country complies with a standard while exporting. In addition, our heterogeneity analysis sheds light on types of regulations and country characteristics associated with stronger diffusion. Consistent with network effect, our results suggest that regulatory diffusion is primarily driven by the adoption of standards with observable compliance and by countries that are relatively open to international trade.

Studying the adoption of features *within* a regulation, i.e., Labelling regulation, we find that requirements ensuring the safety of the product are adopted the most as the regulation itself diffuses through the trade network. Further, the adoption of features by a country responds strongly to its importers' adoption of similar features, providing additional evidence supporting a network effect.

As future research, one can expand our approach to include multiple commodities, which would allow testing heterogeneity in diffusion across yet another dimension, i.e., by type of product, which depends on aspects such as the commodity's hazardous content, use of the good in final consumption or as intermediate input, and its environmental impacts. We believe that this is a promising line of research with the potential to shed further light on the underlying mechanisms behind the propagation of regulations through trade networks, possibly assisting policy coordination across countries in an increasingly globalized world.

References

AGNEESSENS, F., T. OPSAHL AND J. SKVORETZ, "Node Centrality in Weighted Networks: Generalizing Degree and Shortest Paths," *Social Networks* 32 (2010), 245–251.

AN, G. AND K. E. MASKUS, "The Impacts of Alignment with Global Product Standards on Exports of Firms in Developing Countries," *The World Economy* 32 (2009), 552–574.

ANSELIN, L., "Spatial Econometrics," *A Companion to Theoretical Econometrics* (2003), 310–330.

ANSELIN, L. AND A. BERA, "Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics," *Handbook of Applied Economic Statistics* (1998), 237–289.

BARRAT, A., M. BARTHELEMY, R. PASTOR-SATORRAS AND A. VESPIGNANI, "The architecture of complex weighted networks," *Proceedings of the National Academy of Sciences* 101 (2004), 3747–3752.

BOWEN, D. E., L. FRÉSARD AND J. P. TAILLARD, "What's Your Identification Strategy: Innovation in Corporate Finance Research," *Management Science* 63 (2017), 2529–2548.

CONWAY, P., D. DE ROSA, G. NICOLETTI AND F. STEINER, "Regulation, Competition, and Productivity Convergence," *OECD Economics Department Working Papers* (2004).

CRIBARI-NETO, F. AND A. ZEILEIS, "Beta Regression in R," *Journal of Statistical Software* 34 (2010), 1–24.

CZUBALA, W., B. SHEPHERD AND J. S. WILSON, "Help or Hindrance? The Impact of Harmonised Standards on African Exports," *Journal of African Economics* 18 (2009), 711–744.

DISDIER, A.-C., L. FONTAGNÉ AND M. MIMOUNI, "The Impact of Regulations on Agricultural Trade: Evidence from the SPS and TBT Agreements," *American Journal of Agricultural Economics* 90 (2008), 336–350.

FERRARI, S. L. AND F. CRIBARI-NETO, "Beta Regression for Modelling Rates and Proportions," *Journal of Applied Statistics* 31 (2004), 799–815.

Freeman, L. C., "Centrality in Social Networks: Conceptual Clarification," *Social Networks* 1 (1978), 215–239.

Ganslandt, M. and J. R. Markusen, "Standards and Related Regulations in International Trade," *NBER Working Paper No. 8346* (2001).

Greenhill, B., L. Mosley and A. Prakash, "Trade-based Diffusion of Labor Rights: A Panel Study, 1986-2002," *American Political Science Review* 103 (2009), 669–690.

Greenstone, M., "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures," *Journal of Political Economy* 110 (2002), 1179–1129.

Kelejian, H. H. and G. Piras, "Estimation of spatial models with endogenous weighting matrices, and an application to a demand model for cigarettes," *Regional Science and Urban Economics* 46 (2014), 140–149.

Kutner, M., C. Nachtsheim and J. Neter, *Applied Linear Regression Models, 4th edition* (New York: McGraw-Hill Irwin, 2004).

Latora, V. and M. Marchiori, "Efficient Behavior of Small-World Networks," *Physical Review Letters* 87 (2001).

Maskus, K. E., T. Otsuki and J. S. Wilson, "The Cost of Compliance with Product Standards for Firms in Developing Countries: An Econometric Study," World Bank Policy Research Working Paper No. 3590, 2005.

Mayer, T. and S. Zignago, "Notes on CEPII's Distance Measures: The GeoDist Database," CEPII Working Paper No. 2011-25, 2011.

Moenius, J., "Information versus Product Adaptation: The Role of Standards in Trade," Available at SSRN, doi: `https://ssrn.com/abstract=608022`, 2004.

Official Journal of the European Union, "Regulation (EU) 2019/515 of the European Parliament and of the Council of 19 March 2019 on the mutual recognition of goods lawfully marketed in another Member State and repealing Regulation (EC) No 764/2008," doi: `https://eur-lex.europa.eu/eli/reg/2019/515/oj`, 2019.

Porter, M. E. and C. van der Linde, "Toward a New Conception of the Environment-Competitiveness Relationship," *Journal of Economic Perspectives* 9 (1995), 97–118.

Saikawa, E., "Policy Diffusion of Emission Standards: Is there a Race to the Top?," *World Politics* 65 (2013), 1–33.

Santos Silva, J. M. C. and S. Tenreyro, "The Log of Gravity," *The Review of Economics and Statistics* 88 (2006), 641–658.

Saxena, A. and S. Iyengar, "Centrality Measures in Complex Networks: A Survey," *ArXiv* abs/2011.07190 (2020).

Schmidt, J. and W. Steingress, "No Double Standards: Quantifying the Impact of Standard Harmonization on Trade," *Journal of International Economics* 137 (2022).

Shapiro, J. and R. Walker, "Is Air Pollution Regulation Too Stringent?," NBER Working Paper No. 28199, 2020.

Shepherd, B., "Product Standards, Harmonization, and Trade: Evidence from the Extensive Margin," World Bank Policy Research Working Paper No. 4390, 2007.

Simmons, B. A. and Z. Elkins, "The Globalization of Liberalization: Policy Diffusion in the International Political Economy," *American Political Science Review* 98 (2004), 171–189.

Smithson, M. and J. Verkulien, "A Better Lemon Squeezer? Maximum-Likelihood Regression with Beta-Distributed Dependent Variables," *Psychological Methods* 11 (2006), 54–71.

UNCTAD, "International classification of non-tariff measures: 2019 version," (2019).

Vogel, D., "Environmental Regulation and Economic Integration," *Journal of International Economic Law* 3 (2000), 265–279.

Wimmer, A. and B. Min, "From Empire to Nation-State: Explaining Wars in the Modern World, 1816–2001," *American Sociological Review* 71 (2006).

Winchester, N., M.-L. Rau, C. Goetz, B. Larue, T. Otsuki, K. Shutes, C. Weick, H. L. Burnquist, M. J. Pinto De Souza and R. Nunes de Faria, "The Impact of Regulatory Heterogeneity on Agri-food Trade," *The World Economy* 35 (2012), 973–993.

Yue, K., "Non-tariff Measures, Product Quality and Import Demand," *Economic Inquiry* 60 (2021), 870–900.

Figures

Figure 1: Logit Fits for Fraction of Countries that Adopted

In this figure, each panel represents evolution of 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).

