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Abstract

This paper develops a theoretical and empirical framework for analysing how technological proximity shapes bilateral trade flows. We model technological alignment as a source of reduced effective trade costs and embed it within a structural gravity setting. Using a novel dataset combining sector-level patent information and OECD trade data for 76 countries across 45 sectors over the 1996-2020 period, we construct a granular measure of technological proximity based on revealed technological advantage. Estimating high-dimensional fixed effects gravity models, we find that technological proximity has a positive and economically significant impact on bilateral exports. Instrumental-variable estimates based on shift-share global technology shocks indicate that baseline results are attenuated by endogeneity. We further show that technological proximity mitigates the trade-reducing effects of compliance-intensive regulatory non-tariff measures, particularly sanitary and phytosanitary measures, while having limited interaction with tariffs. In non-services sectors, a 0.1 increase in technological proximity has an export effect comparable to lowering the gross tariff factor by about 6%-7%. Finally, we document substantial regional and sectoral heterogeneity, showing that the trade-enhancing effects of technological proximity are strongest when countries are connected to technological frontier economies and vary markedly across industries. Partial-equilibrium welfare counterfactuals imply positive but modest gains from targeted technological-alignment shocks. The findings highlight the central role of technological compatibility in shaping global trade patterns.

Keywords: technological proximity, international trade, structural gravity, revealed technological advantage, non-tariff measures, trade policy, patent data, global value chains

JEL classification: F13, F14, O33, O14, C23

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1 Introduction

Distance is a persistent theme in international trade theory and encompasses geographical, cultural, and institutional dimensions. Yet, an equally critical but underexplored form is technological distance. This paper explores how technological proximity between countries affects bilateral trade flows by lowering adaptation, coordination, and compliance costs in cross-border exchange. Drawing on patent-based measures of technological specialisation and trade data from the OECD Inter-Country Input-Output (ICIO) tables, we combine a microfounded trade model with a high-dimensional fixed effects gravity estimation strategy. The empirical focus is on gross bilateral exports and on whether technologically compatible partners trade more intensely once standard gravity frictions and trade-policy measures are taken into account.

A large literature has sought to explain why some country-sector pairs trade more intensely than others. The increasing internationalisation of innovation, as reflected in cross-border patenting activity, highlights the growing importance of technological linkages in shaping global economic integration (LaBelle et al., 2023). Capabilities accumulate locally in 'technology space' and diversify into proximate rather than distant activities (Hidalgo et al., 2007; Hausmann and Klinger, 2006; Hidalgo and Hausmann, 2009; Neffke et al., 2011; Neffke and Henning, 2013). In this view, proximity is multidimensional – cognitive/technological, organisational, social, and institutional – and shapes both the *rate* and the *direction* of learning (Boschma, 2005). At the microeconomic level, absorptive capacity determines whether external knowledge can be recognised, assimilated, and exploited (Cohen and Levinthal, 1990). These insights dovetail with empirical evidence that the diffusion of international knowledge is shaped by trade, foreign direct investment (FDI), and migration (Keller, 2004).

These literatures imply that exporting success is not only a function of *own* innovation effort but also of how *compatible* a sector's technological profile is with that of potential partners. If two country-sectors have co-evolved in related technological domains, they face lower informational and organisational frictions for transacting intermediate designs, blueprints, and specialised inputs. Our contribution is to formalise this mechanism at the sector-country level and test it using NACE two-digit export flows: we show that *technological proximity* – measured as the correlation/similarity between sector-country patent (or R&D) portfolios – predicts bilateral trade intensity over and above standard gravity covariates. Unlike Schumpeterian 'frontier vs. follower' approaches, our framework does *not* require asymmetries relative to a global frontier. Instead, it models *co-specialisation and path dependence*: technology portfolios that are historically aligned generate higher *absorptive compatibility* and, in turn, stronger trade. In addition, we document substantial regional heterogeneity in this mechanism. By interacting technological proximity with regional structures, we show that its trade-enhancing effects depend on countries' positions within the global technological hierarchy, with stronger effects for economies connected to the technological frontier.

It is generally assumed that distance – whether geographical, linguistic, cultural, historical (Tinbergen, 1962), or regulatory (Ghodsi and Santeramo, 2026) – presents a barrier to trade between nations. However, it remains unclear whether *technological distance* between two parties would also exhibit comparable deterrent characteristics on trade. On the one hand, if countries are technologically similar, trade might be favoured. If the technological gap is substantial, the products produced by one country may not be complementary to the demand patterns and production networks of the other (Filippini and Molini, 2003). On the other hand, from a Ricardian perspective, different technological capabilities between countries can be a source of comparative advantage, providing an explanation for the specialisation patterns observed even between developed countries (Dollar, 1993). Likewise, technological distance can stimulate trade between developed and developing countries, as emerging economies import technologically advanced products, including to support catching up through technological learning (Esfahani and Tayebi, 2016).

Regulatory distance is especially relevant for this paper because modern trade costs are increasingly shaped by non-tariff measures (NTMs) rather than by tariffs alone. Two regulatory NTM families are central. Sanitary and phytosanitary (SPS) measures are used to protect the life and health of humans, animals, and plants, such as through rules on food safety, pests, diseases, residues, and contaminants. Technical barriers to trade (TBTs) cover technical regulations, standards, testing, certification, labelling, packaging, and conformity-assessment procedures. These measures are not necessarily protectionist, as governments also use them to address market failures, protect consumers and the environment, improve information, and ensure product quality and interoperability. However, they may also raise fixed and variable compliance costs when exporters must adapt products, production processes, documentation, or certification to destination-specific requirements (Beghin et al., 2015; Santeramo and Lamonaca, 2019; Ghodsi, 2023).

The key trade friction is therefore not only the presence of SPS or TBT measures but also the degree to which regulatory systems are aligned. Following Ghodsi and Santeramo (2026), regulatory distance captures divergence in the regulatory objectives pursued by trading partners' SPS and TBT measures. A value close to zero indicates regulatory proximity, in the sense that partners address similar objectives (or even no NTM at all), whereas a larger value indicates that the objectives covered by their measures differ. Bilateral regulatory distance may reduce trade by increasing adaptation, testing, and certification costs. Regulatory distance accumulated along global value chains (GVCs) can have a different interpretation: inputs that have already crossed multiple regulatory environments may embody broader compliance experience, which can make final exporters more adaptable to destination requirements. This distinction is important for the present analysis because technological proximity may help firms understand, verify, and comply with foreign regulatory requirements, especially for compliance-intensive NTMs.

Although a handful of papers have studied this interplay between technological distance and trade flows, these studies feature numerous shortcomings that do not allow robust conclusions to be drawn. Above all, the difficulty in defining and quantifying technological distance leads these papers to resort to simplified measures of technological proximity, such as absolute differences in the number of patent applications (Esfahani and Tayebi, 2016) or indirect indicators, including electricity consumption, telephone penetration, and number of internet users (Filippini and Molini, 2003). These metrics do not allow for a deeper analysis of possible technological complementarities in global trade flows, as they do not differentiate between different technological profiles of countries.

Against the backdrop of rapid technological upgrading, Asia presents an interesting setting for studying this issue. Countries in the region have increasingly opted for economic regionalisation in recent years, as reflected in an increase in the number of free trade agreements (FTAs) (World Trade Organization, 2011; Jagdambe and Kannan, 2020). A prominent example is the Regional Comprehensive Economic Partnership (RCEP) signed in late 2020 by ASEAN+3 economies along with New Zealand and Australia, which aims to eliminate around 90% of tariffs within the bloc over the next two decades.

RCEPs and other regional integration initiatives (e.g. ASEAN and ASEAN+3) reflect the growing weight of Asian economies in the global system, both as producers with rising technological capabilities and as markets characterised by rapidly increasing real incomes. In this context, a secondary objective of the analysis is to examine the role of evolving technological differences between Asian and European countries in shaping trade flows while accounting for the deepening regional integration observed in Asia.

Given that the US remains the technological leader in many fields, the analysis compares several country groups – namely, the European Union (EU), East and Southeast Asian nations (ESEAN), China, the West, and the rest of the world (RoW) – with the US and draws conclusions on the potential interlinkages between technological proximity and trade.

The analysis is based on a novel data set on revealed technological advantages (RTAs) in 680 four-digit cooperative patent classification (CPC) classes and 45 sectors aligned with ICIO classifications, covering all primary, manufacturing, and services sectors in 76 countries around the world during the 1996-2020 period. The data on granted patents are retrieved and compiled from Moody's Analytics' Orbis Intellectual Property database (Bureau van Dijk), which reports patents owned by firms across the global economy. The data set provides additional firm-level information, such as the country and the sectors of activity in which each firm operates. Since firms may be active in multiple sectors of activity,[1] the analysis is carried out both at the primary-sector level and across all sectors in which firms operate in order to better capture the availability of technologies across sectors. The analysis also distinguishes between the priority date (i.e. the first time a granted patent was submitted to any patent office globally), the dates of publication, and the grant dates to provide a more precise understanding of the timing and dynamics of technological proximity.

The key research questions that are therefore investigated in this analysis are as follows: first, we analyse what effect technological proximity in a sector has on bilateral sectorial trade flows between countries. Second, we investigate the relative importance of trade policy vs. countries' technological complementarities on trade integration. Third, we show that the effects of technological proximity on trade vary across regions, particularly between technological leaders and catching-up economies. And, fourth, we indicate how large the estimated effects in tariff-equivalent terms are, how heterogeneous these are across sectors, and what partial-equilibrium welfare changes are implied by technological-alignment shocks.

A key empirical challenge in estimating the effect of technological proximity on trade is endogeneity. Technological alignment between countries may be jointly determined with trade flows,

[1]For instance, Apple Inc. operates in several NACE sectors: 26.20 – Manufacture of computers and peripheral equipment; 26.30 – Manufacture of communication equipment; 26.40 – Manufacture of consumer electronics; 47.54 – Retail sale of electrical household appliances in specialized stores; and 58.29 – Other software publishing.

as more intensive trade relationships can themselves foster knowledge diffusion, learning, and convergence in technological capabilities. Moreover, omitted factors (e.g. unobserved bilateral complementarities or common shocks) may simultaneously affect both technological proximity and trade. To address these concerns, the empirical strategy employs a control-function instrumental variable approach for nonlinear models, following Lin and Wooldridge (2019) and Wooldridge (2015). The instrumental variable strategy relies on shift-share instruments (Borusyak et al., 2025), which exploit exogenous variation in technological proximity driven by global innovation shocks and pre-sample shares of innovation across technological classes while controlling for high-dimensional fixed effects that absorb exporter-sector-time, importer-sector-time, and bilateral heterogeneity. This approach isolates variation in technological alignment that is plausibly independent of contemporaneous bilateral trade flows.

More specifically, the identification strategy combines predetermined technological specialisation with exogenous global innovation dynamics. The baseline period captures countries' sectoral specialisation prior to the estimation window, thereby ensuring that it is predetermined with respect to subsequent trade outcomes. Global shifts in innovation are external to any individual country and reflect changes in the worldwide technological frontier.

The identifying variation arises from the interaction between cross-country heterogeneity in baseline technological composition and common global shocks rather than from the shocks alone. This corresponds to a standard shift-share (Bartik) design, where countries differ in their exposure to global technological trends based on their initial specialisation patterns.

Identification therefore relies on the assumption that global CPC-class innovation shocks are exogenous to bilateral trade flows, conditional on the high-dimensional fixed effects, and that pre-sample technological shares are predetermined. Under these conditions, the variation in predicted technological alignment reflects differential exposure to global technological change rather than endogenous bilateral dynamics.

The remainder of the paper is structured as follows. Section 2 provides an overview of the literature. Section 3 presents the theoretical and conceptual framework. Section 4 discusses the empirical strategy, while Section 5 presents and discusses the results. Section 6 presents partial-equilibrium welfare counterfactuals. Finally, Section 7 concludes.

2 Literature Review

The theoretical and empirical literature on economic growth, innovation, and international trade has evolved through several distinct phases, each progressively internalising the role of technological change as an endogenous force rather than an exogenous residual. The foundational contributions by Solow (1956, 1957) established the centrality of technological progress for explaining long-run growth, yet treated it as an external factor. This exogeneity led to an intellectual shift towards modelling innovation as a purposeful economic activity, giving rise to the endogenous growth literature.

In Romer (1990), technological progress emerges from intentional investment in R&D. By recognising ideas as non-rival and partially excludable goods, Romer's framework demonstrated that economic incentives, market size, and human-capital accumulation jointly determine the rate of innovation. Growth, in this view, is sustained by the accumulation of knowledge through R&D rather than by capital deepening alone. Romer's model also implied that policies affecting education, patent systems, or R&D subsidies can have permanent effects on long-run growth, in what was a profound departure from the policy-neutral implications of the Solow model.

The Schumpeterian model of Aghion and Howitt (1992) extended the endogenous growth framework by introducing creative destruction as the central mechanism of technological progress. Innovation not only generates new technologies but also renders older ones obsolete, establishing a dynamic process of continuous quality improvement. The model explains why competition may have non-monotonic effects on innovation: excessive market power stifles incentives for R&D, while excessive competition erodes monopoly rents necessary to finance it. This Schumpeterian perspective provides micro-foundations for the interplay of innovation, firm dynamics, and productivity growth, linking aggregate performance to market structure and institutional design.

Later refinements, such as Jones (1995) and Segerstrom (1998), addressed the unrealistic scale effects of early endogenous models by introducing population-driven and semi-endogenous dynamics. Building on these, Aghion et al. (2005, 2013) integrated firm heterogeneity, finance, and distance to the frontier to explain why near-frontier economies innovate while followers benefit from imitation. In parallel, Eaton and Kortum (1999, 2002) incorporated random productivity draws and international technology diffusion into quantitative trade, providing a bridge between innovation and observed trade patterns.

Technological proximity is frequently operationalised through co-patenting activities, patent citations, or RTA measures. Fung (2003) showed that firms with closer technological ties (measured via patent citations) display correlated stock returns, implying a broader synchronicity in economic activity. Cantner and Meder (2007), using German patent data, demonstrated that firms prefer research partners with overlapping technological domains, while Ali and Cockburn (2012) found that technology licensing is more likely when firms' patent portfolios are technologically similar. These insights reinforce the notion that technological similarity lowers barriers to collaboration and information exchange.

A complementary strand from evolutionary and spatial economics conceptualises innovation as a path-dependent process. Economic capabilities accumulate locally in a 'technology space', leading countries to diversify into technologically related activities rather than distant ones (Hidalgo et al., 2007; Hausmann and Klinger, 2006; Hidalgo and Hausmann, 2009; Neffke et al., 2011; Neffke and Henning, 2013). Proximity – whether cognitive, technological, organisational, or institutional – conditions both the rate and direction of learning (Boschma, 2005), while absorptive capacity determines how external knowledge is recognised and exploited (Cohen and Levinthal, 1990). Internationally, knowledge diffusion is shaped by trade, foreign direct investment (FDI), and migration (Keller, 2004), while evidence from patent citations shows that knowledge spillovers are geographically localised (Keller, 2004; Jaffe et al., 1993).

Recent empirical work emphasises that relatedness shapes export dynamics. Jun et al. (2017) show that countries experience faster export growth when they already export related products to the same or neighbouring destinations, highlighting the role of capability overlap in shaping trade patterns. Scherngell and Barber (2009) show that countries and regions exchange more when their technological profiles are similar, while others highlight that proximity may act as a substitute for geographic distance in sustaining cross-border collaboration. In this light, technological proximity captures the extent to which two economies' innovation systems have co-evolved along compatible trajectories, reflecting shared capabilities and mutual absorptive potential rather than hierarchical imitation.

This perspective directly informs our analysis. We argue that bilateral trade intensity is partly determined by the degree of technological co-specialisation between countries: sectors whose innovation activities are historically correlated face lower adaptation costs and higher information transparency, facilitating exchange of intermediate inputs, designs, and complex goods. Unlike frontier-vs.-follower models, our approach does not depend on asymmetry in development levels. Instead, it emphasises *path dependence in technological capabilities* (i.e. the cumulative co-evolution of countries in related technological domains) as a driver of trade integration.

Building on the Schumpeterian tradition, a substantial body of research by Aghion et al. (2005, 2013) incorporated firm heterogeneity, financial development, and distance to the technological frontier into the growth process. These models explained why economies close to the frontier rely primarily on innovation, whereas those further behind benefit more from imitation and technology adoption. Such frameworks have been instrumental in explaining cross-country differences in growth and productivity convergence.

The connection between innovation and international trade was formalised by Eaton and Kortum (2002), who introduced a Ricardian model with random productivity draws and technology diffusion across countries. In their framework, trade patterns reflect not only relative factor endowments but also technological capabilities and the international diffusion of ideas.

A second literature relevant to this paper studies regulatory NTMs. SPS measures and TBTs differ from tariffs because they are usually justified by public-policy objectives (e.g. food safety, disease prevention, consumer protection, environmental protection, product quality, and technical interoperability). Their trade effects are therefore theoretically ambiguous. On the cost side, they require firms to comply with additional testing, certification, documentation, labelling, and product-adaptation procedures, which can reduce trade values or volumes and generate tariff-equivalent trade costs (Disdier et al., 2008; Beghin et al., 2015). On the benefit side, regulatory measures can reduce information asymmetries, signal quality, increase consumer confidence, and make products more compatible across markets. Meta-analytic and sectoral evidence therefore finds substantial heterogeneity, especially in agri-food trade, where SPS measures may either restrict trade or support it when they certify quality and safety (Santeramo and Lamonaca, 2019).

The more recent regulatory-distance literature shifts attention from the number of measures to the degree of similarity between regulatory systems. If two countries regulate a sector but pursue different objectives or implement incompatible requirements, exporters face additional adaptation costs even when both partners are highly regulated. Regulatory convergence, harmonisation, and mutual recognition can lower such costs, whereas regulatory divergence tends to weaken direct bilateral trade (Cadot et al., 2015; Inui et al., 2021; Knebel and Peters, 2019). Ghodsi and Santeramo (2026) distinguish bilateral regulatory distance from regulatory distance accumulated along GVCs. They find that bilateral regulatory distance in SPS and TBT measures tends to reduce trade, while GVC-related regulatory distance can be associated with larger exports because upstream exposure to diverse regulatory environments may increase the adaptability of intermediate inputs and final products. This distinction is central for the present paper: technological proximity may reduce the costs of complying with regulatory NTMs by making testing, certification, product adaptation, and technical communication easier between technologically aligned partners.

From a methodological standpoint, earlier empirical approaches relied on coarse measures, such as penetration of information and communications technology (ICT) or aggregated patent counts (Esfahani and Tayebi, 2016; Filippini and Molini, 2003). More recent work, such as Alstott et al. (2017), offers refined tools for quantifying technological proximity through normalised patent networks. Our study adopts a similarly detailed strategy by constructing a sector-specific measure of proximity using RTAs derived from CPC4-classified patent data. This allows us to map technological similarities across 45 sectors and 76 countries.

Building on these foundations, our study offers several contributions. First, we operationalise a highly granular and theoretically grounded measure of technological proximity at the sectoral level. Second, we embed this measure within a structural gravity model that incorporates high-dimensional fixed effects, enabling us to estimate its trade-enhancing effect on gross bilateral exports while controlling for product coverage within sectors. Third, we interact technological proximity with detailed trade-policy instruments (i.e. tariffs, TBTs, SPS measures, and regulatory-distance indices) to assess whether similarity in technological capabilities can mitigate traditional trade frictions. Fourth, we quantify the magnitude of technological proximity in tariff-equivalent terms, document sectoral heterogeneity, and compute the country-specific partial-equilibrium welfare counterfactuals.

While existing studies highlight the role of proximity in knowledge diffusion, innovation networks, and export dynamics, direct evidence linking aggregate technological similarity between countries to bilateral trade patterns remains limited. This paper contributes to filling this gap. Our research advances a nuanced understanding of how technological proximity facilitates trade, especially in regions experiencing rapid economic integration. By aligning with and extending the current literature, we show that global trade dynamics are increasingly shaped not just by cost or distance but also by the compatibility of technological infrastructures.

3 Theoretical Framework

This section develops a multi-country and -sector model of trade in which *technological proximity* between an exporter and an importer lowers effective trade costs by improving the compatibility of production systems. The framework delivers a structural gravity relationship for sectoral bilateral exports and motivates an empirical focus on gross export values conditional on high-dimensional multilateral resistance and observed product coverage.

In this framework, varieties can be interpreted as differentiated units of production that embody distinct combinations of sector-specific technological capabilities. Rather than being directly observed, these capabilities are proxied empirically by the composition of patent classes associated with firms operating in each country-sector. Technological proximity therefore captures the extent to which country-sector pairs possess similar portfolios of production-relevant technologies. Although each variety remains distinct, countries with similar technological portfolios are more likely to produce, adapt, verify, and integrate related varieties at lower cost. In this sense, technological proximity reflects similarity in the technological basis underlying the availability and production of differentiated varieties.

3.1 Demand

Each firm in the exporting country i produces a unique variety ω from the set of varieties Ω_s within a given sector s. In each importing country j, a representative agent has Cobb-Douglas preferences across sectors and constant elasticity of substitution (CES) preferences within each sector s at time t:

$$U_{jt} = \prod_{s\in\mathcal{S}} Q_{jst}^{\beta_s}, \qquad \beta_s > 0,\ \sum_{s\in\mathcal{S}} \beta_s = 1, \tag{1}$$

$$Q_{jst} = \left(\int_{\omega\in\Omega_s} q_{ijst}(\omega)^{\frac{\sigma_s-1}{\sigma_s}}\, d\omega\right)^{\frac{\sigma_s}{\sigma_s-1}}, \qquad \sigma_s > 1. \tag{2}$$

Let E_{jt} denote nominal expenditure in the importing country j and $E_{jst} \equiv \beta_s E_{jt}$ denote sectoral expenditure implied by Equation (1). Standard CES demand implies that expenditures on variety ω with consumer price $p_{ijst}(\omega)$ satisfy

$$q_{ijst}(\omega) = \frac{p_{ijst}(\omega)^{-\sigma_s}}{P_{jst}^{1-\sigma_s}} \frac{E_{jst}}{p_{ijst}(\omega)}, \tag{3}$$

with the sectoral CES price index being

$$P_{jst} = \left(\int_{\omega\in\Omega_s} p_{ijst}(\omega)^{1-\sigma_s}\, d\omega\right)^{\frac{1}{1-\sigma_s}}. \tag{4}$$

3.2 Supply, productivity, and iceberg trade costs

In each sector s, countries are potential suppliers of a continuum of varieties. Production uses labour only. A variety produced in exporter country i has unit input requirement $1/z_{ist}(\omega)$, where $z_{ist}(\omega)$ is a random productivity draw. Following Eaton and Kortum (2002), these draws are sector specific Fréchet distribution with shape $\theta_s > 0$ and scale $T_{ist} > 0$:

$$\Pr(z_{ist}(\omega) \le z) = \exp\{-T_{ist} z^{-\theta_s}\}. \tag{5}$$

Let w_{it} denote the wage in exporter country i. Shipping a variety from i to j in sector s requires iceberg costs $\tau_{ijst} \ge 1$ (so τ_{ijst} units must be shipped for one unit to arrive). We view τ_{ijst} as a reduced-form object that aggregates observed policy frictions (e.g. tariffs, non-tariff measures, and regulatory distance) and unobserved bilateral frictions captured in the empirical application by high-dimensional fixed effects.

3.3 Technological proximity as bilateral compatibility

Technological proximity. Each country-sector (i, s, t) is characterised by a K-dimensional technology-specialisation vector $\mathbf{r}_{ist} \in \mathbb{R}^K$, which we refer to as 'revealed technological advantages (RTA)', and proxied from patent portfolios in the empirical analysis (see Subsection 4.1 below). Once technologies are developed and legally protected, they may diffuse across borders through trade, FDI, licensing, and GVCs. This international mobility of technology implies that, rather than being purely coincidental, similarities in technological portfolios partly reflect underlying patterns of cross-border knowledge diffusion and intellectual property (IP) transmission. As a result, technological proximity also captures the extent to which countries can access, adapt, and deploy similar technologies beyond their domestic boundaries. We summarise *bilateral technological proximity* by an index

$$\rho_{ijst} \equiv \text{corr}(\mathbf{r}_{ist}, \mathbf{r}_{jst}) \in [-1, 1]. \tag{6}$$

Larger values correspond to more similar technology portfolios in sector s between countries i and j. The correlation between country-sector RTA vectors therefore captures the similarity in the technological capabilities underlying production within a sector. Since patents proxy innovation outputs, they reflect both the development of new production techniques and improvements in existing processes that enhance productivity.

An increase in ρ_{ijst} indicates that firms operating in sector s in countries i and j specialise in related technological domains and accumulate similar knowledge bases. This overlap in technological capabilities may facilitate compatibility in production standards, intermediate inputs, organisational know-how, and innovation trajectories. As a result, technologically proximate countries may face lower informational and coordination frictions in cross-border production and trade relationships, thereby increasing productivity and bilateral trade flows within the sector.

Importantly, the technological-proximity measure is constructed from sector-level RTA vectors rather than from product variety-specific patent information. Hence, ρ_{ijst} should not be interpreted as directly measuring the creation of additional product varieties along the extensive margin. Instead, it captures the degree to which countries possess similar technological competencies that improve the efficiency and quality of producing existing or potentially tradable varieties within a sector. In other words, technological proximity enhances the effectiveness with which firms transform inputs into tradable outputs rather than as a direct determinant of variety expansion.

Variable-cost compatibility channel. Technological proximity reduces per-unit adaptation, verification, and integration costs when supplying market j, but it may also reflect underlying patterns of cross-country collaboration and co-specialisation in innovation activities. When firms and research entities in different countries develop and patent technologies in similar domains, this leads to correlated technological portfolios at the sectoral level. Such co-evolution fosters similar production specialisation across countries.

In the spirit of Romer (1990), knowledge accumulation and specialisation in shared technological domains can reduce production and adaptation costs within sectors. When both trading partners experience cost reductions in similar technological areas, the range of intermediate inputs that can be efficiently produced and exchanged is expanded. As a result, countries with similar technological capabilities are better able to supply a wider variety of sector-specific intermediate goods to each other, thereby reinforcing intra-sector trade. This mechanism complements the trade-cost and absorptive-capacity channels.

This means that, for a given trade cost τ_{ijst} between the two countries, the price of a variety ω in sector s supplied by firms in country i to country j may fall when firms in both countries adopt similar and compatible technologies. Higher technological proximity, ρ_{ijst}, implies that firms can use foreign product varieties more efficiently, particularly when these varieties are better matched as intermediate inputs or capital goods in the production of their own variety ω. We capture this mechanism through a multiplicative *compatibility factor*, $\Psi_s(\rho_{ijst}) > 0$, which increases with technological proximity, $\Psi' > 0$, and scales down the delivered marginal cost:

$$p_{ijst}(\omega) = \frac{w_{it}\,\tau_{ijst}}{z_{ist}(\omega)\,\Psi_s(\rho_{ijst})}. \tag{7}$$

A tractable parameterisation that allows $\rho_{ijst} < 0$ while keeping $\Psi_s > 0$ is

$$\Psi_s(\rho_{ijst}) = \exp\{\lambda_s\,\rho_{ijst}\}, \qquad \lambda_s \geq 0. \tag{8}$$

Thus, greater technological proximity reduces the delivered price by lowering the effective iceberg trade cost, $\tau_{ijst}\exp\{-\lambda_s\rho_{ijst}\}$, faced by exporters when serving the destination market.

3.3.1 Policy-specific mitigation

Some trade-policy frictions are plausibly more compliance-intensive than others. For instance, standards and regulatory distance may generate additional bilateral compliance costs when firms in one country need to satisfy the regulatory requirements of another. These costs may partly reflect technological mismatches between countries, especially when compliance requires specific production processes, testing procedures, certification methods, or quality-control technologies.

In this context, technological proximity can facilitate trade by reducing the cost of regulatory adaptation. When firms in two countries possess similar technological capabilities, they may find it easier to comply with each other's standards and regulations because the required technologies, routines, and production methods are already closer to those used domestically. Higher technological proximity can therefore mitigate policy-related trade frictions and generate a comparative advantage for country pairs with more compatible technological structures. This mechanism may be particularly relevant for bilateral intra-industry trade, where firms exchange differentiated varieties within the same sector and where regulatory compatibility can reduce the effective cost of market access.

Since λ_s and Ψ_s are not directly observable in the data, their role can be interpreted as being part of the iceberg trade cost $\tau = \tau(\rho, .)$ associated with delivering variety ω from country i to country j. Thus, although technological proximity does not eliminate formal trade-policy barriers, it may reduce the effective marginal cost of complying with them. Therefore, iceberg trade cost is not only dependent on technological proximity and regulatory-compliance cost but also on their interaction $\tau = \tau(\rho, TP, \rho \times TP)$.

3.4 Trade shares and structural gravity

Importer j sources each variety from the lowest delivered-cost supplier across all exporters. Define the competitiveness term as

$$A_{ijst} \equiv T_{ist} \left(\frac{w_{it}\tau_{ijst}}{\Psi_s(\rho_{ijst})} \right)^{-\theta_s}. \tag{9}$$

Equation (9) is obtained after integrating over the variety-level productivity draws $z_{ist}(\omega)$. Hence, $z_{ist}(\omega)$ no longer appears explicitly in A_{ijst}; its distribution is summarised by the Fréchet scale parameter T_{ist}. Appendix A.1 provides the derivation.

Then, the probability that exporter i supplies a randomly drawn variety to importer j in sector s is

$$\pi_{ijst} = \frac{A_{ijst}}{\Phi_{jst}}, \qquad \Phi_{jst} \equiv \sum_{\ell \in \mathcal{N}} A_{\ell jst}, \tag{10}$$

where Φ_{jst} is the inward multilateral-resistance (or market-competitiveness) term of importer j for sector s at time t, and $\mathcal{N}$ denotes the set of potential source countries. Given CES demand, sectoral bilateral expenditure is

$$X_{ijst} = \pi_{ijst}\, E_{jst}. \tag{11}$$

Combining Equations (9) to (11) yields the sectoral structural-gravity representation

$$X_{ijst} = \frac{T_{ist} \left(\frac{w_{it}\tau_{ijst}}{\Psi_s(\rho_{ijst})} \right)^{-\theta_s}}{\sum_\ell T_{\ell st} \left(\frac{w_{\ell t}\tau_{\ell jst}}{\Psi_s(\rho_{\ell jst})} \right)^{-\theta_s}} E_{jst}. \tag{12}$$

Comparative statics and third-country effects. Equation (12) implies that higher ρ_{ijst} increases A_{ijst} through Equation (8), thereby raising X_{ijst} conditional on E_{jst} and all other competitiveness terms. Because Φ_{jst} aggregates competitiveness of *all* exporters in market j, an increase in ρ_{ijst} mechanically reduces other partners' shares in (j, s, t):

$$\frac{\partial \pi_{kjst}}{\partial \rho_{ijst}} = -\,\pi_{kjst}\pi_{ijst}\,\theta_s\,\frac{\Psi_s'(\rho_{ijst})}{\Psi_s(\rho_{ijst})} < 0 \qquad (k \neq i). \tag{13}$$

This feature motivates the use of importer-sector-time and exporter-sector-time fixed effects in the empirics: the coefficient on proximity is identified from *relative* changes in bilateral competitiveness within importer markets and sectors over time.

3.5 Testable implications

The formal model and the auxiliary assumptions above motivate two empirical implications.

(i) **Direct trade effect.** First, technological proximity raises bilateral exports in sector s by improving exporter competitiveness in market j through the compatibility term $\Psi_s(\rho_{ijst})$

in Equation (12). This is the direct variable-cost channel implied by the structural-gravity framework.

(ii) **Policy-mitigation effect.** Second, under the auxiliary market-access and policy-mitigation assumptions, technological proximity may also attenuate the trade-reducing effects of compliance-intensive policy frictions. This mechanism is not a separate equilibrium result of the baseline model; rather, it motivates the interaction terms between technological proximity and trade-policy variables in the empirical specifications below.

Section 5 maps these implications into a Poisson pseudo-maximum-likelihood (PPML) structural-gravity estimation with high-dimensional fixed effects.

4 Data

In this section, we discuss the data that operationalises the mechanisms outlined in Section 3. The baseline and extended estimation equations are presented in the next section. The empirical analysis uses the OECD Trade in Value Added (TiVA) database[2] at the exporter-importer-sector-year level, covering 76 countries across 45 ICIO-aligned sectors in the 1996-2020 period.

4.1 Measuring technological proximity

Patent data, sector assignment, and ownership. We use granted-patent information from Orbis Intellectual Property (Moody's Analytics / Bureau van Dijk). Patents are classified into four-digit cooperative patent classification (CPC) classes. Firms are linked to sectors using their reported activity codes harmonised to the 45 ICIO-aligned sectors used in the trade data. Because a single firm may operate in multiple activities, we construct two alternative sector assignments when building the technology measures: (i) using only the firm's *primary* activity and (ii) using *all* reported activities. In the benchmark specification, each patent is assigned to every sector in which the owning firm is active. As a robustness check, we use a fractional assignment in which each patent is divided equally across the firm's reported sectors of activity. The benchmark measure captures the presence of technology across all sectors in which the firm operates, whereas the fractional measure assigns weighted patent counts across activities. The results are consistent across both specifications; hence, the benchmark results are reported in the main text, while the fractional-assignment results are available upon request. Patents with multiple owners are split equally among owners (e.g. a patent co-owned by two firms is counted as one half for each owner).

Revealed technological advantage (RTA). Let $P_{f_{is}ct}$ denote the number of patents in CPC class c owned by firm f operating in country i and sector s in year t. We aggregate patent counts to the country-sector level as $P_{cist} \equiv \sum_{f_{is}} P_{f_{is}ct}$. The RTA for technology class c in sector s and country i is computed as:

[2] See https://www.oecd.org/en/topics/sub-issues/trade-in-value-added.html

$$\begin{aligned}
\text{RTA}_{cist} &= \frac{P_{cist}/P_{cst}}{P_{ist}/P_{st}}, \\
P_{cist} &= \sum_{f_{is}} P_{f_{is}ct}, \qquad P_{cst} = \sum_{i} P_{cist}, \\
P_{ist} &= \sum_{c} P_{cist}, \qquad P_{st} = \sum_{i} P_{ist}.
\end{aligned} \tag{14}$$

Equivalently, substituting out the aggregates, Equation 14 can be written as

$$\text{RTA}_{cist} = \left(\frac{\sum_{f_{is}} P_{f_{is}ct}}{\sum_i \sum_{f_{is}} P_{f_{is}ct}} \right) \Bigg/ \left(\frac{\sum_c \sum_{f_{is}} P_{f_{is}ct}}{\sum_i \sum_c \sum_{f_{is}} P_{f_{is}ct}} \right).$$

We compute RTA_{cist} for all technology classes with non-zero world patenting in (s, t). This generates an RTA vector for each country-sector-year, $\mathbf{r}_{ist} \equiv (\text{RTA}_{1ist}, \ldots, \text{RTA}_{Cist})$, with C being the number of CPC classes. The vector constructs the same dimension for all country pairs (i, j) to be able to calculate ρ_{ij} in the next step. Here, countries with $P_{cist} = 0$ mechanically have $\text{RTA}_{cist} = 0$ for that class.

Technological proximity. Technological proximity is measured by the pairwise Pearson correlation of RTA vectors between exporter i and importer j within the same sector and year:

$$\rho_{ijst} = \frac{\sum_{c=1}^{C_{st}} \left(\text{RTA}_{cist} - \overline{\text{RTA}}_{ist}\right)\left(\text{RTA}_{cjst} - \overline{\text{RTA}}_{jst}\right)}{\sqrt{\sum_{c=1}^{C_{st}} \left(\text{RTA}_{cist} - \overline{\text{RTA}}_{ist}\right)^2} \cdot \sqrt{\sum_{c=1}^{C_{st}} \left(\text{RTA}_{cjst} - \overline{\text{RTA}}_{jst}\right)^2}}, \tag{15}$$

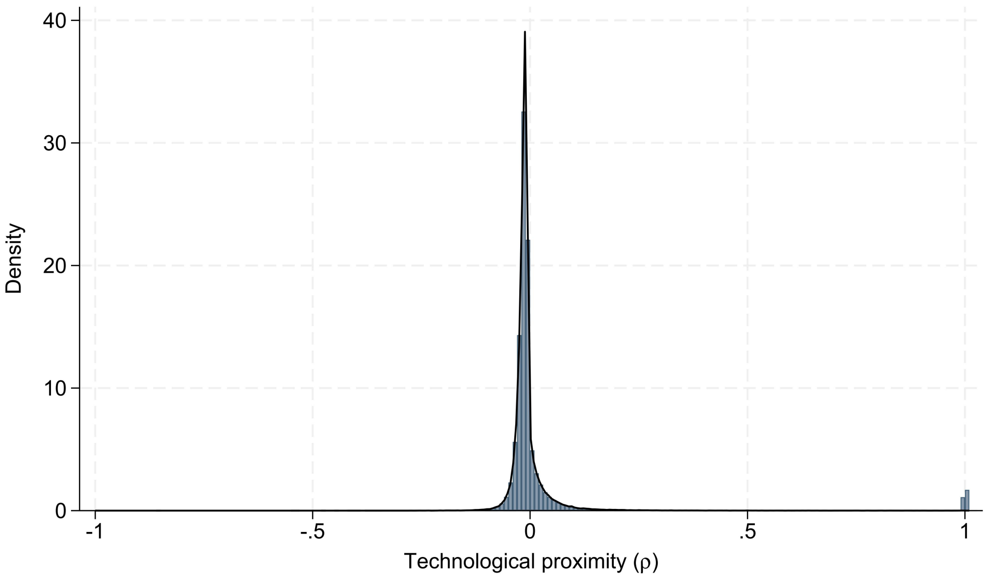
where $\overline{\text{RTA}}_{ist} \equiv \frac{1}{C_{st}} \sum_{c=1}^{C_{st}} \text{RTA}_{cist}$ is the mean RTA across technology classes in (i, s, t) (and analogously for $\overline{\text{RTA}}_{jst}$). By construction, $\rho_{ijst} \in [-1, 1]$, where -1 indicates strong technological dissimilarity and 1 indicates very strong technological proximity.

This approach is computationally simple and, crucially, distinguishes between CPC technology fields when characterising countries' sector-specific technological positions.

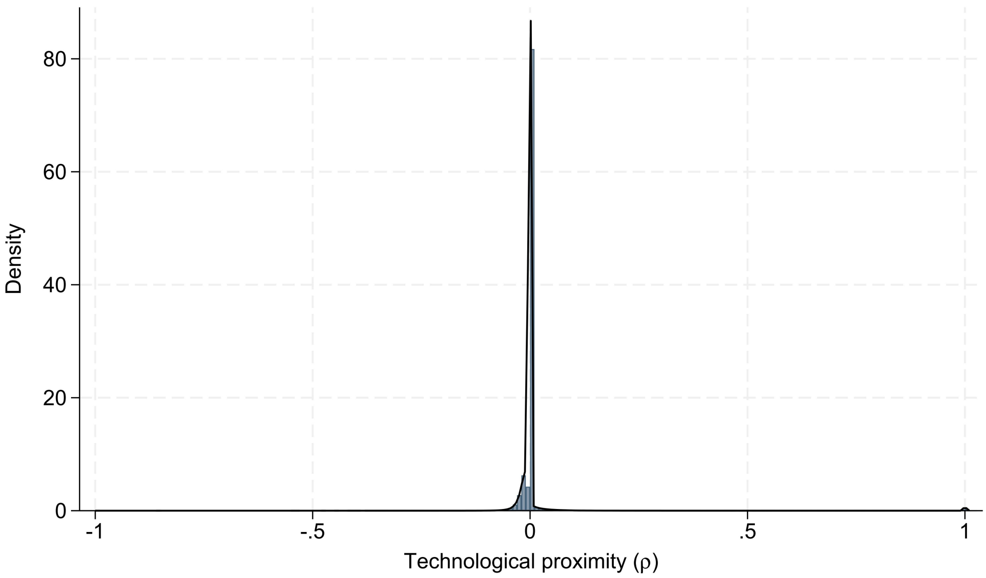
Timing conventions and flow vs. stock measures. We compute ρ_{ijst} under alternative patent-timing conventions (priority, publication, and grant dates) using either patent *flows* (within-year counts) or cumulative patent *stocks* (accumulated since 1900, with an 'exit' adjustment in robustness).

Missing proximity. When either trading partner does not have any patents in a given sector-year (i.e. when $P_{ist} = \sum_c P_{cist} = 0$ or $P_{jst} = \sum_c P_{cjst} = 0$), the correlation in Equation (15) is undefined. In the baseline sample, we set $\rho_{ijst} = 0$ for these observations and include a dummy variable, $\rho_{ijst}^{missing}$, as an additional control in the estimation. This dummy equals one when the original correlation is missing or undefined because at least one partner has no patent activity in the relevant sector-year, and zero otherwise. Robustness exercises are also carried out without this replacement and/or by restricting the sample to patent-active sector-years.

Figure 1 illustrates the distribution of the technological-proximity measure under the two treatments discussed above. Panel (a) reports the density for observations with defined corre-



(a) Defined observations only



(b) Undefined proximity set to zero

Figure 1: Distribution of technological proximity

Notes: Panel (a) shows the distribution of technological proximity, ρ_{ijst}, for observations for which the RTA-based correlation is defined. Panel (b) shows the corresponding baseline measure used in the estimations, where undefined correlations are replaced by zero and the dummy variable $\rho_{ijst}^{missing}$ is included as an additional control. The distribution is highly concentrated around zero, indicating that many country-sector pairs exhibit limited technological overlap. The horizontal axis is bounded between -1 and 1 because technological proximity is measured as a Pearson correlation.

lations only. Panel (b) reports the baseline version used in the estimations, where undefined proximity values are set to zero. The comparison shows that the mass around zero increases substantially once undefined correlations are replaced, which motivates the inclusion of $\rho_{ijst}^{missing}$ as a separate control variable. This ensures that observations with genuinely low technological proximity are distinguished from observations for which proximity is undefined because at least one trading partner has no patent activity in the relevant sector-year. At the same time, the pronounced concentration of the distribution around zero suggests that substantial technological proximity is relatively uncommon across country-sector pairs and may be concentrated among economies with more developed and technologically active innovation systems. This interpretation is consistent with the bilateral and intra-country patterns reported in Table A4, which reveal considerable heterogeneity across countries and regions. In particular, the United States and several advanced European and East Asian economies display comparatively high technological proximity and broad patent activity, whereas many less technologically advanced economies exhibit substantially lower proximity and more limited patent activity. Thus, the concentration around zero partly reflects the fact that strong technological alignment appears to be restricted to a comparatively small subset of country-sector relationships.