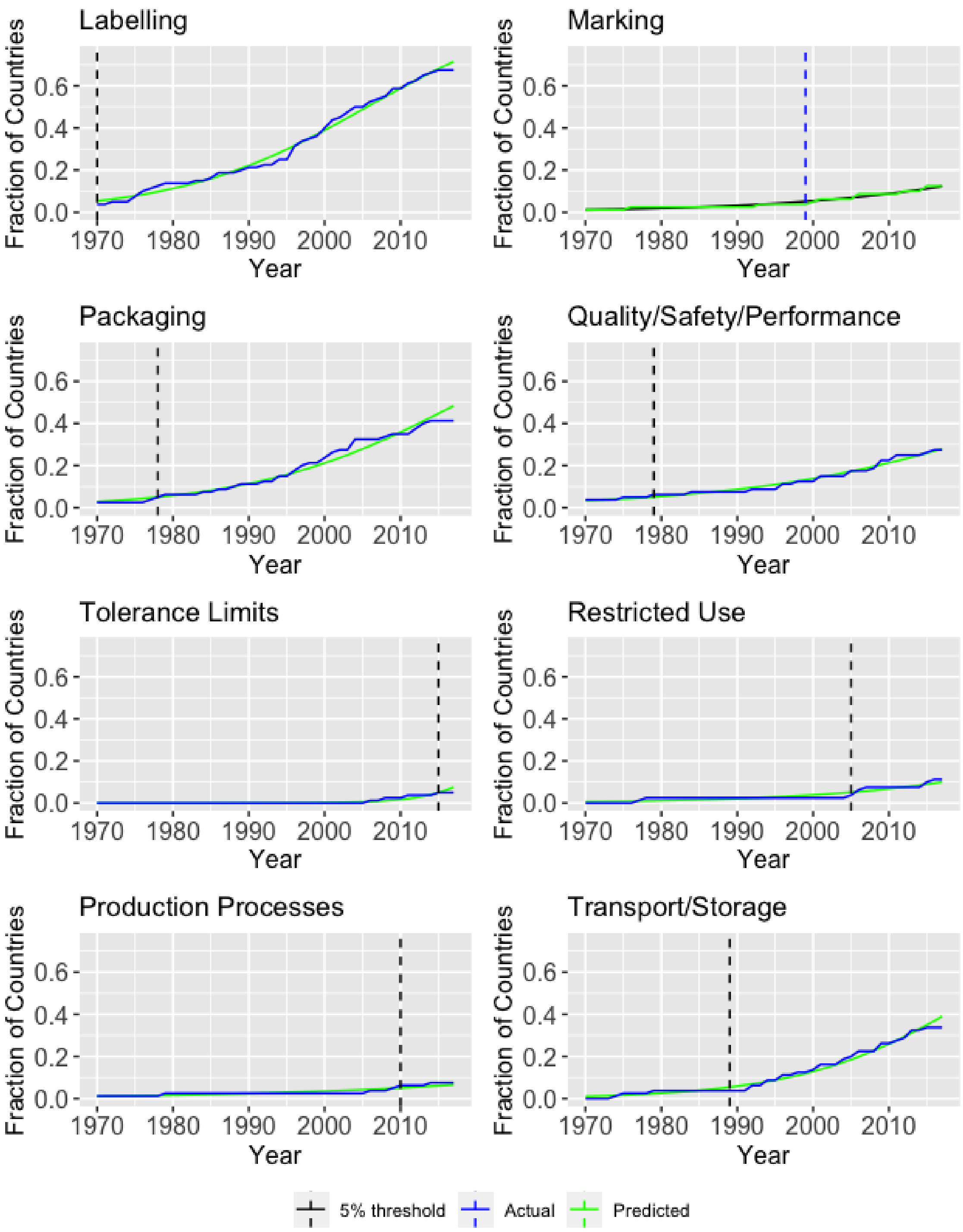


Figure 2: Beta Fits for Coverage Ratio

This figure contains graphs of the evolution of Coverage Ratio of each type of regulation (as specified by NTM code) across years. Coverage ratio is defined as the fraction of within-sample trade that is affected by a regulation; see Section (2.3) for details. The blue lines depict the time series observed in data, whereas the green lines are the fitted values from Beta regressions specified in Equation (2).

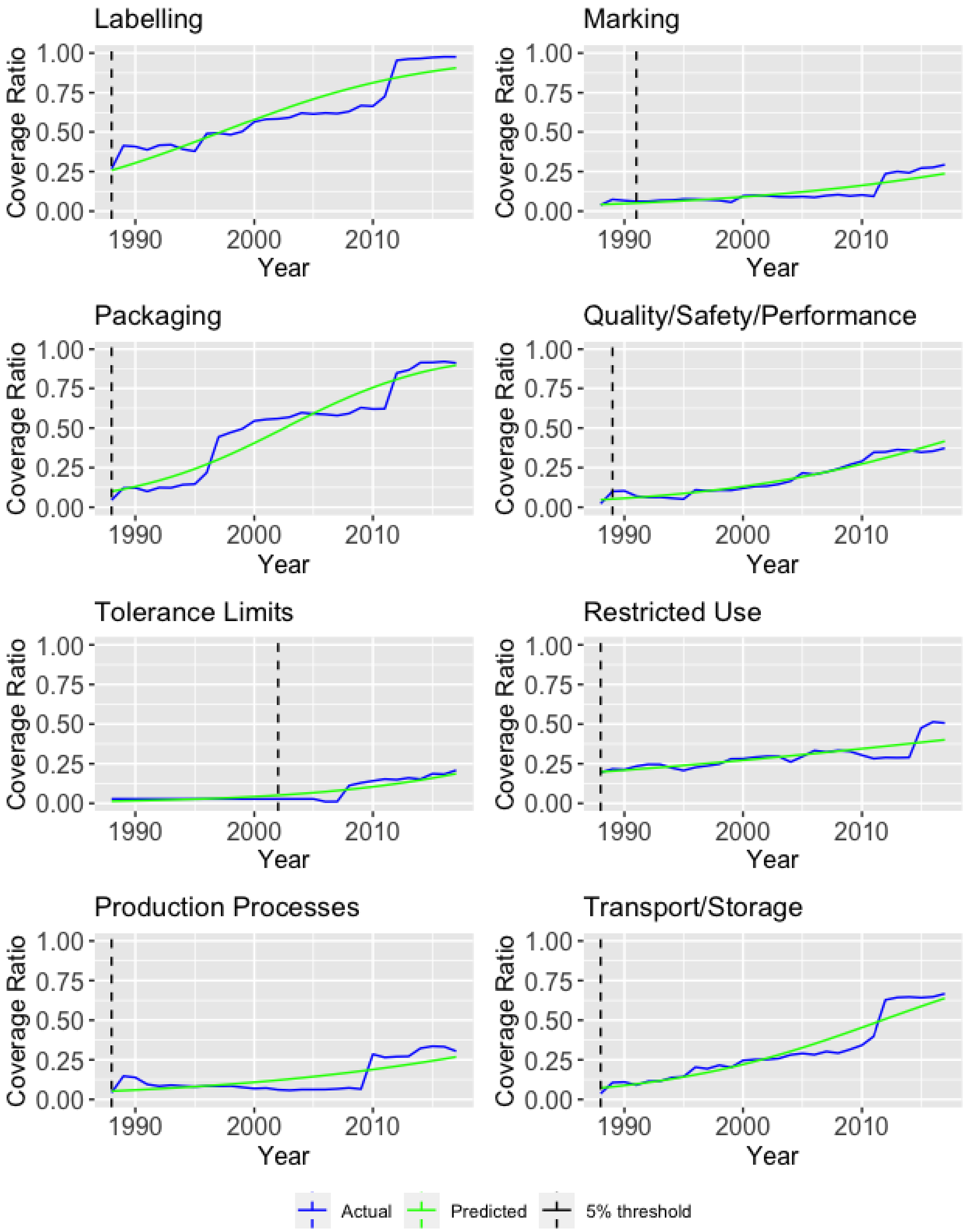


Figure 3: Random Assignment of Adoption

This figure presents the distribution of coefficients from estimation of the baseline specification with randomized adoption of regulations. The top panel presents the coefficients from randomization over importers that adopted each regulation in a year while the bottom panel presents the coefficients from randomization over the regulations that were adopted by each country in a year. See Section 5.2 for details. The mean over 725 iterations is -0.0017 ($s.d. = 0.0233$) in the top panel and 0.00017 ($s.d. = 0.03457$) in the bottom panel.