4.2 Accounting for entry fix costs

In addition to affecting delivered marginal costs, technological proximity may reduce the informational, certification, and adaptation costs that firms face when serving a foreign market. This channel can be interpreted as operating through the fixed cost of market entry. A convenient reduced-form representation of the effective fixed entry cost is

$$F_{ijst}^{\text{eff}} = F_{ijst} \exp\{-\eta_s \rho_{ijst}\}, \qquad \eta_s \geq 0, \tag{16}$$

where F_{ijst} denotes destination-specific market-access costs and F_{ijst}^{eff} denotes the corresponding cost after accounting for technological compatibility. This expression captures a threshold-entry mechanism in the spirit of Melitz-type models: greater technological proximity lowers effective fixed entry costs and may therefore increase the set of firms, varieties, or product lines observed in bilateral sectoral trade.

In a CES environment, such fixed costs shape the extensive margin of trade. Innovation and technological proximity may therefore affect exports not only by reducing variable trade costs but also by expanding the range of traded varieties. To account for this channel in the estimation of gross export values at the sector level, we include product coverage within a sector as a control variable in the gravity equations.

4.3 Outcome, product coverage, and unit of observation

Let X_{ijst} denote gross exports from exporter i to importer j in sector s at time t, measured in current USD and obtained from the OECD's TiVA database. This variable serves as the dependent variable in the reported gravity estimations. We also define the share of positive six-digit Harmonized System (HS) product lines within each sector as follows:

$$sh^{+}_{ijst} \equiv \frac{\#\{p \in s: \; X_{ijpt} > 0\}}{\#\{p \in s\}}, \tag{17}$$

where p indexes HS six-digit products and X_{ijpt} denotes product-level exports. Data on product-level export values are collected from UN COMTRADE and then matched to the ISIC/ICIO industry classification using concordance tables. The superscript '+' indicates that the measure is only based on HS six-digit product lines with positive bilateral trade flows. Thus, sh^{+}_{ijst} captures the share of traded products with positive bilateral exports among all available HS six-digit products mapped to a given ICIO sector.

Since detailed product-level data are only available for goods, this variable is not measured for service sectors. It is therefore merely included as a control in the gross-export regressions for goods sectors. Intra-country flows are not used in constructing this measure, as the underlying product-level data refer to bilateral international trade flows.

4.4 Trade-policy and other bilateral controls

Let $\mathbf{TP}_{ijst}$ denote the vector of time-varying bilateral trade-policy measures used and elaborated in Ghodsi and Santeramo (2026). This vector includes: (i) importer-imposed tariffs on the exporter, t_{ijst}; (ii) exporter-imposed tariffs on the importer, t_{jist}; (iii) intensity measures capturing both partners' summation of the stock of TBTs and SPS measures imposed on sector s, S^{TBT}_{ijst} and S^{SPS}_{ijst}, respectively; (iv) bilateral regulatory-distance indices for TBTs and SPS measures as defined in Ghodsi and Santeramo (2026), D^{TBT}_{ijst} and D^{SPS}_{ijst}, respectively; and (v) GVCs' regulatory distance (GRD) constructed from the ICIO input-output structure (e.g. forward/backward linkages) provided by the OECD.

4.5 Descriptive statistics and benchmark patterns

Tables A4-A5 present descriptive statistics for the main variables used in the analysis over the 1996-2020 period and help motivate both the empirical specification and the benchmark choices adopted below. Table A4 reports exporter-level averages of bilateral technological proximity and intra-country technological proximity under three timing conventions based on patent priority, publication, and grant dates. Publication and grant dates are particularly relevant for international trade, as they reflect the stage at which technologies become publicly disclosed and legally protected, thereby facilitating their potential cross-border diffusion and commercial use. By construction, the correlation measure in Equation (15) equals one for intra-country relations when at least one patent is observed in a given sector, and zero when no patent is observed. Therefore, intra-country averages of technological proximity ρ_{ijst} provide a useful perspective on the prevalence of innovation across sectors within each country.

A first striking result is the exceptional position of the United States. For US intra-country trade linkages, average technological proximity is extremely close to its upper bound, reaching 0.980, 0.989, and 0.985 under the priority, publication, and grant measures, respectively. At the same time, only 22, 12, and 17 US intra-country observations exhibit zero patents and therefore zero technological proximity. These observations correspond to specific sectors – namely, D97T98 (Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use), D50 (Water transport), and D03 (Fishing and aquaculture) – for which patent data are missing in several years. Put differently, for more than 98% of US intra-country linkages, patent activity is present and intra-country technological proximity is effectively equal to one. This feature is important for the regional interaction specifications: the US is not only the global technological leader in substantive terms but also the country in which patent activity is most consistently observed in the data. Using the US as the benchmark region in the interaction models is therefore both economically and statistically well grounded.

Beyond the US, Table A4 reveals substantial heterogeneity across countries and regions. Among large advanced economies, several EU and Western countries also display high intra-country technological proximity, although it is generally below that of the US. Germany, for example, records respective intra-country values of 0.924, 0.954, and 0.951, while France reaches 0.884, 0.935, and 0.932, and the United Kingdom 0.932, 0.972, and 0.970. In East and Southeast Asia, the picture is more uneven. Japan, South Korea, and Taiwan exhibit high intra-country proximity, with Japan at 0.927, 0.950, and 0.948, South Korea at 0.864, 0.941, and 0.940, and Taiwan at 0.691, 0.774, and 0.770.

Turning to the bilateral measure, which is more directly relevant for the empirical analysis of bilateral trade flows, Table A4 reveals a somewhat different cross-country pattern. China stands out among the major economies, with average bilateral technological proximity of 0.030, 0.023, and 0.025 under the priority, publication, and grant measures, respectively. These values exceed those observed for several technological frontier economies. For example, the corresponding averages are 0.019, 0.008, and 0.010 for the United States; 0.014, 0.005, and 0.007 for Germany; and 0.018, 0.009, and 0.012 for Japan. Among other large advanced economies, France records bilateral proximity of 0.027, 0.019, and 0.020, the United Kingdom 0.026, 0.019, and 0.021, and Canada 0.024, 0.016, and 0.018. South Korea also exhibits relatively high bilateral proximity, particularly under the priority-date measure, at 0.025, 0.013, and 0.014.

These bilateral averages should not be interpreted as a ranking of the technological sophistication of countries. Rather, they capture the average similarity between an exporter's sector-specific technological portfolio and those of its foreign partners. The relatively high values observed for China therefore suggest that its technological specialisation overlaps comparatively strongly with that of a broad set of partner countries. Conversely, the lower bilateral averages of technologically advanced economies (e.g. the US, Germany, and Japan) indicate that technological leadership does not necessarily imply greater technological similarity with the average trading partner. This distinction between technological advancement and bilateral technological alignment is important for the interpretation of the gravity estimates, where it is variation in the latter that is hypothesised to reduce adaptation and coordination costs and thereby facilitate bilateral trade.

China therefore occupies an interesting position in the data: although its intra-country technological proximity remains below that those of frontier economies (e.g. the US, Japan, and Germany), its average bilateral technological proximity is comparatively high across all three patent-timing conventions. By contrast, several lower-income economies display very limited patent activity, with countries such as Bangladesh, Brunei, Laos, Myanmar, and Senegal recording zero intra-country proximity throughout. These contrasts reinforce the distinction between domestic patent coverage and bilateral technological alignment in addition to showing that the latter varies systematically across countries in ways that are not simply determined by their position vis-à-vis the technological frontier.

Table A5 reports descriptive statistics for the trade-policy variables in the non-services sample for the year 2020. These variables are the same trade-policy measures used in the benchmark specification and are constructed following the framework developed and described in Ghodsi and Santeramo (2026). In particular, the table reports average tariffs faced and imposed, the stock of TBTs and SPS measures imposed by both trading partners, bilateral regulatory distance in TBTs and SPS measures, and their counterparts accumulated along GVCs. The interpretation of these variables follows the logic developed in that paper: bilateral regulatory distance captures direct divergence in regulatory objectives across trading partners, whereas the GVC variables measure the accumulation of such trade-policy frictions through upstream production linkages.

The descriptive evidence in Table A5 points to substantial cross-country heterogeneity in trade-policy exposure. EU economies typically face moderate average tariffs and display relatively similar regulatory environments. For example, Germany faces an average tariff of 3.54 and imposes 1.83 while exhibiting average TBT and SPS stocks of 26.29 and 10.95, respectively, and bilateral regulatory distances of 0.114 for TBTs and 0.053 for SPS measures. France and Spain show similar patterns. The United Kingdom stands out within Europe by facing and imposing somewhat higher tariffs while also exhibiting lower average stocks of TBTs and SPS measures. In East and Southeast Asia, the policy environment is more heterogeneous: Hong Kong faces relatively high tariffs but imposes none on average in the sample, whereas Indonesia faces 4.36 and imposes 5.91, combined with TBT and SPS stocks of 18.65 and 11.09, respectively. India also stands out among the rest-of-the-world (RoW) economies, facing an average tariff of 4.56 and imposing 11.66, with relatively high TBT and SPS stocks and bilateral regulatory distances. More broadly, the GVC-based indicators are much smaller in absolute magnitude than the bilateral policy measures, which is consistent with the construction of these variables as weighted accumulations along input-output linkages rather than as direct bilateral frictions.

Taken together, Tables A4-A5 underscore two central empirical features of the data. First, technological proximity is highly uneven across countries and especially concentrated within the domestic production structure of frontier economies, most notably the US. Second, countries are exposed to markedly different trade-policy environments, not only through direct bilateral barriers but also through regulatory frictions embodied in GVCs. These descriptive patterns support the use of the US as the benchmark in the regional heterogeneity analysis described below and confirm the empirical relevance of including both bilateral and GVC-related policy measures in the benchmark gravity specification.

4.6 Simple correlation

Before turning to the structural gravity estimates, it is useful to describe the distribution of the technological-proximity measure. Figure 1 above reports the density of the RTA-based technological-proximity measure constructed from priority-date patent information. Panel (a) uses only observations for which the correlation is defined, while Panel (b) shows the baseline version used in the estimations, where undefined correlations are replaced by zero and a missing-proximity dummy is included as an additional control.

The distribution is strongly concentrated around zero, indicating that many country-sector pairs exhibit limited technological overlap.

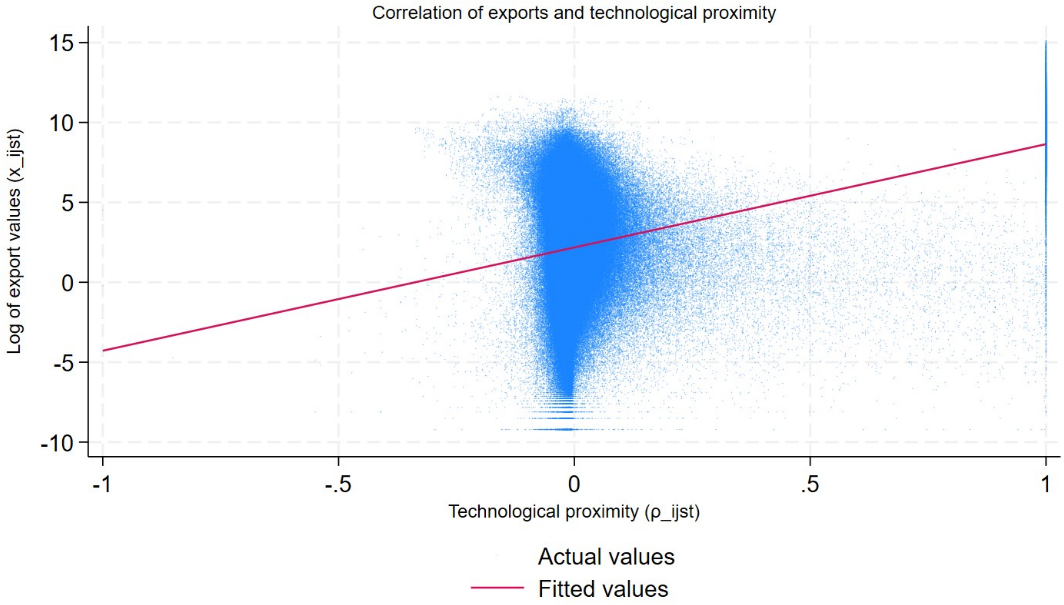


Figure 2: Technological proximity and bilateral exports

Notes: The figure plots the relationship between bilateral gross exports and technological proximity based on the priority-date RTA correlation measure. The vertical axis reports the logarithm of export values, while the horizontal axis reports technological proximity between exporter-importer country-sector pairs. The fitted line represents the unconditional linear association. The figure is descriptive and does not account for multilateral resistance or unobserved heterogeneity, which are addressed in the structural gravity specifications below.

Figure 2 shows a positive unconditional relationship between technological proximity and exports, although the observations are highly dispersed and strongly concentrated at around zero technological proximity. This concentration reflects the sparsity of technological overlap across many country-sector pairs. The figure should therefore only be interpreted as descriptive evidence. The econometric analysis below estimates the same relationship using PPML estimation with exporter-sector-time, importer-sector-time, exporter-importer-sector, and exporter-importer-time fixed effects.

5 Empirical Strategy

5.1 Baseline gravity specifications

Guided by Equation (12), we estimate the effect of technological proximity on trade using PPML estimation, which accommodates heteroskedasticity and naturally retains zero flows (Yotov et al., 2016). The baseline estimating equation is

$$X_{ijst} = \exp\Big(\beta_0\, \rho_{ijst} + \beta_1\, \rho_{ijst}^{missing} + \delta\, sh_{ijst}^{+} + \boldsymbol{\gamma}^{\top}\mathbf{TP}_{ijst} + \omega_{ist} + \omega_{jst} + \omega_{ijs} + \omega_{ijt}\Big) + \nu_{ijst}, \quad (18)$$

where ν_{ijst} represents standard errors that are clustered at the exporter-importer-sector level to allow for arbitrary serial correlation and heteroskedasticity within bilateral-sector relationships. The four high-dimensional fixed effects are: (i) exporter-sector-time, ω_{ist}; (ii) importer-sector-time, ω_{jst}; (iii) exporter-importer-sector, ω_{ijs}; and (iv) exporter-importer-time, ω_{ijt}. Together, these high-dimensional fixed effects absorb multilateral resistance, all exporter- or importer-specific determinants of trade that vary by sector and year, time-invariant bilateral sectoral affinity, and time-varying bilateral shocks (e.g. FTAs). Identification of β_0 and β_1 therefore comes from within-pair changes in technological proximity over time, within bilateral sectors that are not explained by this rich set of fixed effects. The baseline results are presented in the three leftmost columns of Table 1 for the full sample of sectors and in Table 2 for the sample of goods sectors.

Since technological proximity is measured as a Pearson correlation, ρ_{ijst} is bounded between (-1) and (1). This does not create an econometric problem in the present setting given that ρ_{ijst} enters the PPML gravity specification as an explanatory variable rather than as a dependent variable. The bounded support should therefore be taken into account mainly when interpreting the magnitude of the estimated coefficient. In particular, we interpret the estimates in terms of economically plausible changes in proximity (e.g. a 0.1 increase in ρ_{ijst}) rather than a full one-unit change.

5.1.1 Mitigation of trade-policy costs

To allow proximity to mitigate regulatory friction (as noted earlier in Section 3.3.1), one can think about the (log) iceberg cost as

$$\ln \tau_{ijst} = \boldsymbol{\kappa}_s^\top \mathbf{TP}_{ijst} - \boldsymbol{\mu}_s^\top\big(\rho_{ijst} \cdot \mathbf{TP}_{ijst}\big) + \xi_{ijs} + \xi_{ijt}, \tag{19}$$

where $\mathbf{TP}_{ijst}$ is the vector of observed policy frictions and the interaction term captures the idea that higher proximity reduces the marginal trade-cost impact of a given policy component. The terms ξ_{ijs} and ξ_{ijt} collect unobserved time-invariant and -varying bilateral frictions captured by fixed effects.

To test the policy-mitigation mechanism in Equation (19), we estimate specifications that interact technological proximity with individual policy components:

$$X_{ijst} = \exp\Big(\beta_0\, \rho_{ijst} + \beta_1\, \rho_{ijst}^{missing} + \delta\, sh_{ijst}^{+} + \boldsymbol{\gamma}^\top \mathbf{TP}_{ijst} + \boldsymbol{\phi}^\top (\rho_{ijst} \cdot \mathbf{TP}_{ijst}) + \omega_{ist} + \omega_{jst} + \omega_{ijs} + \omega_{ijt}\Big) + \nu_{ijst}, \tag{20}$$

where $\phi^\top$ captures how technological proximity moderates the marginal trade effects of trade-policy measures. The results are presented in Tables 3-5.

5.1.2 Regional heterogeneity of technological proximity

We also estimate heterogeneity across groups of countries g, including the EU28, ESEAN, China, the West, and the rest of the world (RoW), by interacting technological proximity ρ_{ijst} with exporting-region dummies $R_g(i)$ and bilateral-region dummies $R_g(i,j)$. We benchmark the US as the global technological leader in two separate specifications as follows:

$$X_{ijst} = \exp\Big(\beta_{i0}\,\rho_{ijst} + \beta_1\,\rho_{ijst}^{missing} + \sum_g \beta_{gi}\big(\rho_{ijst}\cdot R_g(i)\big) + \gamma^\top \mathbf{TP}_{ijst} + \omega_{ist} + \omega_{jst} + \omega_{ijs} + \omega_{ijt}\Big) + \nu_{ijst}, \tag{21}$$

where β_{i0} captures the effect of technological proximity between the US and its trading partners (including intra-country trade) on US export values as the benchmark, and β_{gi} captures the effect of technological proximity for region $R_g(i)$ as the exporting region relative to the US. The results are presented in Table 6.

$$X_{ijst} = \exp\Big(\beta_{ij0}\,\rho_{ijst} + \beta_1\,\rho_{ijst}^{missing} + \sum_g \beta_{gij}\big(\rho_{ijst}\cdot R_g(i,j)\big) + \gamma^\top \mathbf{TP}_{ijst} + \omega_{ist} + \omega_{jst} + \omega_{ijs} + \omega_{ijt}\Big) + \nu_{ijst} \tag{22}$$

where β_{ij0} captures the effect of technological proximity for US intra-country trade (the benchmark bilateral case), and β_{gij} captures the effect of technological proximity for bilateral region $R_g(i,j)$ relative to US intra-country trade. The results are presented in Table A3 in the Appendix.

5.1.3 Sectoral heterogeneity in technological proximity effects

The baseline specification assumes a common effect of technological proximity across sectors. To account for differences in production structures and knowledge intensity, we allow this effect to vary at the sectoral level by interacting technological proximity with sector indicators. The PPML specification therefore replaces the common coefficient on ρ_{ijst} with sector-specific deviations:

$$X_{ijst} = \exp\Big(\sum_{s'} \beta_{\rho,s'}\,\rho_{ijst}\,\mathbf{1}\{s = s'\} + \beta_1 \rho_{ijst}^{missing} + \delta sh_{ijst}^{+} + \gamma^\top \mathbf{TP}_{ijst} + \omega_{ist} + \omega_{jst} + \omega_{ijs} + \omega_{ijt}\Big) + \nu_{ijst}. \tag{23}$$

Table 7 reports the estimated sectoral coefficients using sector C26 (Manufacture of computer, electronic and optical products) as the benchmark. This is an appropriate benchmark because it is among the most patent-intensive and innovation-oriented sectors, therefore providing a useful reference point for assessing whether technological proximity operates more strongly in frontier-like, technology-intensive activities or in other parts of the economy.

5.2 Endogeneity of technological proximity and instrumental-variable strategy

Although the baseline PPML structural-gravity specification in Equation 18 exploits a very rich set of high-dimensional fixed effects, technological proximity ρ_{ijst} may still be endogenous. Three main concerns motivate an explicit correction strategy.

First, *reverse causality* is plausible: sustained bilateral trade relationships can influence the evolution of sectoral technology portfolios through FDI,[3] learning-by-exporting, supplier up-

[3]As shown by Castelli et al. (2025), subsidiaries of multinational enterprises in a host economy often have

grading, and knowledge diffusion along trade and value-chain links. In this case, observed increases in ρ_{ijst} may partly reflect prior trade integration rather than exogenous technological compatibility. Second, *omitted bilateral sector-time shocks* may jointly affect exports and technology alignment even after controlling for exporter-sector-time, importer-sector-time, exporter-importer-sector, and exporter-importer-time fixed effects. Examples include sector-specific multinational production networks, bilateral R&D collaboration, or coordinated regulatory and standards-setting activities that simultaneously shape innovation trajectories and trade flows. Third, *measurement and selection issues* arise because patent-based proximity is undefined when one or both partners do not have any patenting activity in a given sector-year as well as because patent timing – whether based on priority, publication, or grant dates – may differentially capture economically relevant innovation.

To address these concerns, we instrument technological proximity using a shift-share (Bartik-style) predicted proximity measure that combines *predetermined sector-technology composition* with *exogenous global technology shocks*. The instrument is constructed in four steps.