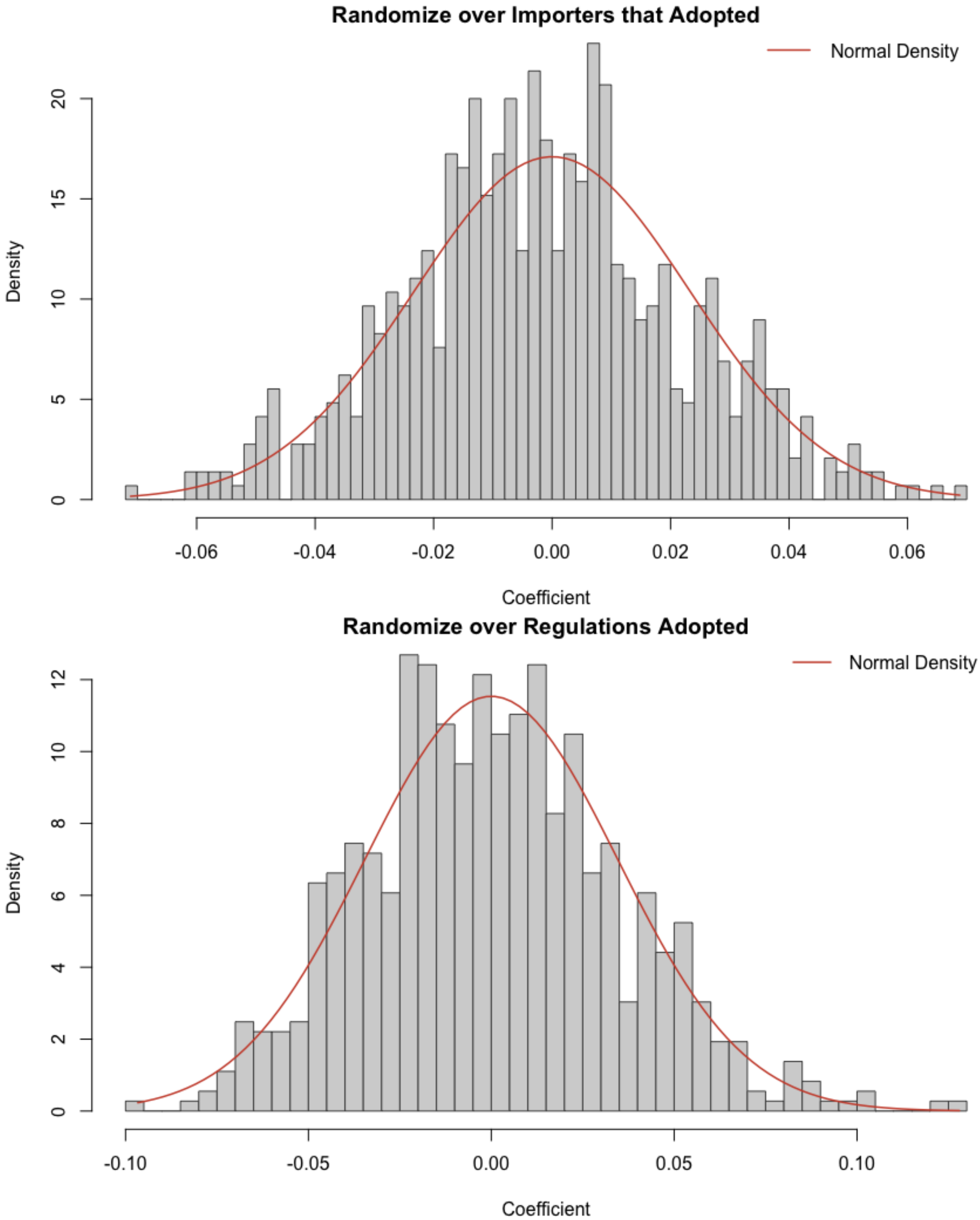
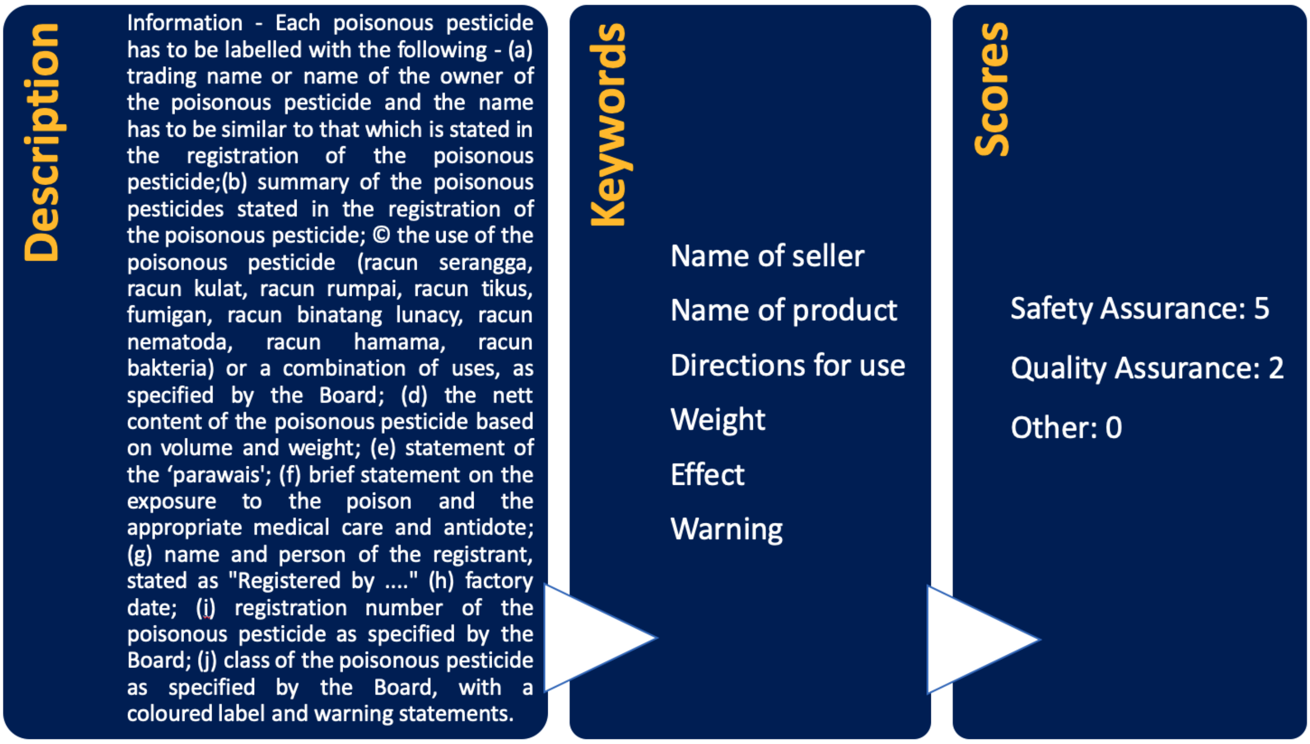


Figure 4: Classification into Functional Roles: Example

This figure provides an example of the procedure we use to calculate functional role scores from measure descriptions. The first panel contains the full text description of a labelling regulation imposed by Malaysia in 1984. The second panel contains the keywords we extract from the text. The third panel reports the scores across the three functional roles per our Generous classification. For details, see Section 6.1.



Tables

Table 1: Summary Statistics

This table reports summary statistics of the variables used in our specifications. Panel A breaks down the main independent variable, *AE*, by NTM code. Panel B reports statistics for other spatial lag variables that capture different diffusion mechanisms and are constructed at the regulation-country-year level. Panel C contains statistics for country-year level control variables. Panel D reports summary statistics of the alternative network centrality measures defined in Section 5.1 For details on the construction of the variables in this table, see Sections 2.2 and 5.1.

Panel A: *AE* by NTM Code	Mean	Median	Std. Deviation	Observations
Tolerance limits	0.037	0.000	0.118	2,320
Restricted use	0.152	0.020	0.243	2,320
Labelling requirements	0.488	0.505	0.368	2,320
Marking requirements	0.079	0.002	0.172	2,320
Packaging requirements	0.353	0.248	0.355	2,320
Production processes	0.083	0.002	0.182	2,320
Transport & storage	0.216	0.075	0.287	2,320
Quality, safety & performance	0.150	0.034	0.224	2,320
Panel B: Spatial Lags	Mean	Median	Std. Deviation	Observations
Knowledge Spillover: Other Chemicals	0.192	0.054	0.270	19,200
Knowledge Spillover: Machinery	0.260	0.114	0.299	19,200
Competitor pressure (CP)	0.168	0.125	0.215	19,200
Adoption by Colonial Partners	0.070	0.000	0.247	19,200
Adoption by Language Partners	0.137	0.045	0.198	19,200
Adoption by Religion Partners	0.148	0.070	0.191	19,200
Panel C: Country-Year Controls	Mean	Median	Std. Deviation	Observations
Competitor Pressure (HHI)	0.361	0.000	1.637	2,389
Official Development Aid (% of GNI)	3.615	0.600	6.831	2,389
Political Regime Score	2.295	5.000	6.747	2,154
GDP/capita (thousands of dollars)	11.326	4.060	15.861	2,338
Foreign Direct Investment (% of GDP)	3.661	2.254	6.100	2,256
Panel D: Other Measures of Centrality	Mean	Median	Std. Deviation	Observations
Country-Year Networks				
Degree	0.264	0.152	0.280	19,200
Harmonic	0.578	0.570	0.226	19,200
Eigenvector	0.439	0.457	0.213	19,200
Betweenness	0.009	0.001	0.023	19,200
Weighted Harmonic	0.030	0.032	0.011	19,200
Weighted Eigenvector	0.055	0.005	0.159	19,200
Weighted Betweenness	0.040	0.011	0.069	19,200
Country-Year-NTM Networks				
Degree	0.052	0.013	0.091	19,200
Harmonic	0.088	0.038	0.119	19,200
Eigenvector	0.176	0.000	0.347	19,200
Betweenness	0.001	0.000	0.005	19,200
Weighted Harmonic	0.004	0.001	0.007	19,200
Weighted Eigenvector	0.098	0.000	0.284	19,200
Weighted Betweenness	0.003	0.000	0.017	19,200

Table 2: Diffusion Mechanisms

This table reports output from the estimation of our baseline specification described in Equation (3), but not allowing the coefficient ρ to vary. The dependent variable is a regulation-country-year adoption indicator that equals one when a country has a regulation in place in a given year. The first (un-numbered) column describes the diffusion mechanism associated with the corresponding independent variable given in the second column. See Sections 2.2 and 3 for details on construction of variables and specifications, respectively. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

		Adopted	
		(1)	(2)
Mechanism:	**Explanatory Variable:**		
Importer Pressure	AE	0.036**	0.065**
		(0.016)	(0.031)
Knowledge Spillover, from Other Chemicals	$KS^{\text{other chem.}}$	−0.065*	0.117**
		(0.036)	(0.047)
Knowledge Spillover, from Machinery	$KS^{\text{machinery}}$	0.025	0.046
		(0.031)	(0.043)
Competitor Pressure	HHI	−0.008**	
		(0.004)	
Competitor Pressure	CP		0.156***
			(0.058)
Adoption by Colonial Partners	CA	−0.145**	0.030
		(0.062)	(0.030)
Adoption by Language Partners	LA	−0.105	0.096
		(0.090)	(0.080)
Adoption by Religion Partners	RA	0.104	0.449***
		(0.121)	(0.095)
Coercion	ODA	0.001	
		(0.001)	
	Political Regime	−0.002	
		(0.002)	
	GDP/capita	0.00001***	
		(0.00000)	
	FDI	−0.001*	
		(0.0004)	
	NTM-Country FE	Y	N
	NTM-Year FE	Y	N
	Country-Year FE	N	Y
	Observations	15,744	18,560
	R^2	0.770	0.454
	Adjusted R^2	0.758	0.375

Table 3: Heterogeneity in Diffusion by Regulation

This table reports output from the estimation of Equation (3), allowing coefficient ρ to vary by type of regulation. The dependent variable is a regulation-country-year adoption indicator that equals one when a country has a regulation in place in a given year. In columns (1) and (2), we interact our main independent variable of interest, AE, with indicators of product and process regulations. In columns (3) and (4), we further break down the effect into regulation level by allowing the diffusion coefficient ρ to vary by NTM code. See Sections 2.2 and 3 for details on construction of variables and specifications, respectively. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

	Adopted			
	(1)	(2)	(3)	(4)
$AE \times$ Product Reg.	0.045^{**}	0.099^{**}		
	(0.022)	(0.041)		
$AE \times$ Process Reg.	0.021	0.011		
	(0.020)	(0.038)		
$AE \times$ Tolerance			-0.040	-0.214^{*}
			(0.047)	(0.125)
$AE \times$ Restricted			0.003	-0.059
			(0.018)	(0.053)
$AE \times$ Labelling			0.087^{**}	0.168^{***}
			(0.035)	(0.059)
$AE \times$ Marking			0.041	-0.014
			(0.041)	(0.059)
$AE \times$ Packaging			0.002	0.153^{**}
			(0.036)	(0.061)
$AE \times$ Production			-0.019	-0.041
			(0.038)	(0.066)
$AE \times$ Transport			0.065	0.092
			(0.041)	(0.061)
$AE \times$ Quality, Safety & Performance			0.040	-0.122
			(0.065)	(0.106)
NTM-Country FE	Y	N	Y	N
NTM-Year FE	Y	N	Y	N
Country-Year FE	N	Y	N	Y
Observations	15,744	18,560	15,744	18,560
R^2	0.770	0.455	0.770	0.460
Adjusted R^2	0.758	0.377	0.758	0.382

Table 4: Heterogeneity in Diffusion by Level of Openness of Countries

This table reports output from the estimation of Equation (4) for different definitions of "Closed" countries. The dependent variable is a regulation-country-year adoption indicator that equals one when a country has a regulation in place in a given year. Columns (1) and (2) classify a country as "Closed" if it lies in the bottom 0.4 quantile while columns (3) and (4) classify a country as "Closed" if it lies in the bottom 0.6 quantile of the distribution of *openness*, respectively. See Sections 2.2 and 3 for details on construction of variables and specifications. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