5.2.1 Instruments

Baseline technology exposure (pre-sample shares). For each country i, sector s, and CPC technology class c, we compute a pre-sample baseline patent share w^0_{isc} using a fixed window prior to the trade sample for the 1985-1995 period:

$$w^0_{isc} = \frac{\sum_{t \in 1985\text{–}1995} P_{isct}}{\sum_{c'} \sum_{t \in 1985\text{–}1995} P_{isc't}}, \tag{24}$$

where P_{isct} denotes the number of patents in class c assigned to country i and sector s in year t. These baseline shares summarise the historical composition of sector-specific technological capabilities and are predetermined with respect to post-1996 trade outcomes.

Global technology shocks (leave-one-out, unilateral). For each sector-class-year (s, c, t), we construct a global patenting shock as the growth of worldwide patenting activity excluding country i:

$$g^{(-i)}_{sct} = \Delta \ln \left(\sum_{k \neq i} P_{ksct} \right). \tag{25}$$

This leave-one-out design ensures that the global shock used to predict country i's technology evolution is not mechanically influenced by country i's own patenting behavior. This leave-one-out construction is important for identification, as it removes the mechanical correlation between a country's own innovation activity and the global shock, thereby strengthening the exogeneity of the instrument. At this stage, the instrument is purely *unilateral*: it depends only on country i, sector s, class c, and year t.

Predicted shift-share country-sector technology vectors. Using the pre-sample shares w^0_{isc} defined in Equation 24 and the global shocks $g^{(-i)}_{sct}$ defined in Equation 25, we construct

different patent portfolios from their global ultimate owners in the home country. This implies that technological proximity may only be imperfectly correlated with FDI linkages.

predicted patent exposure for each country-sector-year:

$$\widehat{P}_{isct} = w^0_{isc} \cdot g^{(-i)}_{sct}. \tag{26}$$

From these predicted patent counts, we compute predicted RTA vectors $\widehat{r}_{ist}$ using the same normalisation as in Equation 14. This yields a predicted technology-specialisation profile for each country-sector-year that only reflects global technology trends filtered through historical specialisation patterns.

Predicted shift-share technological proximity. The predicted bilateral shift-share technological proximity is then defined analogously to the baseline measure in Equation 15:

$$\widehat{\rho}_{ijst} = \mathrm{corr}(\widehat{r}_{ist}, \widehat{r}_{jst}). \tag{27}$$

Although the global shock entering $\widehat{r}_{ist}$ only excludes country i, the correlation operator combines the two unilateral predicted technology vectors. As a result, $\widehat{\rho}_{ijst}$ is a bilateral object by construction while remaining driven entirely by exogenous global technology shocks and predetermined pre-sample technology composition. Since many correlation observations are missing given that at least one trading partner lacks information on $\widehat{r}_{ist}$ or $\widehat{r}_{jst}$, missing values of $\widehat{\rho}_{ijst}$ are set to zero and an indicator variable $\widehat{\rho}^{\text{missing}}_{ijst}$ is included. The latter equals one when the correlation is missing or undefined and zero otherwise.

Conditional on the high-dimensional fixed effects in Equation 18, global CPC-class innovation shocks can only affect bilateral exports through their impact on the relative technological alignment between exporter and importer. Any direct exporter-sector-time or importer-sector-time effects of global innovation trends are absorbed by the fixed effects. The identifying variation therefore comes from differential bilateral alignment induced by common global technology shocks interacting with historically determined sectoral specialisation.

Endogeneity is addressed using a control-function approach for nonlinear models, following Lin and Wooldridge (2019) and Wooldridge (2015), which is suitable for PPML estimation. In principle, the first stage would regress observed technological proximity ρ_{ijst} on the predicted shift-share proximity instruments $\widehat{\rho}_{ijst}$ – constructed using publication $\widehat{\rho^p}_{ijst}$ and grant dates $\widehat{\rho^g}_{ijst}$ – together with the full set of fixed effects Ω, using the ivpoisson command in Stata, which applies a generalised method of movements (GMM) regressor for an exponentiated right-hand side. In practice, however, the inclusion of high-dimensional fixed effects prevents convergence in such specifications.

To overcome this limitation, we follow the procedure proposed by Freeman et al. (2025). Specifically, we first estimate Equation 18 using PPML estimation with high-dimensional fixed effects, excluding the technological proximity variable ρ_{ijst} and the indicator for non-missing correlations $\rho^{\text{missing}}_{ijst}$. The estimated equation to retrieve fixed effects is as follows:

$$X_{ijst} = \exp\Big(\delta\, sh^{+}_{ijst} + \gamma^{\top}\mathbf{TP}_{ijst} + \omega_{ist} + \omega_{jst} + \omega_{ijs} + \omega_{ijt}\Big) + \nu_{ijst}. \tag{28}$$

From this regression, we recover and store the full set of fixed effects Ω: exporter-sector-time $\widehat{\omega}_{ist}$, importer-sector-time $\widehat{\omega}_{jst}$, exporter-importer-sector $\widehat{\omega}_{ijs}$, and exporter-importer-time $\widehat{\omega}_{ijt}$.

These estimated fixed effects, together with the remaining covariates from Equation 18, are then used in a first-stage instrumental-variable (IV) framework to estimate the endogenous technological proximity variable ρ_{ijst} and the corresponding indicator for non-missing observations $\rho_{ijst}^{\text{missing}}$ in a system of two equations as follows:

$$\begin{aligned}\rho_{ijst} = \beta_{10}^{p}\widehat{\rho^{p}}_{ijst} + \beta_{11}^{g}\widehat{\rho^{g}}_{ijst} + \beta_{12}^{p}\widehat{\rho^{p}}_{ijst}^{\text{missing}} + \beta_{13}^{p}\widehat{\rho^{g}}_{ijst}^{\text{missing}} + \delta_{14}sh_{ijst}^{+} + \gamma_1^{\top}\mathbf{TP}_{ijst} + \widehat{\Omega} + \nu_{ijst}^{1},\\ \widehat{\Omega} = \widehat{\omega}_{ist} + \widehat{\omega}_{jst} + \widehat{\omega}_{ijs} + \widehat{\omega}_{ijt}\end{aligned} \tag{29}$$

$$\begin{aligned}\rho_{ijst}^{\text{missing}} = \beta_{20}^{p}\widehat{\rho^{p}}_{ijst} + \beta_{21}^{g}\widehat{\rho^{g}}_{ijst} + \beta_{22}^{p}\widehat{\rho^{p}}_{ijst}^{\text{missing}} + \beta_{23}^{p}\widehat{\rho^{g}}_{ijst}^{\text{missing}} + \delta_{24}sh_{ijst}^{+} + \gamma_2^{\top}\mathbf{TP}_{ijst} + \widehat{\Omega} + \nu_{ijst}^{2},\\ \widehat{\Omega} = \widehat{\omega}_{ist} + \widehat{\omega}_{jst} + \widehat{\omega}_{ijs} + \widehat{\omega}_{ijt}.\end{aligned} \tag{30}$$

5.2.2 IV estimation

The residuals $\hat{\nu}_{ijst}^{1}$ and $\hat{\nu}_{ijst}^{2}$ obtained from the first-stage ordinary least squares (OLS) regressions are subsequently included as additional control variables in the second-stage PPML estimation, together with the original endogenous regressors, as follows:

$$\begin{aligned}X_{ijst} = \exp\Big(\beta_0\,\rho_{ijst} + \beta_1\,\rho_{ijst}^{missing} + \delta\,sh_{ijst}^{+} + \gamma^{\top}\mathbf{TP}_{ijst} + \widehat{\Omega} + \hat{\nu}_{ijst}^{1} + \hat{\nu}_{ijst}^{2}\Big) + \nu_{ijst}^{3},\\ \widehat{\Omega} = \widehat{\omega}_{ist} + \widehat{\omega}_{jst} + \widehat{\omega}_{ijs} + \widehat{\omega}_{ijt}.\end{aligned} \tag{31}$$

Including these residuals controls for unobserved components of technological proximity that are correlated with the error term in Equation 18. This control-function augmentation ensures the consistency of the PPML estimator in the presence of endogenous proximity measures. Although global CPC-class innovation shocks affect many countries simultaneously, exporter-sector-time and importer-sector-time fixed effects absorb common demand and supply movements. Identification therefore arises from heterogeneous baseline technological exposure, which maps global technology shocks into changes in relative bilateral portfolio alignment. Under standard assumptions, this procedure yields consistent estimates of the causal effect of technological proximity on bilateral trade flows, resulting in a consistent and robust error term ν_{ijst}^{3} in Equation 31. Given that the shift-share instrument is constructed from common global shocks, inference based on clustering at the exporter-importer-sector level is conservative, as it allows for correlated error structures across observations with similar exposure to these shocks.

Overall, this strategy preserves the structural-gravity interpretation of the baseline model while purging technological proximity of feedback from trade, unobserved bilateral shocks, and non-random measurement error. The resulting estimates therefore capture the impact of exogenous, globally driven shifts in technological compatibility on export performance.

Equation 31 is estimated using the Stata ivpoisson command with a control-function specification that utilises a GMM regressor for an exponentiated right-hand side to address endogeneity bias. In addition, Equation 18 is also estimated using PPML estimation as a robustness check.

However, for Equation 20, which includes interaction terms between control variables and endogenous technological proximity regressors, the ivpoisson estimator fails to achieve convergence or yield feasible results. Therefore, PPML estimation is employed for these specifications with interaction terms, which is comparable to the robustness check in the baseline specification in Equation 18.

Furthermore, the estimation is conducted over the sample of all industries, including both services and non-services sectors. However, trade-policy variables are only available for the non-services sectors. Thus, the interaction between trade-policy measures and technological proximity is only considered in the estimation for the non-services sectors. The estimation for the non-services sectors is therefore very similar to the specification used by Ghodsi and Santeramo (2026). The only difference is that, in the current study, NACE Sector B09 (Mining support service activities) is excluded from the non-services sample.

5.2.3 Robustness checks

Last but not least, as a robustness check, we construct alternative shift-share instruments based on global patent shares rather than global patent growth rates $g_{sct}^{(-i)}$. In this specification, predicted technological specialisation reflects the interaction between baseline country-sector shares and the level distribution of global innovation across CPC classes rather than changes over time, as in Equation 25. This alternative is motivated by the fact that 'predicted patent counts' based on log-difference growth rates may become negative when global patenting declines, making the construction of RTA measures – defined as shares based on non-negative counts – conceptually problematic. The resulting IV Poisson estimates (available upon request) are quantitatively and qualitatively similar to the baseline results, indicating that the findings are not driven by the specific choice of global shocks. This consistency reinforces the interpretation that technological proximity captures stable patterns of cross-country co-specialisation in innovation rather than transient fluctuations in global technological dynamics. It also suggests that, rather than being driven by short-term global innovation shocks, the identifying variation reflects more persistent differences in countries' technological structures.

6 Empirical Results

This section presents the core empirical evidence from the PPML structural-gravity specifications in Equations (21) and (30) in addition to interpreting the results through the mechanisms derived in Section 3. The dependent variable is gross bilateral exports X_{ijst} over the 1996-2020 period. All regressions include exporter-sector-time, importer-sector-time, exporter-importer-sector, and exporter-importer-time fixed effects, thereby ensuring identification from within-pair-sector variation over time, net of multilateral resistance and bilateral macroeconomic shocks (Tinbergen, 1962; Yotov et al., 2016). Standard errors are clustered at the bilateral-sector level.

Technological proximity ρ_{ijst} is constructed from RTA-based patent portfolios (Equation 20) under alternative timing conventions (priority, publication, and grant dates). We estimate both baseline PPML specifications (Equation 21) and IV-control-function Poisson models (Equation 30), where proximity is instrumented using a shift-share design based on global CPC-class shocks.

6.1 Baseline results: all sectors

Table 1 reports the baseline estimates for the full sample of sectors. A central result of the analysis is that technological proximity exerts a positive and economically meaningful effect on bilateral exports. Across specifications in various columns, the coefficient on technological proximity, ρ_{ijst}, is positive and statistically significant. In the standard PPML specifications, the coefficient ranges from 0.015 to 0.042, implying that a 0.1 increase in technological proximity is associated with an approximately 0.15%-0.42% increase in bilateral exports. However, once endogeneity is addressed using the control-function IV Poisson estimator, the coefficient rises sharply to between 0.48 and 0.53 across all timing conventions. This implies that a 0.1 increase in bilateral technological proximity raises exports by approximately 4.9%-5.4%.

Table 1: PPML regression on gross exports of all sectors, 1996-2020

	Priority	Publication	Grant	Priority	Publication	Grant
ρ_{ijst}	0.015**	0.038***	0.042***	0.53***	0.48***	0.49***
	(0.0064)	(0.0096)	(0.0088)	(0.017)	(0.015)	(0.015)
sh^{+}_{ijst}	0.27***	0.27***	0.27***	0.50***	0.50***	0.50***
	(0.028)	(0.027)	(0.027)	(0.0066)	(0.0066)	(0.0066)
$\rho^{missing}_{ijst}$	-0.0069	-0.036***	-0.038***	-0.13***	-0.12***	-0.12***
	(0.0060)	(0.0086)	(0.0080)	(0.0061)	(0.0053)	(0.0054)
T_{ijst}	-0.75***	-0.75***	-0.75***	-0.84***	-0.83***	-0.83***
	(0.11)	(0.11)	(0.11)	(0.025)	(0.025)	(0.025)
T_{jist}	-0.26**	-0.26**	-0.26**	-0.15***	-0.15***	-0.14***
	(0.10)	(0.10)	(0.10)	(0.026)	(0.026)	(0.026)
TBT_{ijst}	0.011	0.012	0.012	-0.0059***	-0.0062***	-0.0061***
	(0.011)	(0.011)	(0.011)	(0.0018)	(0.0018)	(0.0018)
SPS_{ijst}	0.012	0.012	0.012	0.018***	0.018***	0.018***
	(0.0097)	(0.0097)	(0.0097)	(0.0022)	(0.0022)	(0.0022)
RD^{TBT}_{ijst}	-0.52***	-0.52***	-0.52***	-0.75***	-0.76***	-0.76***
	(0.091)	(0.091)	(0.091)	(0.030)	(0.030)	(0.030)
RD^{SPS}_{ijst}	-0.50***	-0.50***	-0.49***	-0.42***	-0.41***	-0.41***
	(0.12)	(0.12)	(0.12)	(0.034)	(0.034)	(0.034)
GVC^{T}_{ijst}	39.5***	39.4***	39.4***	95.8***	96.7***	96.8***
	(4.40)	(4.41)	(4.41)	(3.71)	(3.74)	(3.74)
GVC^{TBT}_{ijst}	22.7***	22.6***	22.6***	35.1***	34.9***	34.8***
	(2.50)	(2.50)	(2.50)	(1.56)	(1.55)	(1.55)
GVC^{SPS}_{ijst}	9.12	9.20	9.19	43.0***	43.6***	43.4***
	(5.92)	(5.91)	(5.92)	(3.37)	(3.38)	(3.37)
$\hat{\nu}^{1}_{ijst}$				-0.42***	-0.35***	-0.36***
				(0.021)	(0.020)	(0.020)
$\hat{\nu}^{2}_{ijst}$				0.073***	0.058***	0.057***
				(0.0064)	(0.0057)	(0.0058)
Constant	11.5***	11.4***	11.4***	10.9***	10.9***	10.9***
	(0.011)	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)
Observations	5757313	5757313	5757313	5757313	5757313	5757313
Pseudo R-squared	0.999	0.999	0.999			
AIC	35958621.5	35956583.7	35955971.8			
BIC	35958784.3	35956746.5	35956134.6			

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tables A1–A2 in the Appendix provide strong support for the IV strategy. The excluded shift-share instruments are jointly highly significant in the first-stage regressions. Diagnostics for weak instruments, based on the corresponding linear first-stage specifications, yield F-statistics well above conventional thresholds, alleviating concerns about instrument relevance. This indicates that the predicted technological-proximity measures have substantial explanatory power for the endogenous regressors. Overidentification tests based on Hansen's J statistic in the GMM framework fail to reject the null hypothesis of instrument validity, providing further support for the exogeneity of the shift-share instruments. The control-function residuals are also statistically significant in the second-stage regressions, confirming the presence of endogeneity. Taken together, these results suggest that correcting for endogeneity is essential and help explain why the IV estimates of technological proximity are substantially larger than the baseline PPML coefficients.

The contrast between the baseline PPML and IV estimates strongly suggests attenuation bias in the naïve specifications. This is consistent with both measurement error in patent-based proximity indicators and simultaneity in the relationship between trade and innovation alignment. Substantively, these results support the core mechanism derived in Section 3: technologically aligned exporter-importer pairs face lower adaptation and coordination costs and are therefore able to trade more intensively.

The IV results are particularly important because they strengthen the causal interpretation of the proximity effect. In the theoretical framework, proximity enters the bilateral competitiveness term by reducing effective trade costs and facilitating the absorption of foreign knowledge. The estimates are consistent with precisely this channel. Moreover, the fact that publication- and grant-based measures perform somewhat better than the priority-based measure in the baseline PPML estimates suggests that commercially realised or legally validated innovations may be more closely related to actual trade performance than inventions measured only at the first (i.e. filing) stage. At the same time, the similarity of the IV coefficients across all three timing conventions indicates that the underlying relationship is not driven by a particular patent dating convention, mainly because exogenous instruments are based on publication and grant dates.

Reduced-form regressions of bilateral exports on the predicted technological-proximity measures yield qualitatively similar patterns, confirming that the shift-share instruments are strongly correlated with trade outcomes through the technological alignment channel.

The control variables are also informative and broadly consistent with the structural gravity interpretation. The share of positive six-digit HS product lines within a sector, sh^{+}_{ijst}, is positive and highly significant in every specification, with particularly large coefficients in the IV models. This confirms that broader product-market coverage is tightly associated with larger aggregate sectoral exports. The coefficient on sh^{+}_{ijst} should be read as a control for observed product coverage rather than as an estimate of a separate margin of adjustment.

By contrast, the indicator for missing technological proximity, $\rho^{missing}_{ijst}$, is negative and often strongly significant, especially in the IV specifications. This suggests that sector-year observations lacking patent information for at least one partner are systematically associated with weaker bilateral export performance, which is consistent with lower technological sophistication or tradability.

The policy coefficients reveal a nuanced pattern. Import tariffs imposed by the importer on the exporter, T_{ijst}, and tariffs in the reverse direction, T_{jist}, are both negative, confirming the expected trade-reducing role of tariff barriers. Regulatory distance in TBT and SPS measures is also strongly negative, which is consistent with the theoretical argument that divergence in standards raises compliance and adaptation costs.

By contrast, the simple stocks of TBTs and SPS measures are not uniformly negative. In the IV estimates, SPS stocks are positive and significant, while TBT stocks are slightly negative. This pattern suggests that regulation per se is not necessarily trade-reducing; rather, what matters is whether regulatory frameworks are aligned. In other words, regulatory divergence, rather than regulation itself, appears to be the key impediment to trade.

The GVC-related controls are large and positive. This indicates that sectoral trade is strongly embedded in value-chain structures and that regulatory and policy linkages operating through up- and downstream production networks play an important role in shaping bilateral exports.

6.2 Baseline estimates and trade-cost equivalents: non-services sectors

Table 2 focuses on non-services sectors, where policy variables are more consistently observed and compliance costs are more directly relevant, following Ghodsi and Santeramo (2026).

The main result survives and becomes sharper in the IV estimates. In the conventional PPML models, technological proximity is only significant under the priority-date measure, while other measures are insignificant. However, once endogeneity is addressed, the coefficient becomes strongly positive and highly significant across all timing conventions, ranging from 0.38 to 0.41. This implies that a 0.1 increase in technological proximity raises non-services exports by approximately 3.9%-4.2%.

The coefficient on sh^{+}_{ijst} increases substantially relative to the full sample, which is expected because product-line coverage is only observed at the six-digit HS level for non-services sectors. This result indicates that sectoral exports are larger when bilateral trade covers a broader set of product lines. However, this should not be interpreted as evidence that technological proximity changes product-line breadth; the reported estimations only use sh^{+}_{ijst} as a control when explaining gross export values.

The remaining covariates display a coherent pattern. Tariffs remain negative and significant, while regulatory distance in TBT measures remains strongly negative. The positive coefficients on SPS and TBT stocks again suggest that the existence of regulation may coincide with deeper integration or higher product quality, provided that regulatory systems are compatible.

Comparing the full sample with non-services sectors yields an important insight: technological proximity is more tightly linked to observable trade mechanisms in goods sectors, in which production processes, standards, and intermediate inputs are more directly tied to codified technologies.