	Adopted			
	(1)	(2)	(3)	(4)
AE	0.037*	0.106***	0.056**	0.140***
	(0.022)	(0.038)	(0.027)	(0.047)
AE × Closed	−0.003	−0.127**	−0.036	−0.141**
	(0.031)	(0.064)	(0.037)	(0.066)
Total	0.034	-0.021	0.020	-0.001
	(0.023)	(0.053)	(0.023)	(0.044)
NTM-Country FE	Y	N	Y	N
NTM-Year FE	Y	N	Y	N
Country-Year FE	N	Y	N	Y
Observations	15,744	18,560	15,744	18,560
R^2	0.770	0.455	0.771	0.456
Adjusted R^2	0.758	0.377	0.758	0.378

Table 5: Unweighted Centrality Measures

This table reports output from the estimation of Equation (3) replacing AE with alternative measures of network centrality. Panel A uses centrality scores at the country-year level, which measure countries' centrality in the overall exports of organic chemicals. Panel B uses centrality scores at the country-year-NTM level, which, for each regulation, measure centrality in exports to countries with the regulation in place. See Section 5.1 for details on construction of variables and specifications. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

Panel A. Country-Year level Export Networks

	Adopted			
	(1)	(2)	(3)	(4)
Degree	0.118**			
	(0.059)			
Harmonic		−0.007		
		(0.023)		
Eigenvector			−0.080	
			(0.052)	
Betweenness				−0.840
				(0.552)
NTM-country FE	Y	Y	Y	Y
NTM-year FE	Y	Y	Y	Y
Country-year FE	N	N	N	N
Observations	15,272	15,272	15,272	15,272
R^2	0.777	0.776	0.776	0.776
Adjusted R^2	0.764	0.764	0.764	0.764

Panel B. Country-Year-NTM level Export Networks

	Adopted							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Degree	0.416**	0.590***						
	(0.197)	(0.198)						
Harmonic			0.224**	0.788***				
			(0.100)	(0.172)				
Eigenvector					1.040***	0.463***		
					(0.031)	(0.073)		
Betweenness							17.330***	25.072***
							(3.113)	(4.802)
NTM-country FE	Y	N	Y	N	Y	N	Y	N
NTM-year FE	Y	N	Y	N	Y	N	Y	N
Country-year FE	N	Y	N	Y	N	Y	N	Y
Observations	15,272	17,920	15,272	17,920	15,272	17,920	15,272	17,920
R^2	0.777	0.460	0.776	0.463	0.921	0.609	0.796	0.519
Adjusted R^2	0.765	0.382	0.764	0.386	0.917	0.553	0.785	0.450

Table 6: Weighted Centrality Measures

This table reports output from the estimation of Equation (3) replacing AE with weighted measures of network centrality. Panel A uses centrality scores at the country-year level, which measure countries' centrality in the overall exports of organic chemicals. Panel B uses centrality scores at the country-year-NTM level, which, for each regulation, measures centrality in exports to countries with the regulation in place. See Section 5.1 for details on construction of variables and specifications. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

Panel A. Country-Year level Export Networks

	Adopted		
	(1)	(2)	(3)
Harmonic	−0.394		
	(0.302)		
Eigenvector		0.041	
		(0.081)	
Betweenness			−0.105
			(0.065)
NTM-Country FE	Y	Y	Y
NTM-Year FE	Y	Y	Y
Country-Year FE	N	N	N
Observations	15,272	15,272	15,272
R^2	0.776	0.776	0.776
Adjusted R^2	0.764	0.764	0.764

Panel B. Country-Year-NTM level Export Networks

	Adopted					
	(1)	(2)	(3)	(4)	(5)	(6)
Harmonic	1.063	4.044**				
	(0.961)	(1.787)				
Eigenvector			0.724***	0.128***		
			(0.081)	(0.035)		
Betweenness					4.706***	7.005***
					(0.659)	(1.281)
NTM-Country FE	Y	N	Y	N	Y	N
NTM-Year FE	Y	N	Y	N	Y	N
Country-Year FE	N	Y	N	Y	N	Y
Observations	15,272	17,920	15,272	17,920	15,272	17,920
R^2	0.776	0.455	0.801	0.462	0.796	0.520
Adjusted R^2	0.764	0.377	0.790	0.385	0.785	0.451

Table 7: Diffusion Mechanisms without EU

This table reports output from the estimation of our baseline specification described in Equation (3), but not allowing the coefficient ρ to vary. The dependent variable is a regulation-country-year adoption indicator that equals one when a country has a regulation in place in a given year. The first (un-numbered) column describes the diffusion mechanism associated with the corresponding independent variable given in the second column. Observations related to the EU are removed while constructing the spatial lag terms and other covariates. See Sections 2.2 and 3 for details on construction of variables and specifications, respectively. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

		Adopted	
		(1)	(2)
Mechanism:	**Explanatory Variable:**		
Importer Pressure	AE	0.042***	0.087***
		(0.015)	(0.030)
Knowledge Spillover, from Other Chemicals	$KS^{\text{other chem.}}$	−0.033	0.127***
		(0.035)	(0.049)
Knowledge Spillover, from Machinery	$KS^{\text{machinery}}$	0.020	0.253***
		(0.086)	(0.087)
Competitor Pressure	HHI	−0.006	
		(0.005)	
Competitor Pressure	CP		0.291***
			(0.053)
Adoption by Colonial Partners	CA	0.006	−0.038
		(0.017)	(0.027)
Adoption by Language Partners	LA	0.013	0.146***
		(0.013)	(0.031)
Adoption by Religion Partners	RA	0.014	0.200***
		(0.017)	(0.047)
Coercion	ODA	0.001*	
		(0.001)	
	Political Regime	−0.002	
		(0.002)	
	GDP/capita	0.00001***	
		(0.00000)	
	FDI	−0.001**	
		(0.0004)	
	NTM-Country FE	Y	N
	NTM-Year FE	Y	N
	Country-Year FE	N	Y
	Observations	15,512	18,328
	R^2	0.771	0.442
	Adjusted R^2	0.758	0.362

Table 8: Results–Dominant Functional Roles

This table reports the output from the estimation of Equations (8) and (9) under two classifications–Generous and Parsimonious. The first and third columns report results of the OLS estimation, whereas the second and fourth columns report PPML estimates. The dependent variable is functional role-country-year level score calculated using measure descriptions of labelling requirements. For details on construction of the variable, see Section 6.1. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at Functional Role-Country and Functional Role-Year level.

	Generous		Parsimonious	
	OLS	PPML	OLS	PPML
log(%AE+1)×Safety Assurance	0.250***	0.692***	0.179***	0.593***
	(0.0158)	(0.144)	(0.0161)	(0.152)
log(%AE+1)×Quality Assurance	0.0611***	0.419***	-0.0693***	0.137
	(0.0152)	(0.148)	(0.0159)	(0.156)
log(%AE+1)×Other	0.0158	0.462***		
	(0.0163)	(0.164)		
Country-Year FE	Y	Y	Y	Y
Observations	1,854	4,524	885	1,972
R^2	0.644		0.741	

Table 9: Results–Diffusion in Functional Roles

This table reports the output from the estimation of Equations (10) and (11) under two classifications–Generous and Parsimonious. The first and third columns report results of the OLS estimation, whereas the second and fourth columns report PPML estimates. The dependent variable is functional role-country-year level score calculated using measure descriptions of labelling requirements. For details on construction of the variable, see Section 6.1. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at Functional Role-Country and Functional Role-Year level.

	Generous		Parsimonious	
	OLS	PPML	OLS	PPML
$\log(\%\mathrm{AE}_f + 1)$	0.287***	0.608***	0.289***	0.698***
	(0.0165)	(0.116)	(0.0157)	(0.110)
$\log(\%\mathrm{AE}_{-f} + 1)$	-0.103***	0.0993	-0.199***	-0.124*
	(0.0162)	(0.109)	(0.0166)	(0.0752)
Country-Year FE	Y	Y	Y	Y
Observations	1,854	4,524	885	1,972
R^2	0.585		0.714	

Online Appendix to
"Trade Networks and Regulatory Standards Diffusion"

Sergio Rocha and Prakrati Thakur

University of Illinois

Figure A.1: Share of Trade among Countries within Sample in World Trade

This figure depicts the share of trade among countries within our sample in total world trade in the HS2 category 29–Organic Chemicals. Specifically, we compute the ratio of total trade flows among countries within our sample to total world trade flows of organic chemicals for each year. This figure reports the evolution of that ratio over the sample years. The low percentage share for the year 1988 suggests poor reporting for countries within our sample in the original data source UN Comtrade. However, our results are robust to excluding the year 1988 from our sample.

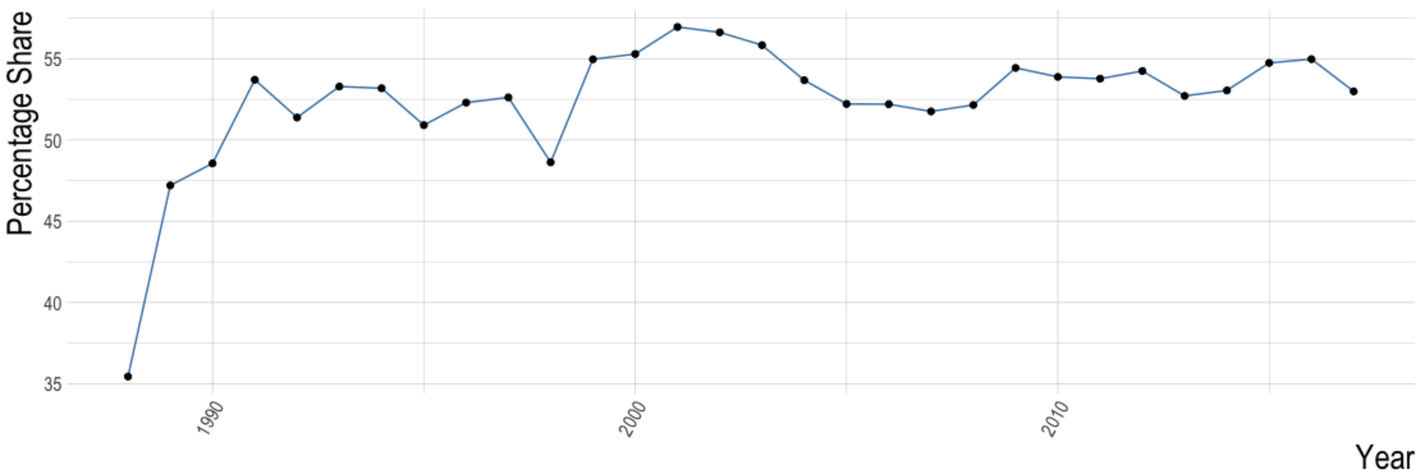


Figure A.2: Evolution of Functional Roles

This figure shows the evolution of functional role scores over the sample years. The first picture partitions the evolution of the total score into the three functional roles per our Generous classification. The second picture reports evolution of scores of the two functional roles under the Parsimonious classification. For details, see Section 6.1.

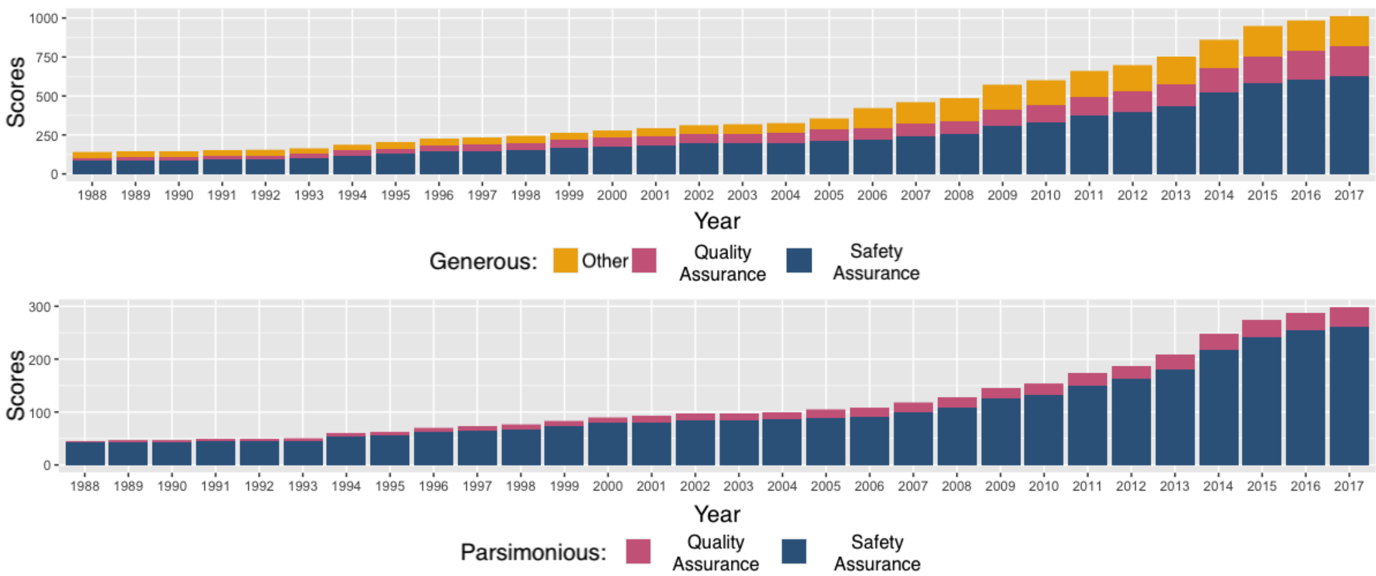


Table A.1: Example TBT Regulations

This table provides an example of a regulation under each NTM code, obtained from the manual on International Classification on Non-Tariff Measures (UNCTAD, 2019). See Section 2.1 for details.

B210: Tolerance Limits

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

B220:Restricted Use

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

B310: Labelling

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

B320: 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.*

B330: Packaging

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

B410: Production Processes

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

B420: Transport and Storage

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

B700: Quality, Safety , or Performance Requirements

- ***Examples:*** *Doors must resist a certain minimum high temperature. Toys for children under three years of age shall not contain articles smaller than a certain size. There are minimum conditions for the performance of pedal bicycles in relation to handlebars, seats and brakes.*

Table A.2: List of Countries with their Average Share in within-sample Trade

This table reports a list of all the countries in our sample and their respective shares in within-sample trade of commodity HS2 29–Organic Chemicals. To obtain the figures reported in the table, we compute shares of each country for every sample year in within-sample trade, and then, average those values over the years. The list is decreasing in countries' shares of sample trade.