To gauge the economic magnitude of this effect, we also express the estimated impact of technological proximity in tariff-equivalent terms. In an alternative IV specification for non-services sectors, tariffs are entered as $\ln(1+t_{ijst})$ rather than in levels. This change in functional form implies that the estimated coefficient captures the semi-elasticity of exports with respect to

Table 2: PPML regression on gross exports of non-services sectors, 1996-2020

	Priority	Publication	Grant	Priority	Publication	Grant
ρ_{ijst}	0.030***	-0.0053	0.0042	0.41***	0.38***	0.38***
	(0.0099)	(0.014)	(0.013)	(0.030)	(0.027)	(0.028)
sh^{+}_{ijst}	0.88***	0.88***	0.88***	1.45***	1.47***	1.47***
	(0.054)	(0.054)	(0.054)	(0.012)	(0.012)	(0.012)
$\rho^{missing}_{ijst}$	-0.0045	-0.026*	-0.029**	-0.19***	-0.16***	-0.17***
	(0.0096)	(0.014)	(0.013)	(0.011)	(0.0096)	(0.0099)
T_{ijst}	-0.41***	-0.41***	-0.41***	-0.44***	-0.43***	-0.43***
	(0.12)	(0.12)	(0.12)	(0.037)	(0.037)	(0.037)
T_{jist}	-0.24*	-0.25**	-0.25*	-0.11***	-0.094***	-0.094***
	(0.13)	(0.13)	(0.13)	(0.031)	(0.031)	(0.031)
TBT_{ijst}	0.047***	0.047***	0.047***	0.023***	0.023***	0.023***
	(0.017)	(0.017)	(0.017)	(0.0021)	(0.0021)	(0.0021)
SPS_{ijst}	0.034***	0.034***	0.034***	0.032***	0.032***	0.032***
	(0.011)	(0.011)	(0.011)	(0.0028)	(0.0028)	(0.0028)
RD^{TBT}_{ijst}	-0.25**	-0.25**	-0.25**	-0.34***	-0.35***	-0.36***
	(0.10)	(0.10)	(0.10)	(0.036)	(0.036)	(0.036)
RD^{SPS}_{ijst}	-0.22*	-0.23*	-0.22*	-0.0030	-0.0015	0.0014
	(0.13)	(0.13)	(0.13)	(0.046)	(0.046)	(0.046)
GVC^{T}_{ijst}	54.5***	54.6***	54.5***	99.6***	100.2***	100.4***
	(5.25)	(5.24)	(5.25)	(4.31)	(4.34)	(4.34)
GVC^{TBT}_{ijst}	24.0***	24.0***	24.0***	40.5***	40.4***	40.3***
	(2.92)	(2.92)	(2.92)	(1.99)	(1.99)	(1.99)
GVC^{SPS}_{ijst}	12.8*	12.8*	12.9*	37.7***	38.4***	38.1***
	(7.73)	(7.73)	(7.73)	(3.82)	(3.84)	(3.83)
$\hat{\nu}^{1}_{ijst}$				-0.36***	-0.32***	-0.33***
				(0.050)	(0.048)	(0.048)
$\hat{\nu}^{2}_{ijst}$				0.15***	0.10***	0.10***
				(0.012)	(0.011)	(0.011)
Constant	10.1***	10.1***	10.1***	9.24***	9.20***	9.21***
	(0.044)	(0.044)	(0.044)	(0.014)	(0.014)	(0.014)
Observations	2682185	2682185	2682185	2682185	2682185	2682185
Pseudo R-squared	0.998	0.998	0.998			
AIC	20461847.4	20462023.0	20462151.2			
BIC	20462001.0	20462176.7	20462304.8			

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

proportional changes in the gross tariff factor, $(1+t_{ijst})$, rather than the effect of a 1 percentage point (pp) change in the tariff rate, as in Table 2. As a result, the estimated coefficient on importer-imposed tariffs is larger in absolute value (around -0.58 to -0.59) and not directly comparable to the level-based estimates reported earlier.

Let $\hat{\beta}_\rho$ denote the coefficient on technological proximity and $\hat{\gamma}_t < 0$ the coefficient on $\ln(1 + t_{ijst})$. The tariff-equivalent change associated with a change $\Delta\rho$ is obtained by equating the export effect of technological proximity to the export effect of a change in tariffs:

$$\hat{\beta}_\rho \Delta\rho = -\hat{\gamma}_t \Delta \ln(1 + t_{ijst}). \tag{32}$$

Hence,

$$\Delta \ln(1 + t_{ijst}) = \frac{\hat{\beta}_\rho \Delta\rho}{|\hat{\gamma}_t|}. \tag{33}$$

Using the IV estimates in Table 2, where $\hat{\beta}_\rho$ ranges from about 0.38 to 0.41 and $\hat{\gamma}_t$ from about -0.58 to -0.59, a 0.1 increase in technological proximity is equivalent to a reduction in $\ln(1 + t_{ijst})$ of approximately 0.064-0.071 log points. This corresponds to roughly a 6.2%-6.9% decline in the gross tariff factor $(1 + t_{ijst})$. Put differently, the export-enhancing effect of a 0.1 increase in technological proximity is comparable to lowering the gross tariff factor by about 6%-7%. For example, starting from an ad-valorem tariff of 10%, this would approximately correspond to reducing the tariff to around 2.5%-3.0%. This comparison is reduced-form and should not be interpreted as a structural trade elasticity; rather, it provides an economically intuitive benchmark for the magnitude of technological proximity relative to an observable trade-policy barrier.

6.3 Technological proximity and policy interactions

Tables 3-5 examine whether technological proximity mitigates the effects of trade-policy barriers in non-services sectors.

The most robust mitigation effects arise for SPS-related frictions. Across all specifications, the interaction between technological proximity and SPS intensity is positive and highly significant. The interaction with SPS regulatory distance is also positive and, in several cases, strongly significant. These findings indicate that technologically aligned countries are better able to cope with sanitary and phytosanitary barriers, likely because similar capabilities facilitate testing, certification, and compliance. Furthermore, as shown by the first-stage results of the IV strategy presented in Table A1, SPS regulatory distance is positively and significantly associated with technological proximity, whereas regulatory distance in TBT measures exhibits a negative relationship with technological proximity.

For TBT-related frictions, the evidence is more mixed but still supportive. The interaction between proximity and TBT intensity becomes positive and significant in the publication- and grant-based specifications, suggesting that technological alignment can mitigate the negative effects of certain technical barriers.

By contrast, there is no robust evidence that technological proximity offsets tariffs. In some specifications, tariff interactions are negative, implying that tariffs may even be more binding when countries are technologically close. This is consistent with the idea that tariffs represent direct price wedges that cannot be easily mitigated through technological compatibility.

The interactions with GVC-related variables suggest diminishing marginal returns to technological proximity in highly integrated value-chain relationships. When trade is already deeply embedded in production networks, part of the coordination role of proximity may already be internalised within those networks.

Table 3: PPML regression on non-services gross exports using patent flows (priority date), 1996-2020, with $\rho_{ijst} \times TP_{ijst}$

	T_{ijst}	T_{jist}	TBT_{ijst}	SPS_{ijst}	RD^{TBT}_{ijst}	RD^{SPS}_{ijst}	GVC^{T}_{ijst}	GVC^{TBT}_{ijst}	GVC^{SPS}_{ijst}
ρ_{ijst}	0.035***	0.035***	0.026***	0.021**	0.023**	0.025**	0.060***	0.043***	0.033***
	(0.0099)	(0.010)	(0.010)	(0.0099)	(0.010)	(0.0098)	(0.010)	(0.011)	(0.010)
$\rho_{ijst} \times TP_{ijst}$	-1.21***	-1.22***	0.021	0.092***	0.65	1.00**	-284.2***	-39.2**	-24.2
	(0.45)	(0.45)	(0.025)	(0.028)	(0.42)	(0.49)	(34.4)	(17.8)	(31.6)
sh^{+}_{ijst}	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***	0.89***	0.88***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.053)	(0.053)	(0.054)
$\rho^{missing}_{ijst}$	-0.0078	-0.0077	-0.0020	0.00091	-0.00043	-0.0012	-0.017*	-0.010	-0.0058
	(0.0096)	(0.0096)	(0.0097)	(0.0097)	(0.0097)	(0.0096)	(0.0098)	(0.0097)	(0.0096)
T_{ijst}	-0.41***	-0.41***	-0.41***	-0.41***	-0.41***	-0.41***	-0.41***	-0.41***	-0.41***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
T_{jist}	-0.24*	-0.25**	-0.24*	-0.24*	-0.24*	-0.24*	-0.27**	-0.25**	-0.25*
	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
TBT_{ijst}	0.047***	0.047***	0.047***	0.047***	0.047***	0.047***	0.045***	0.046***	0.047***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
SPS_{ijst}	0.034***	0.034***	0.034***	0.036***	0.034***	0.034***	0.034***	0.037***	0.035***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
RD^{TBT}_{ijst}	-0.26**	-0.26**	-0.25**	-0.25**	-0.24**	-0.25**	-0.27***	-0.28***	-0.25**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
RD^{SPS}_{ijst}	-0.22*	-0.22*	-0.22*	-0.23*	-0.22*	-0.21*	-0.18	-0.22*	-0.22*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)
GVC^{T}_{ijst}	54.5***	54.6***	54.5***	54.5***	54.5***	54.5***	53.0***	55.1***	54.7***
	(5.25)	(5.25)	(5.25)	(5.25)	(5.25)	(5.25)	(5.18)	(5.27)	(5.24)
GVC^{TBT}_{ijst}	24.0***	24.0***	23.9***	24.1***	23.9***	23.9***	22.7***	23.3***	24.0***
	(2.92)	(2.92)	(2.92)	(2.91)	(2.92)	(2.92)	(2.93)	(2.82)	(2.91)
GVC^{SPS}_{ijst}	12.7*	12.7*	12.8*	12.5	12.8*	12.8*	15.9**	11.6	11.3
	(7.72)	(7.72)	(7.74)	(7.75)	(7.73)	(7.73)	(7.20)	(7.48)	(6.97)
Constant	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Observations	2682185	2682185	2682185	2682185	2682185	2682185	2682185	2682185	2682185
Pseudo R-squared	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
AIC	20461022.8	20461024.7	20461618.2	20459202.7	20461178.6	20461073.9	20427313.0	20456247.8	20461228.9
BIC	20461189.3	20461191.2	20461784.6	20459369.1	20461345.0	20461240.3	20427479.4	20456414.2	20461395.3

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: PPML regression on non-services gross exports using patent flows (publication date), 1996-2020, with $\rho_{ijst} \times TP_{ijst}$

	T_{ijst}	T_{jist}	TBT_{ijst}	SPS_{ijst}	RD^{TBT}_{ijst}	RD^{SPS}_{ijst}	GVC^{T}_{ijst}	GVC^{TBT}_{ijst}	GVC^{SPS}_{ijst}
ρ_{ijst}	-0.0089	-0.0030	-0.020	-0.016	-0.026*	-0.019	0.024*	0.0064	-0.0017
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)
$\rho_{ijst} \times TP_{ijst}$	0.42	-0.28	0.042*	0.066**	1.01**	1.49***	-193.8***	-22.4	-21.6
	(0.44)	(0.43)	(0.025)	(0.027)	(0.41)	(0.52)	(36.3)	(13.9)	(25.9)
sh^{+}_{ijst}	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***	0.89***	0.88***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
$\rho^{missing}_{ijst}$	-0.024*	-0.028**	-0.017	-0.019	-0.014	-0.017	-0.042***	-0.033**	-0.029**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
T_{ijst}	-0.40***	-0.41***	-0.41***	-0.41***	-0.42***	-0.41***	-0.42***	-0.41***	-0.42***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
T_{jist}	-0.25**	-0.25**	-0.25**	-0.25*	-0.25**	-0.25**	-0.24*	-0.24*	-0.24*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)
TBT_{ijst}	0.047***	0.047***	0.048***	0.047***	0.047***	0.047***	0.046***	0.046***	0.047***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
SPS_{ijst}	0.034***	0.034***	0.034***	0.037***	0.034***	0.035***	0.035***	0.036***	0.034***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
RD^{TBT}_{ijst}	-0.25**	-0.25**	-0.25**	-0.25**	-0.23**	-0.25**	-0.26**	-0.26**	-0.25**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
RD^{SPS}_{ijst}	-0.22*	-0.23*	-0.23*	-0.25**	-0.23*	-0.21*	-0.21*	-0.23*	-0.22*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
GVC^{T}_{ijst}	54.6***	54.6***	54.5***	54.6***	54.4***	54.5***	51.8***	55.1***	54.8***
	(5.24)	(5.24)	(5.24)	(5.24)	(5.23)	(5.24)	(5.22)	(5.25)	(5.23)
GVC^{TBT}_{ijst}	24.0***	24.0***	23.9***	24.1***	23.8***	23.9***	23.3***	23.3***	23.9***
	(2.92)	(2.92)	(2.92)	(2.92)	(2.91)	(2.92)	(2.96)	(2.86)	(2.90)
GVC^{SPS}_{ijst}	12.9*	12.8*	13.1*	12.8*	13.1*	13.0*	14.8**	11.5	11.0
	(7.73)	(7.72)	(7.70)	(7.73)	(7.71)	(7.72)	(7.41)	(7.49)	(7.01)
Constant	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***
	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)
Observations	2682185	2682185	2682185	2682185	2682185	2682185	2682185	2682185	2682185
Pseudo R-squared	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
AIC	20461876.5	20461966.5	20460923.1	20460288.3	20460004.6	20459818.6	20445207.2	20459871.3	20461580.1
BIC	20462042.9	20462132.9	20461089.5	20460454.7	20460171.1	20459985.0	20445373.6	20460037.8	20461746.6

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: PPML regression on non-services gross exports using patent flows (grant date), 1996-2020, with $\rho_{ijst} \times TP_{ijst}$

	T_{ijst}	T_{jist}	TBT_{ijst}	SPS_{ijst}	RD_{ijst}^{TBT}	RD_{ijst}^{SPS}	GVC_{ijst}^{T}	GVC_{ijst}^{TBT}	GVC_{ijst}^{SPS}
ρ_{ijst}	0.00045	0.0057	-0.0095	-0.0059	-0.015	-0.0090	0.032**	0.013	0.0078
	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.015)	(0.014)
$\rho_{ijst} \times TP_{ijst}$	0.49	-0.21	0.041*	0.069**	1.07***	1.57***	-200.0***	-19.4	-24.2
	(0.42)	(0.43)	(0.024)	(0.027)	(0.41)	(0.51)	(36.6)	(13.9)	(27.6)
sh_{ijst}^{+}	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***	0.88***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
$\rho_{ijst}^{missing}$	-0.026**	-0.030**	-0.020	-0.022*	-0.016	-0.020	-0.043***	-0.034***	-0.031**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
T_{ijst}	-0.40***	-0.41***	-0.41***	-0.41***	-0.42***	-0.41***	-0.41***	-0.41***	-0.42***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
T_{jist}	-0.25**	-0.25**	-0.25**	-0.24*	-0.25**	-0.25*	-0.24*	-0.24*	-0.24*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)
TBT_{ijst}	0.047***	0.047***	0.048***	0.047***	0.047***	0.048***	0.046***	0.046***	0.047***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
SPS_{ijst}	0.034***	0.034***	0.034***	0.037***	0.034***	0.035***	0.035***	0.036***	0.034***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
RD_{ijst}^{TBT}	-0.25**	-0.25**	-0.25**	-0.25**	-0.23**	-0.26**	-0.25**	-0.26**	-0.25**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
RD_{ijst}^{SPS}	-0.22*	-0.22*	-0.22*	-0.24*	-0.23*	-0.21*	-0.21*	-0.23*	-0.22*
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
GVC_{ijst}^{T}	54.6***	54.5***	54.4***	54.5***	54.4***	54.4***	52.0***	55.1***	54.8***
	(5.25)	(5.25)	(5.24)	(5.25)	(5.24)	(5.25)	(5.19)	(5.25)	(5.23)
GVC_{ijst}^{TBT}	24.0***	24.0***	23.9***	24.1***	23.8***	23.9***	23.3***	23.3***	23.9***
	(2.92)	(2.92)	(2.92)	(2.92)	(2.91)	(2.92)	(2.97)	(2.86)	(2.90)
GVC_{ijst}^{SPS}	12.9*	12.8*	13.0*	12.8*	13.1*	13.0*	14.8**	11.9	10.9
	(7.73)	(7.72)	(7.72)	(7.74)	(7.71)	(7.73)	(7.40)	(7.48)	(6.97)
Constant	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***	10.1***
	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)
Observations	2682185	2682185	2682185	2682185	2682185	2682185	2682185	2682185	2682185
Pseudo R-squared	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
AIC	20461964.7	20462121.1	20461057.9	20460322.5	20459889.4	20459736.7	20444881.7	20460507.4	20461605.8
BIC	20462131.1	20462287.5	20461224.3	20460488.9	20460055.9	20459903.2	20445048.1	20460673.8	20461772.3

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Importantly, the main effect of technological proximity becomes unstable once interactions are included. This should not be overinterpreted, however, as the marginal effect of proximity is conditional on the level of policy frictions. The interaction results therefore highlight that the trade effect of technological proximity depends on the regulatory environment.

6.4 Regional heterogeneity of technological proximity

Table 6 and Table A3 provide evidence on how the trade-enhancing effects of technological proximity vary across regions. These specifications exploit variation in the interaction between technological proximity and regional dummies, allowing the impact of technological alignment to differ across exporting regions (Table 6) and bilateral regional pairs (Table A3) while benchmarking the United States as the global technological leader.

Exporter-region heterogeneity (Table 6). The results reveal substantial heterogeneity in how technological proximity translates into export performance across regions. When focusing on the preferred specifications based on publication and grant dates, the coefficient on technological proximity for the United States (i.e. the benchmark region) is positive and statistically significant, indicating that higher technological alignment systematically increases US export performance. This finding is consistent with the interpretation that the US, as the technological frontier, benefits from compatibility with foreign markets through reduced adaptation and coordination costs.

In contrast, the interaction terms for other regions are generally negative and statistically significant relative to the US benchmark. In particular, with the exception of China, the coefficients for other regions are large in magnitude and negative, suggesting that, conditional on the same level of technological proximity, these regions experience a weaker trade-enhancing effect compared to the US. These results imply that technological proximity does not operate symmetrically across regions; rather, its effectiveness depends on countries' positions within the global technological hierarchy.

One interpretation is that proximity to a technological leader (e.g. the US) generates stronger gains due to higher potential to gain from technology absorption and deeper integration into global innovation networks. By contrast, for regions that are themselves undergoing technological convergence or catch-up, proximity may reflect intra-regional similarity that does not necessarily translate into stronger external demand or competitiveness gains.

China represents a notable exception. While its coefficients are not consistently significant across specifications, they are generally closer to zero and occasionally positive, suggesting that China's trade response to technological proximity is more comparable to that of the US than to those of other regions. This pattern is consistent with China's intermediate position between technological frontier economies and catching-up regions.

Bilateral heterogeneity (Table A3). The bilateral interaction results in Table A3 provide a more granular view of these patterns. It is important to note that the first region denotes the exporting region, while the second denotes the importing region. Accordingly, the notation USCN refers to the US-China relationship when the US is the exporting country.

Table 6: PPML regression on gross exports in all sectors, 1996-2020, with technological proximity interacted with exporting-region dummies

	Priority	Publication	Grant
US # ρ_{ijst} - benchmark	0.0054	0.35***	0.31**
	(0.064)	(0.13)	(0.13)
CN # ρ_{ijst}	0.082	0.018	0.075
	(0.073)	(0.14)	(0.14)
ESEAN # ρ_{ijst}	-0.0055	-0.35***	-0.31**
	(0.066)	(0.13)	(0.13)
EU # ρ_{ijst}	-0.025	-0.34***	-0.29**
	(0.065)	(0.13)	(0.13)
ROW # ρ_{ijst}	0.055	-0.37***	-0.34***
	(0.066)	(0.13)	(0.13)
West # ρ_{ijst}	-0.018	-0.26*	-0.26*
	(0.065)	(0.13)	(0.13)
sh^{+}_{ijst}	0.27***	0.27***	0.27***
	(0.027)	(0.027)	(0.027)
$\rho^{missing}_{ijst}$	-0.0076	-0.022***	-0.024***
	(0.0059)	(0.0080)	(0.0076)
T_{ijst}	-0.75***	-0.74***	-0.75***
	(0.11)	(0.11)	(0.11)
T_{jist}	-0.26**	-0.26**	-0.27***
	(0.10)	(0.10)	(0.10)
TBT_{ijst}	0.011	0.0099	0.0094
	(0.011)	(0.011)	(0.011)
SPS_{ijst}	0.012	0.013	0.013
	(0.0097)	(0.0097)	(0.0097)
RD^{TBT}_{ijst}	-0.52***	-0.52***	-0.52***
	(0.091)	(0.091)	(0.091)
RD^{SPS}_{ijst}	-0.49***	-0.48***	-0.47***
	(0.12)	(0.12)	(0.12)
GVC^{T}_{ijst}	39.6***	39.5***	39.5***
	(4.38)	(4.39)	(4.39)
GVC^{TBT}_{ijst}	22.6***	22.2***	22.1***
	(2.50)	(2.49)	(2.49)
GVC^{SPS}_{ijst}	9.13	9.69*	9.64
	(5.91)	(5.89)	(5.92)
Constant	11.5***	11.3***	11.3***
	(0.018)	(0.032)	(0.032)
Observations	5757313	5757313	5757313
Pseudo R-squared	0.999	0.999	0.999
AIC	35954555.6	35936794.4	35933926.4
BIC	35954786.2	35937025.0	35934157.0

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A first key result is that while Table 6 shows that technological proximity for the US (measured using priority dates) does not have a statistically significant effect on its exports to all trading partners, Table A3 indicates that priority dates play the most significant role for intra-country trade. In particular, it is the timing of patent priority (i.e. the first incidence of innovative output) that is most relevant for intra-country trade between sectors and regions in the US. Sectors in which innovation leads to technological proximity equal to one at this early stage tend to exhibit higher intra-country trade compared to sectors without any innovative activity. By contrast, this effect is less pronounced when considering later stages of the innovation process (e.g. publication and grant dates). Indeed, publication and grant dates appear to be more relevant for extra-country trade of the US, as they are associated with the formal protection of intellectual property (IP) and the subsequent expansion of exports to foreign markets. This distinction highlights the differing roles of innovation and IP protection within domestic versus international trade contexts.