Country	% of Trade Flows	Country	% of Trade Flows
European Union	22.81	Bahrain	0.04
USA	22.65	Tunisia	0.04
Japan	10.24	Sri Lanka	0.03
China	8.04	Myanmar	0.03
Switzerland	7.37	Paraguay	0.03
Singapore	4.33	El Salvador	0.03
Canada	3.60	Honduras	0.02
Brazil	2.54	Kazakhstan	0.02
Mexico	2.49	Ivory Coast	0.02
Saudi Arabia	1.80	Barbados	0.02
Thailand	1.75	Jamaica	0.02
Indonesia	1.61	Cuba	0.02
Malaysia	1.25	Lebanon	0.02
Hong Kong	1.24	Brunei Darussalam	0.02
Australia	1.08	Ghana	0.01
Argentina	0.81	Cambodia	0.01
Israel	0.76	Bolivia	0.01
Russian Federation	0.75	Nicaragua	0.01
Colombia	0.52	Senegal	0.01
Venezuela	0.50	Laos	0.01
Panama	0.45	Cameroon	0.01
Pakistan	0.37	Papua New Guinea	0.01
Philippines	0.32	Ethiopia	0.01
Chile	0.30	Antigua and Barbuda	0.004
United Arab Emirates	0.26	Togo	0.003
Viet Nam	0.26	Niger	0.002
New Zealand	0.23	Mali	0.002
Kuwait	0.15	Burkina Faso	0.002
Qatar	0.13	Kyrgyzstan	0.002
Bahamas	0.13	Liberia	0.002
Oman	0.11	Benin	0.002
Peru	0.11	Suriname	0.001
Morocco	0.08	Afghanistan	0.001
Nigeria	0.08	Guyana	0.001
Algeria	0.08	State of Palestine	0.001
Uruguay	0.07	Dominica	0.001
Ecuador	0.07	Gambia	0.001
Guatemala	0.07	Cape Verde	0.0003
Jordan	0.07	Grenada	0.0003
Costa Rica	0.05	Tajikistan	0.0003

Table A.3: Logit Regressions for Faction of Countries that Adopted

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 that varies at the country and year levels. The independent variable is year. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively.

	Tolerance	Restricted	Labelling	Marking	Packaging	Production	Transport	Quality/Safety
Year	0.217^{***}	0.060^{***}	0.081^{***}	0.053^{***}	0.073^{***}	0.039^{***}	0.086^{***}	0.052^{***}
	(0.039)	(0.008)	(0.003)	(0.006)	(0.004)	(0.007)	(0.005)	(0.004)
Constant	-440.765^{***}	-122.878^{***}	-161.662^{***}	-108.976^{***}	-148.295^{***}	-80.316^{***}	-174.219^{***}	-106.054^{***}
	(77.579)	(15.038)	(6.427)	(12.518)	(7.562)	(14.490)	(9.789)	(8.121)
R^2	0.232	0.064	0.168	0.056	0.129	0.029	0.150	0.066
Observations	3,840	3,840	3,840	3,840	3,840	3,840	3,840	3,840
$\hat{p} \geq 5\%$	2015	2005	1970	1999	1978	2010	1989	1979
$\hat{p} \geq 10\%$	-	2017	1979	2013	1989	-	1997	1993
$\hat{p} \geq 20\%$	-	-	1989	-	2000	-	2007	2009
$\hat{p} \geq 40\%$	-	-	2001	-	2013	-	-	-

Table A.4: Beta Regressions for Coverage Ratio

This table reports the output of Beta regressions specified in Equation (2), 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 at year level. We define coverage ratio as the fraction of within-sample trade that is affected by a regulation. The independent variable is year. See Section (2.3) for details. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively.

	Tolerance	Restricted	Labelling	Marking	Packaging	Production	Transport	Quality/Safety
Year	0.097^{***}	0.034^{***}	0.115^{***}	0.067^{***}	0.151^{***}	0.065^{***}	0.108^{***}	0.092^{***}
	(0.012)	(0.005)	(0.012)	(0.007)	(0.011)	(0.012)	(0.007)	(0.005)
Constant	-197.539^{***}	-69.731^{***}	-229.013^{***}	-136.962^{***}	-302.915^{***}	-132.200^{***}	-216.447^{***}	-185.100^{***}
	(24.118)	(9.228)	(23.667)	(14.609)	(21.152)	(23.827)	(13.691)	(9.489)
Observations	30	30	30	30	30	30	30	30
R^2	0.548	0.673	0.764	0.738	0.916	0.391	0.911	0.893
$\hat{p} \geq 5\%$	2002	1988	1988	1991	1988	1988	1988	1989
$\hat{p} \geq 10\%$	2010	1988	1988	2002	1989	1999	1992	1997
$\hat{p} \geq 20\%$	-	1989	1988	2014	1994	2012	1999	2006
$\hat{p} \geq 40\%$	-	2017	1994	-	2000	-	2008	2017

Table A.5: Correlation Matrix

This table reports pairwise correlations between the variables used in regressions. See Section 2.2 for details on construction of each variable.

	Adopted	AE	$KS^{\text{other chem.}}$	$KS^{\text{machinery}}$	HHI	CP	CA	LA	RA	ODA	Pol. Reg.	GDP/capita	FDI
Adopted	1	0.329	0.330	0.257	0.041	0.387	0.195	0.324	0.415	-0.128	0.057	0.213	0.073
AE	0.329	1	0.492	0.389	0.048	0.600	0.380	0.472	0.547	-0.119	0.076	0.146	0.048
$KS^{\text{other chem.}}$	0.330	0.492	1	0.628	0.015	0.597	0.435	0.507	0.627	-0.064	0.081	-0.0001	0.086
$KS^{\text{machinery}}$	0.257	0.389	0.628	1	0.004	0.449	0.377	0.381	0.436	-0.102	0.216	0.064	0.098
HHI	0.041	0.048	0.015	0.004	1	0.022	0.009	0.023	0.023	-0.114	0.152	0.295	-0.022
CP	0.387	0.600	0.597	0.449	0.022	1	0.416	0.593	0.708	-0.102	0.027	0.093	0.054
CA	0.195	0.380	0.435	0.377	0.009	0.416	1	0.396	0.382	-0.058	0.074	0.018	0.036
LA	0.324	0.472	0.507	0.381	0.023	0.593	0.396	1	0.589	-0.015	0.012	0.085	0.102
RA	0.415	0.547	0.627	0.436	0.023	0.708	0.382	0.589	1	-0.038	0.021	0.060	0.098
ODA	-0.128	-0.119	-0.064	-0.102	-0.114	-0.102	-0.058	-0.015	-0.038	1	-0.004	-0.325	0.148
Political Regime	0.057	0.076	0.081	0.216	0.152	0.027	0.074	0.012	0.021	-0.004	1	0.082	0.022
GDP/capita	0.213	0.146	-0.0001	0.064	0.295	0.093	0.018	0.085	0.060	-0.325	0.082	1	0.047
FDI	0.073	0.048	0.086	0.098	-0.022	0.054	0.036	0.102	0.098	0.148	0.022	0.047	1

Table A.6: Heterogeneity in Diffusion by Regulation without EU

This table reports output from the estimation of Equation (3) for different specifications, allowing the coefficient ρ to vary by type of regulation. The dependent variable is a regulation-country-year adoption indicator that equals one when a country has a regulation in place in a given year. In columns (1) and (2), we interact our main independent variable of interest, AE, with indicators of product and process regulations. In columns (3) and (4), we further break down the effect into regulation level by allowing the diffusion coefficient ρ to vary by NTM code. See Sections 2.2 and 3 for details on construction of variables and specifications, respectively. Observations related to the EU are removed while constructing the spatial lag terms and other covariates. See Sections 2.2 and 3 for details on construction of variables and specifications. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