Another important result is that intra-regional technological proximity does not universally promote trade. In several cases – including ESEAN-ESEAN, EU-EU, and West-West pairs – the coefficients are negative or insignificant, particularly under the priority-based measure. This suggests that technological similarity within regions may reflect overlapping specialisation patterns that limit gains from trade, which is consistent with reduced scope for complementarities.

By contrast, proximity between technologically asymmetric partners often generates stronger trade effects. For example, proximity within China (CNCN) becomes strongly positive and statistically significant in the publication and grant specifications, reflecting the growing importance of innovative sectors with technological proximity equal to one in China's domestic market. Similarly, interactions involving the US and other regions (e.g. US-China, EU-US, and RoW-US) tend to display positive or increasingly positive coefficients in the publication and grant specifications, indicating that alignment with the technological frontier is particularly beneficial.

A more nuanced pattern emerges when considering the direction of trade between the US and China. As an exporter, US exports to China exhibit positive coefficients for publication and grant dates that are statistically significant at the 10% level. By contrast, as an importer, US imports from China display a negative coefficient that is statistically significant at the 10% level when technological proximity is measured using priority dates. This suggests that the effects of technological proximity may differ depending on the direction of trade.

The asymmetry between the two directions of trade is economically noteworthy. Over the estimation period, the results suggest that US exports to China benefit more strongly from technological proximity than Chinese exports to the US. In particular, the positive coefficients for US exports to China become larger under the publication- and grant-date measures, whereas the corresponding coefficients for Chinese exports to the US remain negative. This pattern suggests that technological compatibility between the two economies does not generate symmetric trade effects. Rather, the gains from proximity appear to depend on the respective roles of the exporter and importer within bilateral production and innovation relationships.

One possible interpretation is related to the role of the US as an important provider of advanced technologies, including through multinational enterprises, licensing relationships, and exports of technologically sophisticated intermediate and capital goods. Greater technological proximity with China may make US technologies, production processes, and specialised inputs easier for Chinese firms to absorb, adapt, and integrate into their own production systems. This mechanism would be consistent with the stronger effects observed for the publication- and grant-based measures, as these stages are more closely associated with the public disclosure, legal protection, and potential commercial diffusion of technological knowledge. From this perspective, technological alignment with China may strengthen the competitiveness of US exporters by lowering adaptation, coordination, and integration costs in the Chinese market. Conversely, technological similarity alone may be less sufficient to generate comparable export gains for Chinese firms serving the US market, where other dimensions of market access, technological specialisation, and regulatory compliance may remain important. This interpretation should nevertheless be regarded as suggestive given that the present framework does not directly identify multinational-enterprise or FDI channels.

At the same time, several negative coefficients arise in relationships involving ESEAN and RoW partners (e.g. ESEAN-RoW, RoW-China), suggesting that technological similarity among less advanced or more heterogeneous economies does not systematically translate into higher trade flows. This pattern is consistent with the idea that technological proximity is most effective when it reflects compatibility with high-productivity, innovation-intensive production systems rather than similarity at lower levels of technological development.

6.5 Sectoral heterogeneity

Table 7 extends the heterogeneity analysis by interacting technological proximity with sector dummies. The results indicate substantial heterogeneity across sectors, with stronger effects in sectors that rely more on complex or specialised knowledge and weaker effects in more standardised industries.

The results show that the benchmark effect for C26 (Manufacture of computer, electronic and optical products) is only positive and statistically significant when technological proximity is measured using priority dates. This suggests that, in the most innovation-intensive sector, early-stage technological alignment is particularly relevant for trade. In other words, proximity in the underlying technological search and invention process appears to be associated with higher export performance in C26 even before technologies are published or formally granted.

Table 7: PPML regression on gross exports in all sectors, 1996-2020, with technological proximity interacted with sector dummies

	Priority	Publication	Grant
C26 # ρ_{ijst} - benchmark	0.19***	-0.048	-0.022
	(0.044)	(0.074)	(0.067)
A01_02 # ρ_{ijst}	-0.21***	0.0036	-0.013
	(0.050)	(0.082)	(0.074)
A03 # ρ_{ijst}	-0.38***	-0.10	-0.12
	(0.074)	(0.097)	(0.088)
B05_06 # ρ_{ijst}	0.045	0.13	0.021
	(0.098)	(0.14)	(0.17)
B07_08 # ρ_{ijst}	-0.33***	0.23*	0.18
	(0.076)	(0.12)	(0.11)
B09 # ρ_{ijst}	-0.057	0.54***	0.46***
	(0.092)	(0.12)	(0.13)
C10T12 # ρ_{ijst}	-0.24***	0.060	0.063
	(0.049)	(0.079)	(0.072)
C13T15 # ρ_{ijst}	-0.11**	0.14	0.21**
	(0.054)	(0.091)	(0.096)
C16 # ρ_{ijst}	-0.12*	0.23**	0.21**
	(0.066)	(0.11)	(0.11)
C17_18 # ρ_{ijst}	-0.26***	0.082	0.048

Continued on next page

Table 7 (continued)

	Priority	Publication	Grant
	(0.054)	(0.080)	(0.072)
C19 # ρ_{ijst}	-0.16***	-0.027	-0.064
	(0.055)	(0.083)	(0.075)
C20 # ρ_{ijst}	-0.16***	-0.015	-0.035
	(0.052)	(0.080)	(0.073)
C21 # ρ_{ijst}	-0.30***	-0.033	-0.16*
	(0.066)	(0.096)	(0.090)
C22 # ρ_{ijst}	-0.097**	0.059	0.049
	(0.048)	(0.091)	(0.083)
C23 # ρ_{ijst}	-0.20***	0.083	0.021
	(0.049)	(0.079)	(0.071)
C24 # ρ_{ijst}	-0.16***	-0.014	-0.033
	(0.053)	(0.078)	(0.073)
C25 # ρ_{ijst}	-0.20***	0.15*	0.13*
	(0.049)	(0.081)	(0.075)
C27 # ρ_{ijst}	-0.24***	0.0080	-0.0064
	(0.056)	(0.083)	(0.077)
C28 # ρ_{ijst}	-0.21***	-0.015	-0.00073
	(0.056)	(0.098)	(0.088)
C29 # ρ_{ijst}	-0.20***	-0.13	-0.16*
	(0.057)	(0.095)	(0.087)
C30 # ρ_{ijst}	-0.14*	0.073	0.077
	(0.079)	(0.12)	(0.11)
C31T33 # ρ_{ijst}	-0.087	0.22**	0.14*
	(0.060)	(0.094)	(0.084)
D # ρ_{ijst}	-0.22***	-0.062	-0.13
	(0.067)	(0.13)	(0.091)
E # ρ_{ijst}	-0.24***	0.30***	0.31***
	(0.055)	(0.11)	(0.11)
F # ρ_{ijst}	-0.15***	0.056	-0.0052
	(0.058)	(0.082)	(0.076)
G # ρ_{ijst}	-0.17***	0.13	0.089
	(0.048)	(0.078)	(0.070)
H49 # ρ_{ijst}	-0.17***	0.19**	0.16**
	(0.047)	(0.077)	(0.070)
H50 # ρ_{ijst}	-0.27***	0.23***	0.22***
	(0.054)	(0.082)	(0.074)
H51 # ρ_{ijst}	-0.11**	0.29***	0.28***
	(0.053)	(0.094)	(0.083)
H52 # ρ_{ijst}	-0.063	0.13*	0.13*
	(0.050)	(0.080)	(0.074)
H53 # ρ_{ijst}	-0.027	0.036	-0.024
	(0.067)	(0.093)	(0.086)
I # ρ_{ijst}	-0.15***	0.18**	0.15**
	(0.048)	(0.079)	(0.072)
J58T60 # ρ_{ijst}	-0.22***	-0.41***	-0.42***
	(0.070)	(0.092)	(0.083)
J61 # ρ_{ijst}	-0.35***	-0.24***	-0.28***
	(0.050)	(0.083)	(0.077)

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Table 7 (continued)

	Priority	Publication	Grant
J62_63 # ρ_{ijst}	-0.39***	-0.49***	-0.49***
	(0.064)	(0.11)	(0.11)
K # ρ_{ijst}	-0.27***	0.10	0.062
	(0.056)	(0.10)	(0.099)
L # ρ_{ijst}	-0.18***	0.27***	0.25***
	(0.053)	(0.080)	(0.073)
M # ρ_{ijst}	-0.12*	0.12	0.085
	(0.066)	(0.14)	(0.13)
N # ρ_{ijst}	-0.19***	0.17*	0.13
	(0.057)	(0.093)	(0.084)
O # ρ_{ijst}	-0.18***	0.025	0.0046
	(0.054)	(0.083)	(0.075)
P # ρ_{ijst}	-0.35***	-0.087	-0.11
	(0.067)	(0.11)	(0.10)
Q # ρ_{ijst}	-0.22***	0.29***	0.27***
	(0.049)	(0.093)	(0.085)
R # ρ_{ijst}	-0.34***	-0.025	-0.044
	(0.051)	(0.082)	(0.076)
S # ρ_{ijst}	-0.29***	0.027	-0.0026
	(0.051)	(0.083)	(0.076)
sh^{+}_{ijst}	0.27***	0.27***	0.27***
	(0.027)	(0.027)	(0.027)
$\rho^{missing}_{ijst}$	-0.0072	-0.018**	-0.019**
	(0.0061)	(0.0086)	(0.0083)
T_{ijst}	-0.75***	-0.75***	-0.76***
	(0.11)	(0.11)	(0.11)
T_{jist}	-0.26**	-0.25**	-0.26**
	(0.10)	(0.10)	(0.10)
TBT_{ijst}	0.012	0.011	0.010
	(0.011)	(0.011)	(0.011)
SPS_{ijst}	0.012	0.011	0.012
	(0.0097)	(0.0097)	(0.0097)
RD^{TBT}_{ijst}	-0.52***	-0.53***	-0.53***
	(0.091)	(0.091)	(0.090)
RD^{SPS}_{ijst}	-0.50***	-0.49***	-0.49***
	(0.12)	(0.12)	(0.12)
GVC^{T}_{ijst}	39.7***	39.6***	39.5***
	(4.38)	(4.38)	(4.38)
GVC^{TBT}_{ijst}	22.5***	22.6***	22.6***
	(2.51)	(2.50)	(2.50)
GVC^{SPS}_{ijst}	8.98	9.15	9.20
	(5.93)	(5.94)	(5.92)
Constant	11.5***	11.4***	11.4***
	(0.012)	(0.013)	(0.013)
Observations	5757313	5757313	5757313
Pseudo R-squared	0.999	0.999	0.999
AIC	35940584.5	35911928.8	35905893.0
BIC	35941330.6	35912674.9	35906639.2

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

By contrast, the coefficients based on publication and grant dates for C26 are not statistically significant, indicating that later stages of the patenting process do not generate an additional benchmark effect once the full set of high-dimensional fixed effects and trade-policy controls are included. These findings are consistent with the estimates reported in Table 2, where only non-services sectors are included. The only difference is that the coefficient of technological proximity for C26 is now smaller than the average effect across all non-services sectors presented in Table 2.

Relative to C26, many sectors display negative and statistically significant interaction terms under the priority-date measure. This pattern indicates that early-stage technological proximity contributes less to exports in those sectors than it does in C26. The result is consistent with the interpretation that priority-date proximity is most informative in technologically dynamic sectors where invention itself is closely connected to production capabilities, product adaptation, and export competitiveness. In less patent-intensive or more mature sectors, technological proximity based on priority dates may capture weaker commercial relevance or more limited tradable complementarity.

The publication- and grant-date specifications reveal a different pattern. Several sectors exhibit positive and statistically significant coefficients relative to C26, including Mining support activities (B09), Repair and installation-related manufacturing (C31T33), Utilities and environmental services (E), Transport-related services (H49-H51), Real estate (L), and Health and social work (Q). These estimates suggest that, outside the frontier manufacturing benchmark, technological proximity becomes more trade-relevant once innovations are publicly disclosed or legally protected. This is plausible for sectors in which the commercial use of technology depends less on first invention and more on codified, observable, and protected technologies that can be adopted, certified, or embedded in production and service delivery.

At the same time, some knowledge-intensive service sectors – especially Publishing, audiovisual and broadcasting activities (J58-J60), Telecommunications (J61), and IT and other information services (J62-J63) – display negative and statistically significant coefficients in the publication- and grant-date specifications. This suggests that technological similarity in these sectors does not automatically translate into stronger bilateral exports. One possible interpretation is that digital and information-related services are characterised by strong domestic capabilities, platform effects, non-trade modes of delivery, or overlapping specialisation patterns, such that technological proximity may generate competition rather than complementarity. Hence, the trade-enhancing effect of technological proximity is not uniform across all technology-intensive sectors.

Overall, Table 7 reinforces the view that the impact of technological proximity is sector-specific. Its trade effect is strongest when the timing and economic meaning of the patent measure match the way technologies are commercialised in a given sector. Priority-date proximity matters most for C26, where early innovation is closely tied to export competitiveness, while publication- and grant-date proximity appears more relevant in sectors where technologies only become tradable or operational after disclosure, protection, standardisation, or adoption. These results complement the regional heterogeneity findings by showing that the impact of technological proximity depends not only on countries' positions in the global technology hierarchy but also on the sectoral context in which technological capabilities are deployed.

6.6 Discussion

Taken together, the results show that technological proximity is not merely a correlate of trade but a fundamental determinant of bilateral exchange. It operates as a form of 'latent compatibility infrastructure' that reduces effective trade costs by facilitating coordination, adaptation, and knowledge absorption between trading partners. In this sense, technological proximity acts as a non-policy trade facilitator comparable in magnitude to formal trade agreements or regulatory harmonisation.

At the same time, its trade effects are not uniform. They are strongly conditioned by the global structure of technological capabilities and by countries' positions within the technological hierarchy. Proximity to frontier economies yields the largest gains, reflecting higher absorptive capacity and deeper integration into global innovation networks. By contrast, proximity among non-frontier or structurally similar economies may generate weaker or even negative effects, as technological similarity may reflect overlapping specialisation rather than complementarity. What matters, therefore, is not technological convergence per se but its direction (i.e. whether countries align with technologically advanced partners or primarily with peers at similar levels of development).

The empirical results provide consistent support for the mechanisms derived from the theoretical framework. Technological proximity directly increases gross bilateral exports conditional on product coverage, high-dimensional fixed effects, and observed trade-policy measures. The reported results should therefore be interpreted as evidence on export values rather than on separate product-line margins. In addition, technological proximity mitigates compliance-intensive non-tariff barriers, particularly SPS-related frictions, while having limited ability to offset tariff barriers. This highlights that technological alignment primarily reduces coordination and regulatory costs rather than explicit price-based trade barriers.

More broadly, these findings suggest that bilateral trade integration depends not only on traditional gravity variables and policy measures but also on the compatibility of countries' technological capabilities. Technological co-specialisation therefore emerges as a distinct and quantitatively important determinant of export-market access and trade performance.

These results carry several policy implications. First, strengthening domestic technological capabilities and sectoral specialisation can have indirect but substantial effects on trade by improving compatibility with foreign markets. Investments in R&D, innovation systems, and sector-specific upgrading are therefore central not only for productivity growth but also for international trade integration.

Second, international economic integration should place greater emphasis on technological and regulatory alignment. Agreements that promote harmonisation of standards, mutual recognition, and interoperability of technologies are likely to yield stronger trade gains than those focusing solely on tariff reductions.

Third, regional integration processes can be reinforced by underlying technological linkages. Policies that support cross-border innovation networks, joint research initiatives, and knowledge diffusion can enhance complementarities and facilitate deeper trade integration.

Finally, for developing and catching-up economies, aligning technological capabilities with those of major trading partners can improve export performance. At the same time, the limited ability of technological proximity to offset tariff barriers underscores the continued importance of conventional trade liberalisation alongside technological upgrading.

7 Welfare Counterfactuals

The empirical results indicate that technological proximity increases bilateral trade flows by improving the compatibility of production structures across countries. This section provides a welfare interpretation of these estimates within the structural gravity framework developed in Section 3. Rather than to solve a full dynamic model of endogenous innovation, the objective is to quantify how changes in technological proximity affect welfare via their impact on bilateral sourcing shares.

The counterfactual exercise follows the sufficient-statistics approach of Arkolakis et al. (2012), in which welfare changes can be expressed as a function of domestic expenditure shares and trade elasticities. In the present framework, technological proximity enters bilateral trade costs through the compatibility term $\Psi_s(\rho_{ijst})$, thereby affecting welfare via its impact on sourcing patterns.

Counterfactual sourcing shares

Recall that bilateral exports can be written as

$$X_{ijst} = \pi_{ijst} E_{jst}, \tag{34}$$

where π_{ijst} denotes the share of expenditure in country j on sector s varieties sourced from exporter i, and E_{jst} is total sectoral expenditure.

Sourcing shares are given by

$$\pi_{ijst} = \frac{A_{ijst}}{\Phi_{jst}}, \qquad \Phi_{jst} = \sum_{\ell} A_{\ell jst}, \tag{35}$$

where

$$A_{ijst} = T_{ist} \left(\frac{w_{it}\tau_{ijst}}{\Psi_s(\rho_{ijst})} \right)^{-\theta_s}. \tag{36}$$

Using the parameterisation $\Psi_s(\rho_{ijst}) = \exp\{\lambda_s \rho_{ijst}\}$, the proportional change in bilateral competitiveness induced by a change in technological proximity is

$$\widehat{A}_{ijst} = \exp\left(\hat{\beta}_{\rho,s} \Delta\rho_{ijst}\right), \tag{37}$$

where $\hat{\beta}_{\rho,s} = \theta_s \lambda_s$ is identified from the gravity estimation.

Counterfactual sourcing shares are therefore given by

$$\pi'_{ijst} = \frac{\pi_{ijst} \exp\left(\hat{\beta}_{\rho,s} \Delta\rho_{ijst}\right)}{\sum_{\ell} \pi_{\ell jst} \exp\left(\hat{\beta}_{\rho,s} \Delta\rho_{\ell jst}\right)}. \tag{38}$$

This formulation highlights that observed sourcing shares already embed baseline competitiveness, so the counterfactual only requires proportional changes in relative competitiveness.

Welfare and the domestic expenditure share

Sectoral welfare in country j is given by

$$W_{jst} = \frac{E_{jst}}{P_{jst}}, \tag{39}$$

where P_{jst} is the CES price index. Under the Fréchet-CES structure, the price index satisfies

$$P_{jst} \propto \Phi_{jst}^{-1/\theta_s}. \tag{40}$$

Let $\lambda_{jjst} = \pi_{jjst}$ denote the domestic expenditure share. Holding domestic competitiveness fixed, changes in λ_{jjst} capture changes in overall market competitiveness:

$$\frac{W'_{jst}}{W_{jst}} = \left(\frac{\lambda'_{jjst}}{\lambda_{jjst}}\right)^{-1/\theta_s}. \tag{41}$$

This expression provides a sufficient statistic for welfare, following Arkolakis et al. (2012). A decline in the domestic share reflects improved access to foreign suppliers, a lower price index, and higher real income. The magnitude of the welfare response is governed by the trade elasticity θ_s.

Aggregate welfare changes are obtained by weighting sectoral welfare changes using expenditure shares:

$$\ln\left(\frac{W'_{jt}}{W_{jt}}\right) = \sum_s \omega_{jst} \left[-\frac{1}{\theta_s} \ln\left(\frac{\lambda'_{jjst}}{\lambda_{jjst}}\right)\right], \tag{42}$$

where $\omega_{jst} = E_{jst} / \sum_s E_{jst}$.

Data and implementation

The required sourcing shares are constructed using the OECD Inter-Country Input-Output tables. For each country pair (i, j) and sector s, total absorption is computed as

$$X_{ijst} = \sum_{r \in S} Z_{is,jr,t} + F_{is,j,t}, \tag{43}$$

where $Z_{is,jr,t}$ denotes intermediate flows and $F_{is,j,t}$ final demand. Total expenditure is

$$E_{jst} = \sum_i X_{ijst}, \qquad \pi_{ijst} = \frac{X_{ijst}}{E_{jst}}. \tag{44}$$

The counterfactuals are implemented in four steps: (i) constructing baseline sourcing and domestic shares; (ii) computing bilateral competitiveness changes using $\exp(\hat{\beta}_{\rho,s}\Delta\rho_{ijst})$; (iii) obtaining counterfactual sourcing shares by renormalisation; and (iv) computing welfare changes using the domestic-share formula. These exercises should be interpreted as partial-equilibrium counterfactuals. They reallocate sourcing shares across suppliers within sectors after an exogenous change in technological proximity while holding endogenous innovation, wages, aggregate expenditure, and the broader equilibrium structure fixed.

7.1 Counterfactual scenarios and economic interpretation

We consider two counterfactual scenarios to assess the welfare implications of changes in technological proximity. In the first scenario, technological proximity between the EU and each partner region increases by one standard deviation of the corresponding bilateral proximity distribution across all sectors. In the second scenario, EU-region technological proximity converges halfway towards the global frontier in each sector, defined as the level of the US.

Table 8 reports the resulting welfare effects implied by these two scenarios. In both cases, welfare changes are computed from the induced variation in domestic expenditure shares using the sufficient-statistics formula in Equation 41.

Table 8: Welfare effects of EU-region technological-proximity counterfactuals (percentage change in welfare)

Exporter	Region	One-standard-deviation increase					Halfway convergence to sectoral frontier				
		EU–US	EU–China	EU–ESEAN	EU–West	EU–RoW	EU–US	EU–China	EU–ESEAN	EU–West	EU–RoW
ARG	ROW					0.05					0.11
AUS	West				0.03					0.05	
AUT	EU	0.07	0.05	0.04	0.08	0.07	0.10	0.07	0.07	0.13	0.13
BEL	EU	0.08	0.04	0.03	0.03	0.06	0.06	0.03	0.05	0.06	0.11
BGD	ROW					0.11					0.21
BGR	EU	0.03	0.07	0.03	0.03	0.13	0.04	0.08	0.06	0.04	0.26
BLR	ROW					0.18					0.48
BRA	ROW					0.04					0.09
BRN	ESEAN			0.02					0.03		
CAN	West				0.05					0.08	
CHE	West				0.45					0.65	
CHL	ROW					0.06					0.14
CHN	CN		0.08					0.09			
CIV	ROW					0.17					0.28
CMR	ROW					0.15					0.28
COL	ROW					0.05					0.07
CRI	ROW					0.12					0.19
CYP	EU	0.02	0.01	0.03	0.01	0.08	0.01	0.01	0.06	0.02	0.15
CZE	EU	0.03	0.04	0.02	0.04	0.08	0.06	0.05	0.04	0.08	0.21
DEU	EU	0.08	0.08	0.05	0.07	0.08	0.16	0.13	0.11	0.11	0.17
DNK	EU	0.14	0.05	0.04	0.09	0.06	0.14	0.05	0.07	0.13	0.10
ESP	EU	0.04	0.02	0.02	0.03	0.08	0.04	0.03	0.03	0.05	0.17

Continued on next page

Table 8 (continued)

Exporter	Region	One-standard-deviation increase					Halfway convergence to sectoral frontier				
		EU–US	EU–China	EU–ESEAN	EU–West	EU–RoW	EU–US	EU–China	EU–ESEAN	EU–West	EU–RoW
EST	EU	0.07	0.03	0.03	0.09	0.10	0.11	0.04	0.08	0.18	0.18
FIN	EU	0.06	0.06	0.05	0.05	0.09	0.09	0.08	0.09	0.08	0.17
FRA	EU	0.06	0.04	0.04	0.04	0.06	0.06	0.06	0.07	0.06	0.11
GBR	EU	0.08	0.03	0.03	0.04	0.04	0.13	0.05	0.06	0.06	0.08
GRC	EU	0.04	0.02	0.03	0.02	0.07	0.04	0.02	0.07	0.03	0.16
HKG	ESEAN			0.12					0.21		
HRV	EU	0.03	0.01	0.01	0.03	0.03	0.04	0.01	0.02	0.04	0.06
HUN	EU	0.07	0.06	0.03	0.05	0.10	0.11	0.10	0.07	0.08	0.21
IDN	ESEAN			0.04					0.07		
IND	ROW					0.04					0.08
IRL	EU	0.42	0.10	0.07	0.08	0.08	0.26	0.13	0.11	0.10	0.14
ISL	West				0.53					0.60	
ISR	ROW					0.09					0.17
ITA	EU	0.06	0.03	0.03	0.05	0.07	0.13	0.06	0.07	0.07	0.15
JOR	ROW					0.04					0.06
JPN	ESEAN			0.03					0.09		
KAZ	ROW					0.21					0.32
KHM	ESEAN			0.17					0.30		
KOR	ESEAN			0.05					0.11		
LAO	ESEAN			0.06					0.11		
LTU	EU	0.05	0.02	0.03	0.08	0.13	0.08	0.02	0.05	0.12	0.25
LUX	EU	0.04	0.04	0.03	0.04	0.08	0.05	0.04	0.05	0.06	0.16
LVA	EU	0.04	0.02	0.02	0.05	0.09	0.07	0.03	0.06	0.10	0.19
MAR	ROW					0.28					0.58
MEX	ROW					0.04					0.08
MLT	EU	0.04	0.09	0.06	0.02	0.04	0.04	0.09	0.09	0.02	0.07
MMR	ESEAN			0.03					0.06		
MYS	ESEAN			0.08					0.12		
NGA	ROW					0.12					0.19
NLD	EU	0.05	0.03	0.05	0.04	0.06	0.06	0.03	0.09	0.06	0.11
NOR	West				0.65					0.81	
NZL	West				0.05					0.06	
PAK	ROW					0.06					0.11
PER	ROW					0.07					0.15
PHL	ESEAN			0.05					0.08		
POL	EU	0.03	0.02	0.01	0.04	0.07	0.05	0.02	0.02	0.07	0.15
PRT	EU	0.05	0.04	0.01	0.03	0.05	0.08	0.05	0.03	0.06	0.12
ROU	EU	0.02	0.03	0.02	0.02	0.07	0.03	0.04	0.03	0.03	0.17
RUS	ROW					0.18					0.38
SAU	ROW					0.08					0.14
SEN	ROW					0.11					0.23
SGP	ESEAN			0.11					0.14		
SVK	EU	0.08	0.10	0.02	0.05	0.08	0.12	0.20	0.04	0.10	0.22
SVN	EU	0.05	0.03	0.02	0.06	0.11	0.08	0.04	0.04	0.10	0.21
SWE	EU	0.10	0.07	0.05	0.11	0.07	0.14	0.08	0.09	0.19	0.15
THA	ESEAN			0.07					0.12		
TUR	ROW					0.19					0.42

Continued on next page

Table 8 (continued)

Exporter	Region	One-standard-deviation increase					Halfway convergence to sectoral frontier				
		EU–US	EU–China	EU–ESEAN	EU–West	EU–RoW	EU–US	EU–China	EU–ESEAN	EU–West	EU–RoW
TWN	ESEAN			0.06					0.11		
UKR	ROW					0.16					0.33
USA	US	0.06					0.08				
VNM	ESEAN			0.08					0.14		
ZAF	ROW					0.12					0.27

The implied welfare effects are positive but quantitatively modest. This is expected given that the counterfactuals only affect selected bilateral EU-region links rather than the entire global matrix of trade costs. As a result, the induced changes in domestic expenditure shares are small and the corresponding welfare gains remain limited. Nevertheless, the direction of the effects is consistent with the mechanism of the model: higher technological proximity raises the relative competitiveness of technologically compatible foreign suppliers, reduces the domestic expenditure share, and lowers the sectoral price index.

The one-standard-deviation shocks generate the largest average welfare gains when EU technological proximity increases with the RoW and Western economies. The average welfare change across exporters is approximately 0.00066& for the EU-RoW shock and 0.00042% for the EU-West shock, compared with 0.00027% for the EU-US shock. The largest individual gains in this scenario are observed for Ireland under the EU-US shock, with welfare gains of 0.42%; Norway under the EU-West shock, with gains of 0.65%; and Morocco under the EU-RoW shock, with gains of 0.28%. These patterns indicate that the welfare consequences of technological proximity depend not only on the magnitude of the bilateral shock but also on the importance of the affected trade relationship within each country's expenditure structure.

The frontier-convergence scenario generally produces larger welfare effects than the one-standard-deviation scenario. This is particularly evident for EU-RoW and EU-West convergence, where the average welfare gains increase to approximately 0.00132% and 0.00060%, respectively. The largest individual effect is observed for Norway under the EU-West frontier-convergence scenario, with welfare gains of 0.81%, followed by Morocco under the EU-RoW scenario, with gains of 0.58%. These results are consistent with the interpretation that convergence towards the technological frontier has stronger welfare implications than a uniform standard-deviation shock, as it targets economically meaningful gaps in sector-specific technological compatibility.

Overall, the counterfactual results should be interpreted as partial-equilibrium effects. They capture the welfare consequences of reallocating expenditure across suppliers in response to exogenous changes in technological proximity while holding wages, aggregate expenditure, endogenous innovation, and trade relations with other countries fixed. Technological proximity affects welfare by reducing the effective cost of sourcing from foreign suppliers with overlapping technological capabilities. Higher proximity increases the competitiveness of foreign producers, raises aggregate market competitiveness Φ_{jst}, and reduces the domestic expenditure share. This lowers the sectoral price index and increases real income.

In this sense, technological proximity operates as a latent form of compatibility infrastructure. It generates welfare gains through improved access to technologically aligned foreign varieties, complementing traditional trade-cost reductions.

The small magnitudes should therefore not be read as evidence that technological proximity is unimportant. Rather, they show that the welfare gains from localised bilateral technological-alignment shocks operate through narrow changes in sourcing patterns. Larger effects would be expected under broader shocks that simultaneously increase technological proximity across many trading partners or sectors.

These partial-equilibrium calculations do not incorporate endogenous adjustments in relative prices or income. As a result, welfare changes are primarily driven by direct changes in bilateral trade costs and the associated variation in domestic expenditure shares.

As a robustness extension, we consider a reallocation-consistent counterfactual in which bilateral trade shares are updated proportionally and re-normalised across exporters. This introduces trade diversion effects and allows changes in EU technological proximity to affect third countries through shifts in relative competitiveness while maintaining tractability within the structural gravity framework.

8 Summary and Conclusions

This paper develops a unified theoretical and empirical framework for analysing how technological proximity shapes bilateral trade flows at the sectoral level. Building on a multi-country and -sector model with heterogeneous productivity, we show that technological alignment between trading partners can reduce effective trade frictions by improving compatibility of production processes, lowering adaptation costs, and facilitating the exchange of complex goods and inputs.

Using a novel dataset that combines sector-level patent information with OECD trade data for 76 countries across 45 sectors over the 1996-2020 period, we construct a granular measure of technological proximity based on revealed technological advantage (RTA). By embedding this measure within a structural gravity framework with high-dimensional fixed effects, we provide robust evidence that technological proximity is a quantitatively important determinant of bilateral trade.

Several main findings emerge. First, technological proximity exerts a strong and positive effect on bilateral exports. This effect is economically meaningful and becomes substantially larger once endogeneity is addressed using a shift-share instrumental-variable strategy. The difference between baseline and instrumental-variable (IV) estimates suggests the presence of attenuation bias in naïve specifications, which is likely driven by measurement error and reverse causality between trade and technological alignment.

Second, the results indicate that technological proximity operates through improved bilateral competitiveness. In the structural gravity framework, proximity increases the relative attractiveness of an exporter within a given market by lowering effective trade costs. In non-services sectors, the tariff-equivalent calculation shows that a 0.1 increase in technological proximity has an export effect comparable to a 6%-7% reduction in the gross tariff factor, providing an intuitive benchmark for the magnitude of the estimated effect.

Third, technological proximity interacts with trade policy in a non-trivial way. While tariffs remain robustly trade-reducing, proximity mitigates the adverse effects of compliance-intensive regulatory non-tariff measures, particularly sanitary and phytosanitary (SPS) regulations. The evidence suggests that regulatory divergence, rather than regulation itself, constitutes the primary barrier to trade, and that technological compatibility facilitates compliance with such measures. In contrast, proximity does not systematically offset tariff barriers, which operate as direct price distortions.

Fourth, the effects are heterogeneous across both regions and sectors. The benefits of technological proximity are significantly larger when countries are linked to technological frontier economies, while proximity among less advanced or structurally similar regions yields weaker or even negative trade effects. Sectoral estimates further show that technological proximity is most trade-relevant when the timing and economic content of patent information match the way in which technologies are commercialised within each industry.

Finally, the partial-equilibrium welfare counterfactuals imply positive but modest welfare gains from targeted technological-alignment shocks. The magnitudes are small because the exercises affect selected bilateral links and hold wages, aggregate expenditure, endogenous innovation, and broader equilibrium feedbacks fixed. They nevertheless show that technological proximity can generate welfare gains by reducing effective sourcing costs, reallocating expenditure towards technologically compatible suppliers, and lowering domestic expenditure shares.

Taken together, these findings highlight that global trade integration is shaped not only by traditional dimensions of distance but also by the alignment of technological capabilities across countries. In this context, technological co-specialisation refers to the extent to which trading partners exhibit similar patterns of RTA across technological fields. Such alignment can enhance the feasibility and efficiency of cross-border exchange by reducing adaptation, coordination, and compliance costs, particularly in sectors characterised by complex production processes and regulatory requirements.

References

Aghion, P., Akcigit, U., and Howitt, P. (2013). *What Do We Learn from Schumpeterian Growth Theory?* Handbook of Economic Growth, Vol. 2B, Elsevier.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics*, 120(2):701–728.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

Ali, A. and Cockburn, I. (2012). Buyer behavior in markets for technology: Technology proximity between firm portfolio and in-licensed patents. Technical report, Working paper.

Alstott, J., Triulzi, G., Yan, B., and Luo, J. (2017). Mapping technology space by normalizing patent networks. *Scientometrics*, 110:443–479.

Arkolakis, C., Costinot, A., and Rodriguez-Clare, A. (2012). New trade models, same old gains? *American Economic Review*, 102(1):94–130.

Beghin, J. C., Maertens, M., and Swinnen, J. (2015). Nontariff measures and standards in trade and global value chains. *Annual Review of Resource Economics*, 7(1):425–450.

Borusyak, K., Hull, P., and Jaravel, X. (2025). A practical guide to shift-share instruments. *Journal of Economic Perspectives*, 39(1):181–204.

Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39(1):61–74.

Cadot, O., Asprilla, A., Gourdon, J., Knebel, C., and Peters, R. (2015). Deep regional integration and non-tariff measures: A methodology for data analysis.

Cantner, U. and Meder, A. (2007). Technological proximity and the choice of cooperation partner. *Journal of Economic Interaction and Coordination*, 2:45–65.

Castelli, C., Davies, R. B., Flórez Mendoza, J., and Ghodsi, M. (2025). Drivers of FDI in the EU: Regulatory distance and revealed technological advantage. wiiw Working Paper 264, The Vienna Institute for International Economic Studies (wiiw).

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1):128–152.

Disdier, A.-C., Fontagne, L., and Mimouni, M. (2008). The impact of regulations on agricultural trade: Evidence from the SPS and TBT agreements. *American Journal of Agricultural Economics*, 90(2):336–350.

Dollar, D. (1993). Technological differences as a source of comparative advantage. *The American Economic Review*, 83(2):431–435.

Eaton, J. and Kortum, S. (1999). International technology diffusion: Theory and measurement. *International Economic Review*, 40(3):537–570.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Esfahani, S. O. and Tayebi, S. K. (2016). Technological distance and bilateral trade in Asia. *Korea and the World Economy*, 17(2):243–265.

Filippini, C. and Molini, V. (2003). The determinants of east asian trade flows: A gravity equation approach. *Journal of asian Economics*, 14(5):695–711.

Freeman, R., Larch, M., Theodorakopoulos, A., and Yotov, Y. V. (2025). Unlocking new methods to estimate country-specific effects and trade elasticities with the structural gravity model. *Journal of Applied Econometrics*, n/a(n/a).

Fung, M. K. (2003). Technological proximity and co-movements of stock returns. *Economics Letters*, 79(1):131–136.

Ghodsi, M. (2023). Exploring the 'non-tariff measures black box': Whose regulatory NTMs on which products improve the imported quality? *International Economics*, 173:45–67.

Ghodsi, M. and Santeramo, F. (2026). SPS and TBT measures through the lens of bilateral and gvc-related regulatory distance. *International Economics*, 185:100674.

Hausmann, R. and Klinger, B. (2006). The structure of the product space and the evolution of comparative advantage. Technical report, CID Working Paper No. 146, Harvard University.

Hidalgo, C. A. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26):10570–10575.

Hidalgo, C. A., Klinger, B., Barabási, A.-L., and Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837):482–487.

Inui, T., Ikeuchi, K., Obashi, A., and Yang, Q. (2021). The impact of regulatory distance from global standards on a country's centrality in global value chains. *International Economics*, 166:95–115.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):577–598.

Jagdambe, S. and Kannan, E. (2020). Effects of asean-india free trade agreement on agricultural trade: The gravity model approach. *World Development Perspectives*, 19:100212.

Jones, C. I. (1995). R&D-based models of economic growth. *Journal of Political Economy*, 103(4):759–784.

Jun, B., Alshamsi, A., Gao, J., and Hidalgo, C. A. (2017). Relatedness, knowledge diffusion, and the evolution of bilateral trade. *arXiv preprint arXiv:1709.05392*.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3):752–782.

Knebel, C. and Peters, R. (2019). Non-tariff measures and the impact of regulatory convergence in ASEAN. In Ing, L. Y., Cadot, O., and Peters, R., editors, *Non-Tariff Measures in ASEAN*. Economic Research Institute for ASEAN and East Asia, Jakarta.

LaBelle, J., Martinez-Zarzoso, I., Santacreu, A. M., and Yotov, Y. V. (2023). Cross-border patenting, globalization, and development. Cesifo working paper.

Lin, W. and Wooldridge, J. M. (2019). Chapter 2 - Testing and correcting for endogeneity in nonlinear unobserved effects models. In Tsionas, M., editor, *Panel Data Econometrics*, pages 21–43. Academic Press.

Neffke, F. and Henning, M. (2013). Skill relatedness and firm diversification. *Strategic Management Journal*, 34(3):297–316.

Neffke, F., Henning, M., and Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87(3):237–265.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5):S71–S102.

Santeramo, F. G. and Lamonaca, E. (2019). The effects of non-tariff measures on agri-food trade: A review and meta-analysis of empirical evidence. *Journal of Agricultural Economics*, 70(3):595–617.

Scherngell, T. and Barber, M. J. (2009). Spatial interaction modelling of cross-region R&D collaborations: Empirical evidence from the 5th eu framework programme. *Papers in Regional Science*, 88(3):531–547.

Segerstrom, P. S. (1998). Endogenous growth without scale effects. *American Economic Review*, 88(5):1290–1310.

Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1):65–94.

Solow, R. M. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics*, 39(3):312–320.

Tinbergen, J. (1962). Shaping the world economy; suggestions for an international economic policy.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, 50(2):420–445.

World Trade Organization (2011). *World Trade Report 2011: The WTO and Preferential Trade Agreements: From Co-Existence to Coherence*. World Trade Organization, Geneva, Switzerland.

Yotov, Y. V., Piermartini, R., Larch, M., et al. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. WTO iLibrary.

Appendix A

A.1 From variety-level productivity draws to the competitiveness term

This appendix clarifies why the realised variety-level productivity draw $z_{ist}(\omega)$ appears in the delivered price in Equation (7), but does not appear explicitly in the competitiveness term in Equation (9). The reason is that Equation (9) is not the delivered price of a particular variety. Instead, it is an ex ante exporter-importer-sector competitiveness term obtained after integrating over the Fréchet distribution of productivity draws. The individual draw $z_{ist}(\omega)$ is therefore summarised by the Fréchet scale parameter T_{ist}.

Let

$$a_{ijst} \equiv \frac{w_{it}\tau_{ijst}}{\Psi_s(\rho_{ijst})}. \tag{A1}$$

For a given variety ω, the delivered unit cost is

$$c_{ijst}(\omega) = \frac{a_{ijst}}{z_{ist}(\omega)}. \tag{A2}$$

Using the Fréchet productivity distribution in Equation (5), for any cost threshold $c > 0$, the distribution of delivered costs satisfies

$$\begin{aligned}
\Pr\{c_{ijst}(\omega) \le c\} &= \Pr\left\{\frac{a_{ijst}}{z_{ist}(\omega)} \le c\right\} && \text{(A3)}\\
&= \Pr\left\{z_{ist}(\omega) \ge \frac{a_{ijst}}{c}\right\} && \text{(A4)}\\
&= 1 - \exp\left\{-T_{ist}\left(\frac{a_{ijst}}{c}\right)^{-\theta_s}\right\} && \text{(A5)}\\
&= 1 - \exp\left\{-T_{ist}a_{ijst}^{-\theta_s}c^{\theta_s}\right\}. && \text{(A6)}
\end{aligned}$$

Thus, delivered costs have a Weibull-type distribution with exporter-destination-sector scale

$$A_{ijst} = T_{ist}a_{ijst}^{-\theta_s} = T_{ist}\left(\frac{w_{it}\tau_{ijst}}{\Psi_s(\rho_{ijst})}\right)^{-\theta_s}, \tag{A7}$$

which is Equation (9) in the main text.

The sourcing-share expression follows from the same cost distribution. Since the survival function of delivered costs from exporter i is $\exp\{-A_{ijst}c^{\theta_s}\}$, the probability that exporter i is the lowest-cost supplier in market (j, s, t) is

$$\begin{aligned}
\pi_{ijst} &= \int_0^\infty \theta_s A_{ijst}c^{\theta_s-1}\exp\left\{-\left(\sum_{\ell\in\mathcal{N}} A_{\ell jst}\right)c^{\theta_s}\right\}dc && \text{(A8)}\\
&= \frac{A_{ijst}}{\sum_{\ell\in\mathcal{N}} A_{\ell jst}} = \frac{A_{ijst}}{\Phi_{jst}}. && \text{(A9)}
\end{aligned}$$

This shows that the realised productivity draw $z_{ist}(\omega)$ is integrated out before the trade-share equation is obtained. Adding $z_{ist}(\omega)$ directly to A_{ijst} would incorrectly make the competitiveness term variety-specific, whereas A_{ijst} is the distributional object that summarises exporter i's expected ability to supply varieties at low cost to importer j in sector s.