	Adopted			
	(1)	(2)	(3)	(4)
AE × Product Reg.	0.050**	0.135***		
	(0.020)	(0.038)		
AE × Process Reg.	0.027	0.010		
	(0.020)	(0.039)		
AE × Tolerance			−0.010	−0.235**
			(0.048)	(0.105)
AE × Restricted			0.009	−0.075
			(0.014)	(0.052)
AE × Labelling			0.082**	0.211***
			(0.036)	(0.054)
AE × Marking			0.033	−0.012
			(0.034)	(0.059)
AE × Packaging			0.032	0.198***
			(0.036)	(0.059)
AE × Production			−0.030	−0.063
			(0.032)	(0.066)
AE × Transport			0.085*	0.117*
			(0.044)	(0.065)
AE × Quality, Safety & Performance			0.035	−0.011
			(0.050)	(0.088)
NTM-Country FE	Y	N	Y	N
NTM-Year FE	Y	N	Y	N
Country-Year FE	N	Y	N	Y
Observations	15,512	18,328	15,512	18,328
R^2	0.771	0.445	0.771	0.452
Adjusted R^2	0.758	0.366	0.758	0.373

Table A.7: Heterogeneity in Diffusion by Level of Openness of Countries without EU

This table reports output from the estimation of Equation (4) for different definitions of “Closed” countries. The dependent variable is a regulation-country-year adoption indicator that equals one when a country has a regulation in place in a given year. Columns (1) and (2) classify a country as “Closed” if it lies in the bottom 0.4 quantile while columns (3) and (4) classify a country as “Closed” if it lies in the bottom 0.6 quantile of the distribution of *openness*, respectively. Observations related to the EU are removed while constructing the spatial lag terms and other covariates. See Sections 2.2 and 3 for details on construction of variables and specifications. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

	Adopted			
	(1)	(2)	(3)	(4)
AE	0.041**	0.131***	0.056**	0.166***
	(0.020)	(0.038)	(0.026)	(0.046)
AE × Closed	0.001	−0.128**	−0.023	−0.140**
	(0.028)	(0.059)	(0.034)	(0.062)
$Total$	0.042**	0.004	0.033*	0.026
	(0.020)	(0.047)	(0.020)	(0.041)
NTM-Country FE	Y	N	Y	N
NTM-Year FE	Y	N	Y	N
Country-Year FE	N	Y	N	Y
Observations	15,512	18,328	15,512	18,328
R^2	0.771	0.444	0.771	0.445
Adjusted R^2	0.758	0.365	0.759	0.365

Table A.8: Main Results & Heterogeneity by Regulation with $AE = [W_{t-2} y_{rt-1}]$

This table reports output from the estimation of our baseline specification described in Equation (3) with an alternative structure on our main spatial lag variable, AE. Specifically, we compute AE by multiplying two-year lagged trade matrices by one-year lagged adoption vectors. The dependent variable is a regulation-country-year adoption indicator that equals one when a country has a regulation in place in a given year. Columns (1) and (2) report the coefficient to the main diffusion variable. Columns (3) and (4) break down the result by product and process standards, whereas columns (5) and (6) further split the result by NTM code. See Sections 2.2, 3, and 5.4 for details on construction of variables and specifications. Significance levels are indicated by *, **, and *** at the 10%, 5%, and 1% level, respectively. Standard errors are two-way clustered at NTM-Country and NTM-Year level.

	Adopted					
	(1)	(2)	(3)	(4)	(5)	(6)
AE	0.036**	0.064**				
	(0.016)	(0.032)				
AE × Product Reg.			0.043**	0.097**		
			(0.022)	(0.041)		
AE × Process Reg.			0.023	0.010		
			(0.021)	(0.039)		
AE × Tolerance					−0.036	−0.250*
					(0.049)	(0.128)
AE × Restricted					0.002	−0.061
					(0.018)	(0.054)
AE × Labelling					0.081**	0.182***
					(0.037)	(0.058)
AE × Marking					0.034	−0.044
					(0.042)	(0.063)
AE × Packaging					0.007	0.147**
					(0.034)	(0.059)
AE × Production					−0.017	−0.065
					(0.037)	(0.071)
AE × Transport					0.071*	0.094
					(0.043)	(0.062)
AE × Quality, Safety & Performance					0.038	−0.071
					(0.066)	(0.110)
NTM-Country FE	Y	N	Y	N	Y	N
NTM-Year FE	Y	N	Y	N	Y	N
Country-Year FE	N	Y	N	Y	N	Y
Observations	15,272	17,920	15,272	17,920	15,272	17,920
R^2	0.776	0.455	0.776	0.456	0.777	0.459
Adjusted R^2	0.764	0.377	0.764	0.378	0.764	0.381

Table A.9: Keywords and Classification

This table reports the full list of keywords used to construct functional role scores from measure descriptions of labelling regulations. The first column contains the keyword. The second and the third columns report functional roles assigned to the keyword according to Generous and Parsimonious classifications, respectively. For details, see Section 6.1.

Keyword	Generous	Parsimonious
Authorization	Safety Assurance	Safety Assurance
Batch No.	Safety Assurance, Quality Assurance	
Certificate	Safety Assurance	Safety Assurance
Character	Safety Assurance	
Chemical formulae	Safety Assurance	Safety Assurance
Chemical symbol	Safety Assurance	Safety Assurance
Color	Safety Assurance	
Condition	Quality Assurance	
Controls on use	Safety Assurance	Safety Assurance
Country of origin	Safety Assurance, Quality Assurance	
Date of finding	Quality Assurance	
Date of production	Quality Assurance	
Date of sale	Quality Assurance	
Directions for use	Safety Assurance	Safety Assurance
Discounts	Other	
Effect	Safety Assurance	Safety Assurance
Equivalent label	Other	
Expiry	Safety Assurance	Safety Assurance
Hire-purchase terms	Other	
Import licence	Safety Assurance	
Ingredients	Safety Assurance, Quality Assurance	
Ink	Safety Assurance	
Labelling	Other	
Language	Safety Assurance	Safety Assurance
Legislation	Other	
Licence	Safety Assurance	Safety Assurance
Locations	Quality Assurance	
Name of clinic	Safety Assurance	
Name of consumer	Safety Assurance	Safety Assurance
Name of importer	Safety Assurance	
Name of manufacturer	Safety Assurance	
Name of product	Safety Assurance, Quality Assurance	
Name of seller	Safety Assurance	
Name	Safety Assurance	
Physical and chemical properties	Safety Assurance	Safety Assurance
Place of label	Safety Assurance	Safety Assurance
Price	Other	
Product Description	Safety Assurance, Quality Assurance	
Quality	Quality Assurance	Quality Assurance
Quantity	Safety Assurance, Quality Assurance	
Rating	Quality Assurance	Quality Assurance
Registration number by body conducting CA	Safety Assurance	
Safety	Safety Assurance	Safety Assurance
Signatures	Safety Assurance	Safety Assurance
Size	Safety Assurance	Quality Assurance
Symbol	Safety Assurance	Safety Assurance
Test results	Safety Assurance	Safety Assurance
Testing	Safety Assurance	Safety Assurance
Trademark	Safety Assurance	
Warning	Safety Assurance	Safety Assurance
Warranty	Quality Assurance	Quality Assurance
Weight	Quality Assurance	Quality Assurance

Table A.10: Summary Statistics-Functional Roles

This table reports summary statistics for the functional role scores.The panels correspond to the two keyword classifications. For details, see Section 6.1.

	Generous			Parsimonious	
	Safety Assurance	Quality Assurance	Other	Safety Assurance	Quality Assurance
Min	0	0	0	0	0
Max	10	5	1	5	2
Mean	1.602	0.490	0.454	0.680	0.089
Std. Dev.	1.991	0.918	0.498	0.917	0.294
Total	716	219	203	304	40
#Measure Descriptions	264	124	203	209	39