Table A1: First-stage IV regressions for both endogenous regressors across all sectors, 1996-2020

	ρ_{ijst}			$\rho_{ijst}^{missing}$		
	Priority	Publication	Grant	Priority	Publication	Grant
sh_{ijst}^{+}	0.011***	0.011***	0.011***	-0.24***	-0.24***	-0.23***
	(0.0011)	(0.0010)	(0.0010)	(0.0032)	(0.0029)	(0.0029)
T_{ijst}	-0.0026***	0.00021	-0.00046	0.21***	0.29***	0.29***
	(0.00047)	(0.00056)	(0.00053)	(0.0072)	(0.0079)	(0.0077)
T_{jist}	-0.0030***	-0.000092	-0.00085*	0.18***	0.26***	0.26***
	(0.00045)	(0.00053)	(0.00051)	(0.0070)	(0.0076)	(0.0074)
TBT_{ijst}	-0.0010***	-0.0014***	-0.0013***	-0.0012*	-0.0050***	-0.0042***
	(0.000067)	(0.000077)	(0.000074)	(0.00073)	(0.00077)	(0.00075)
SPS_{ijst}	-0.000081	-0.00023**	-0.00022**	-0.0060***	-0.0091***	-0.0083***
	(0.000083)	(0.000095)	(0.000092)	(0.0010)	(0.0011)	(0.0010)
RD_{ijst}^{TBT}	-0.014***	-0.023***	-0.021***	-0.072***	-0.21***	-0.23***
	(0.00080)	(0.00097)	(0.00092)	(0.010)	(0.011)	(0.011)
RD_{ijst}^{SPS}	0.021***	0.021***	0.022***	0.037***	0.051***	0.066***
	(0.0011)	(0.0012)	(0.0011)	(0.012)	(0.012)	(0.012)
GVC_{ijst}^{T}	-1.39***	-1.29***	-1.31***	33.3***	43.2***	42.9***
	(0.11)	(0.12)	(0.12)	(1.58)	(1.90)	(1.86)
GVC_{ijst}^{TBT}	-0.54***	-0.79***	-0.78***	-2.25**	-5.29***	-6.02***
	(0.076)	(0.094)	(0.093)	(0.89)	(0.97)	(0.96)
GVC_{ijst}^{SPS}	-1.09***	-1.48***	-1.46***	16.1***	22.0***	19.8***
	(0.22)	(0.25)	(0.25)	(2.18)	(2.23)	(2.18)
$\widehat{\omega}_{ist}$	0.00063***	0.00055***	0.00056***	-0.026***	-0.030***	-0.029***
	(0.000046)	(0.000048)	(0.000047)	(0.00021)	(0.00022)	(0.00021)
$\widehat{\omega}_{jst}$	0.00069***	0.00075***	0.00074***	-0.021***	-0.024***	-0.023***
	(0.000044)	(0.000049)	(0.000047)	(0.00024)	(0.00026)	(0.00025)
$\widehat{\omega}_{ijs}$	0.00099***	0.0012***	0.0012***	-0.015***	-0.017***	-0.016***
	(0.000038)	(0.000044)	(0.000042)	(0.00016)	(0.00016)	(0.00016)
$\widehat{\omega}_{ijt}$	-0.00028***	-0.00055***	-0.00047***	-0.0088***	-0.020***	-0.019***
	(0.000024)	(0.000027)	(0.000026)	(0.00024)	(0.00028)	(0.00027)
$\widehat{\rho^{p}}_{ijst}$	0.25***	0.28***	0.27***	-0.033***	-0.021***	-0.026***
	(0.0039)	(0.0038)	(0.0038)	(0.0046)	(0.0040)	(0.0040)
$\widehat{\rho^{p}}_{ijst}^{\text{missing}}$	0.0047***	0.0038***	0.0040***	-0.13***	-0.18***	-0.16***
	(0.0010)	(0.0011)	(0.00100)	(0.0066)	(0.0070)	(0.0063)
$\widehat{\rho^{g}}_{ijst}$	0.31***	0.35***	0.34***	0.014***	0.044***	0.039***
	(0.0047)	(0.0045)	(0.0045)	(0.0050)	(0.0043)	(0.0044)
$\widehat{\rho^{g}}_{ijst}^{\text{missing}}$	0.0029***	0.0017	0.0022**	-0.27***	-0.28***	-0.29***
	(0.0010)	(0.0011)	(0.00100)	(0.0067)	(0.0071)	(0.0064)
Constant	0.011***	0.012***	0.012***	0.71***	0.64***	0.65***
	(0.00054)	(0.00061)	(0.00059)	(0.0021)	(0.0022)	(0.0021)
Observations	5757313	5757313	5757313	5757313	5757313	5757313

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: PPML regression on gross exports of non-services sectors, 1996-2020

	Priority	Publication	Grant	Priority	Publication	Grant
sh^{+}_{ijst}	0.014***	0.018***	0.016***	-0.43***	-0.40***	-0.41***
	(0.00089)	(0.0010)	(0.00099)	(0.0047)	(0.0046)	(0.0046)
T_{ijst}	-0.0034***	0.0015**	0.000024	0.21***	0.32***	0.31***
	(0.00053)	(0.00062)	(0.00059)	(0.0077)	(0.0086)	(0.0084)
T_{jist}	-0.0030***	0.0018***	0.00016	0.13***	0.23***	0.22***
	(0.00054)	(0.00062)	(0.00059)	(0.0075)	(0.0083)	(0.0081)
TBT_{ijst}	-0.0010***	-0.0014***	-0.0013***	-0.0039***	-0.0073***	-0.0068***
	(0.000063)	(0.000077)	(0.000072)	(0.00073)	(0.00077)	(0.00075)
SPS_{ijst}	0.000073	-0.000047	-0.000045	-0.010***	-0.015***	-0.014***
	(0.000086)	(0.000100)	(0.000096)	(0.0010)	(0.0011)	(0.0010)
RD^{TBT}_{ijst}	-0.015***	-0.022***	-0.022***	-0.10***	-0.22***	-0.24***
	(0.00078)	(0.00096)	(0.00091)	(0.010)	(0.011)	(0.011)
RD^{SPS}_{ijst}	0.022***	0.024***	0.024***	0.046***	0.058***	0.076***
	(0.0010)	(0.0012)	(0.0011)	(0.012)	(0.012)	(0.012)
GVC^{T}_{ijst}	-1.18***	-1.27***	-1.25***	29.8***	35.7***	36.0***
	(0.11)	(0.12)	(0.12)	(1.66)	(1.86)	(1.85)
GVC^{TBT}_{ijst}	-0.43***	-0.62***	-0.62***	-0.81	-2.38**	-2.92***
	(0.077)	(0.096)	(0.095)	(1.02)	(1.06)	(1.04)
GVC^{SPS}_{ijst}	-0.99***	-1.47***	-1.42***	15.4***	21.4***	19.5***
	(0.25)	(0.28)	(0.28)	(2.52)	(2.55)	(2.52)
$\widehat{\omega}_{ist}$	0.00018***	-0.000048	0.000018	-0.0089***	-0.012***	-0.012***
	(0.000062)	(0.000063)	(0.000062)	(0.00030)	(0.00032)	(0.00031)
$\widehat{\omega}_{jst}$	0.00040***	0.00023***	0.00027***	-0.023***	-0.028***	-0.026***
	(0.000068)	(0.000074)	(0.000071)	(0.00040)	(0.00045)	(0.00043)
$\widehat{\omega}_{ijs}$	0.00079***	0.00092***	0.00088***	-0.0082***	-0.012***	-0.011***
	(0.000039)	(0.000048)	(0.000045)	(0.00024)	(0.00026)	(0.00025)
$\widehat{\omega}_{ijt}$	-0.00039***	-0.00047***	-0.00041***	-0.00019	-0.0071***	-0.0058***
	(0.000030)	(0.000033)	(0.000032)	(0.00023)	(0.00027)	(0.00026)
$\widehat{\rho^{p}}_{ijst}$	0.23***	0.26***	0.25***	-0.017***	-0.0035	-0.0086*
	(0.0049)	(0.0047)	(0.0047)	(0.0058)	(0.0050)	(0.0051)
$\widehat{\rho^{p}}^{\text{missing}}_{ijst}$	0.0044***	0.0047***	0.0050***	-0.077***	-0.096***	-0.11***
	(0.0013)	(0.0013)	(0.0012)	(0.0065)	(0.0070)	(0.0065)
$\widehat{\rho^{g}}_{ijst}$	0.33***	0.37***	0.36***	0.049***	0.079***	0.070***
	(0.0066)	(0.0063)	(0.0064)	(0.0069)	(0.0060)	(0.0061)
$\widehat{\rho^{g}}^{\text{missing}}_{ijst}$	0.0035***	0.00061	0.0011	-0.28***	-0.33***	-0.30***
	(0.0013)	(0.0013)	(0.0012)	(0.0067)	(0.0073)	(0.0067)
Constant	0.0066***	0.0053***	0.0059***	0.87***	0.77***	0.80***
	(0.00055)	(0.00061)	(0.00059)	(0.0030)	(0.0033)	(0.0032)
Observations	2682185	2682185	2682185	2682185	2682185	2682185

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: PPML regression on gross exports in all sectors, 1996-2020, with technological proximity interacted with bilateral region dummies

	Priority	Publication	Grant
USUS # ρ_{ijst} - benchmark	0.13***	0.093	0.070
	(0.042)	(0.068)	(0.049)
USCN # ρ_{ijst}	0.47	0.86*	0.89*
	(0.47)	(0.49)	(0.47)
USESEAN # ρ_{ijst}	-0.67***	0.18	-0.0020
	(0.25)	(0.38)	(0.36)
USEU # ρ_{ijst}	-0.31**	0.22	0.26
	(0.15)	(0.28)	(0.27)
USROW # ρ_{ijst}	-0.14	0.14	0.24
	(0.18)	(0.24)	(0.24)
USWest # ρ_{ijst}	-0.15	0.12	0.11
	(0.19)	(0.17)	(0.17)
CNUS # ρ_{ijst}	-0.70*	-0.58	-0.60
	(0.40)	(0.41)	(0.38)
CNCN # ρ_{ijst}	-0.028	0.34***	0.39***
	(0.056)	(0.089)	(0.070)
CNESEAN # ρ_{ijst}	-0.21	0.26	0.30*
	(0.15)	(0.18)	(0.18)
CNEU # ρ_{ijst}	-0.17	-0.19	-0.19
	(0.13)	(0.16)	(0.17)
CNROW # ρ_{ijst}	-0.14	-0.36**	-0.37***
	(0.11)	(0.17)	(0.14)
CNWest # ρ_{ijst}	-0.073	-0.061	-0.16
	(0.22)	(0.18)	(0.18)
ESEANUS # ρ_{ijst}	-0.36	0.072	0.042
	(0.31)	(0.31)	(0.30)
ESEANCN # ρ_{ijst}	-0.44**	0.086	0.11
	(0.20)	(0.23)	(0.24)
ESEANESEAN # ρ_{ijst}	-0.13***	-0.099	-0.068
	(0.044)	(0.069)	(0.051)
ESEANEU # ρ_{ijst}	-0.11	0.16	0.20
	(0.13)	(0.15)	(0.15)
ESEANROW # ρ_{ijst}	-0.47***	-0.46***	-0.39**
	(0.16)	(0.15)	(0.17)
ESEANWest # ρ_{ijst}	-0.031	-0.37**	-0.29*
	(0.17)	(0.19)	(0.16)
EUUS # ρ_{ijst}	0.042	0.40	0.47**
	(0.18)	(0.26)	(0.24)
EUCN # ρ_{ijst}	-0.096	0.068	0.055
	(0.16)	(0.21)	(0.21)
EUESEAN # ρ_{ijst}	-0.042	0.00093	0.019
	(0.12)	(0.14)	(0.14)
EUEU # ρ_{ijst}	-0.16***	-0.089	-0.054
	(0.043)	(0.068)	(0.050)
EUROW # ρ_{ijst}	-0.087	-0.037	-0.044
	(0.069)	(0.083)	(0.067)
EUWest # ρ_{ijst}	-0.15**	-0.20**	-0.16*

Continued on next page

Table A3 (continued)

	Priority	Publication	Grant
	(0.075)	(0.093)	(0.086)
ROWUS # ρ_{ijst}	0.0042	0.40	0.60**
	(0.17)	(0.26)	(0.27)
ROWCN # ρ_{ijst}	-0.40**	-0.46**	-0.18
	(0.19)	(0.21)	(0.19)
ROWESEAN # ρ_{ijst}	-0.19	-0.38**	-0.35**
	(0.15)	(0.17)	(0.16)
ROWEU # ρ_{ijst}	-0.19***	0.12	0.18**
	(0.069)	(0.099)	(0.086)
ROWROW # ρ_{ijst}	-0.071	-0.12*	-0.11**
	(0.044)	(0.069)	(0.051)
ROWWest # ρ_{ijst}	-0.18	-0.19	-0.056
	(0.16)	(0.19)	(0.20)
WestUS # ρ_{ijst}	0.31	0.060	-0.21
	(0.19)	(0.21)	(0.23)
WestCN # ρ_{ijst}	-0.41	0.25	0.27
	(0.44)	(0.29)	(0.31)
WestESEAN # ρ_{ijst}	-0.063	0.15	0.13
	(0.16)	(0.22)	(0.20)
WestEU # ρ_{ijst}	-0.19*	-0.22*	-0.18
	(0.10)	(0.12)	(0.12)
WestROW # ρ_{ijst}	-0.28*	-0.090	-0.045
	(0.16)	(0.17)	(0.15)
WestWest # ρ_{ijst}	-0.15***	0.0076	-0.0017
	(0.045)	(0.074)	(0.055)
sh^{+}_{ijst}	0.27***	0.27***	0.27***
	(0.027)	(0.027)	(0.027)
$\rho^{missing}_{ijst}$	-0.0085	-0.021***	-0.023***
	(0.0059)	(0.0078)	(0.0074)
T_{ijst}	-0.75***	-0.74***	-0.74***
	(0.11)	(0.11)	(0.11)
T_{jist}	-0.26***	-0.26**	-0.26***
	(0.10)	(0.10)	(0.10)
TBT_{ijst}	0.011	0.0086	0.0077
	(0.011)	(0.011)	(0.011)
SPS_{ijst}	0.013	0.014	0.014
	(0.0096)	(0.0096)	(0.0096)
RD^{TBT}_{ijst}	-0.53***	-0.52***	-0.52***
	(0.091)	(0.091)	(0.090)
RD^{SPS}_{ijst}	-0.49***	-0.48***	-0.48***
	(0.12)	(0.12)	(0.12)
GVC^{T}_{ijst}	39.7***	39.5***	39.5***
	(4.38)	(4.40)	(4.41)
GVC^{TBT}_{ijst}	22.7***	22.5***	22.4***
	(2.50)	(2.49)	(2.48)
GVC^{SPS}_{ijst}	8.76	9.41	9.41
	(5.91)	(5.86)	(5.89)
Constant	11.4***	11.4***	11.4***
	(0.015)	(0.020)	(0.016)

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Table A3 (continued)

	Priority	Publication	Grant
Observations	5757313	5757313	5757313
Pseudo R-squared	0.999	0.999	0.999
AIC	35947365.9	35923167.5	35918045.9
BIC	35948003.5	35923805.1	35918683.5

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Descriptive statistics by exporter: bilateral and intra-country technological proximity measures, 1996-2020

Exporter	Region	Avg. bilateral exports	Avg. ρ_{ijst} (priority)	Avg. ρ_{ijst} (publication)	Avg. ρ_{ijst} (grant)	Avg. intra-country ρ_{ijst} (priority)	Avg. intra-country ρ_{ijst} (publication)	Avg. intra-country ρ_{ijst} (grant)	Zero intra-country ρ_{ijst} (priority)	Zero intra-country ρ_{ijst} (publication)	Zero intra-country ρ_{ijst} (grant)
ARG	ROW	177.18	0.022	0.013	0.014	0.127	0.208	0.192	982	891	909
AUS	West	526.14	0.023	0.015	0.017	0.918	0.957	0.945	92	48	62
AUT	EU	179.66	0.020	0.010	0.012	0.737	0.782	0.772	296	245	256
BEL	EU	245.39	0.022	0.014	0.017	0.833	0.887	0.876	188	127	140
BGD	ROW	63.40	–	–	–	0.000	0.000	0.000	1125	1125	1125
BGR	EU	23.69	0.022	0.012	0.015	0.172	0.325	0.292	931	759	796
BLR	ROW	23.46	0.017	0.006	0.007	0.051	0.092	0.090	1068	1021	1024
BRA	ROW	717.19	0.023	0.015	0.018	0.870	0.898	0.875	146	115	141
BRN	ESEAN	6.18	–	–	–	0.000	0.000	0.000	1125	1125	1125
CAN	West	664.57	0.024	0.016	0.018	0.892	0.916	0.911	121	95	100
CHE	West	305.63	0.022	0.013	0.015	0.745	0.783	0.779	287	244	249
CHL	ROW	92.25	0.020	0.013	0.015	0.552	0.641	0.610	504	404	439
CHN	CN	4,528.08	0.030	0.023	0.025	0.739	0.822	0.815	294	200	208
CIV	ROW	12.97	0.027	0.009	0.015	0.004	0.009	0.007	1120	1115	1117
CMR	ROW	10.10	–	0.005	0.017	0.000	0.001	0.002	1125	1124	1123
COL	ROW	109.57	0.022	0.011	0.012	0.182	0.272	0.239	920	819	856
CRI	ROW	15.75	–	–	–	0.000	0.000	0.000	1125	1125	1125
CYP	EU	9.84	0.015	0.003	0.006	0.127	0.166	0.148	982	938	958
CZE	EU	106.81	0.023	0.016	0.018	0.764	0.854	0.845	265	164	174
DEU	EU	1,643.47	0.014	0.005	0.007	0.924	0.954	0.951	86	52	55
DNK	EU	137.78	0.020	0.011	0.014	0.723	0.810	0.780	312	214	247
EGY	ROW	83.91	0.024	0.009	0.012	0.124	0.157	0.147	986	948	960
ESP	EU	603.14	0.024	0.015	0.017	0.749	0.844	0.828	282	175	194
EST	EU	10.28	0.017	0.008	0.011	0.125	0.191	0.173	984	910	930
FIN	EU	116.04	0.021	0.011	0.014	0.770	0.839	0.835	259	181	186
FRA	EU	1,151.32	0.027	0.019	0.020	0.884	0.935	0.932	130	73	76
GBR	EU	1,192.52	0.026	0.019	0.021	0.932	0.972	0.970	77	32	34
GRC	EU	101.81	0.024	0.012	0.015	0.256	0.373	0.351	837	705	730
HKG	ESEAN	134.19	0.021	0.012	0.014	0.490	0.576	0.549	574	477	507
HRV	EU	22.96	0.021	0.010	0.013	0.148	0.238	0.202	959	857	898
HUN	EU	63.77	0.023	0.015	0.017	0.744	0.834	0.821	288	187	201

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Table A4 (continued)

Exporter	Region	Avg. bilateral exports	Avg. ρ_{ijst} (priority)	Avg. ρ_{ijst} (publication)	Avg. ρ_{ijst} (grant)	Avg. intra-country ρ_{ijst} (priority)	Avg. intra-country ρ_{ijst} (publication)	Avg. intra-country ρ_{ijst} (grant)	Zero intra-country ρ_{ijst} (priority)	Zero intra-country ρ_{ijst} (publication)	Zero intra-country ρ_{ijst} (grant)
IDN	ESEAN	316.97	0.045	0.018	0.022	0.044	0.095	0.088	1075	1018	1026
IND	ROW	784.99	0.024	0.015	0.018	0.586	0.619	0.587	466	429	465
IRL	EU	130.18	0.022	0.012	0.014	0.607	0.687	0.659	442	352	384
ISL	West	8.09	0.016	0.007	0.009	0.117	0.157	0.148	993	948	959
ISR	ROW	104.34	0.022	0.014	0.016	0.628	0.686	0.665	419	353	377
ITA	EU	1,006.01	0.022	0.014	0.016	0.871	0.889	0.882	145	125	133
JOR	ROW	11.81	0.046	0.021	0.021	0.021	0.049	0.041	1101	1070	1079
JPN	ESEAN	2,482.23	0.018	0.009	0.012	0.927	0.950	0.948	82	56	59
KAZ	ROW	91.86	0.014	0.006	0.007	0.056	0.081	0.076	1062	1034	1039
KHM	ESEAN	5.47	0.017	0.008	0.009	0.037	0.043	0.043	1083	1077	1077
KOR	ESEAN	683.16	0.025	0.013	0.014	0.864	0.941	0.940	153	66	67
LAO	ESEAN	3.28	–	–	–	0.000	0.000	0.000	1125	1125	1125
LTU	EU	16.51	0.017	0.007	0.010	0.179	0.252	0.227	924	842	870
LUX	EU	35.51	0.016	0.008	0.010	0.282	0.369	0.347	808	710	735
LVA	EU	12.22	0.022	0.012	0.015	0.086	0.162	0.149	1028	943	957
MAR	ROW	38.95	0.017	0.011	0.012	0.080	0.151	0.140	1035	955	968
MEX	ROW	465.10	0.024	0.014	0.017	0.383	0.479	0.460	694	586	607
MLT	EU	5.54	0.017	0.006	0.008	0.140	0.153	0.138	968	953	970
MMR	ESEAN	22.82	–	–	–	0.000	0.000	0.000	1125	1125	1125
MYS	ESEAN	153.48	0.019	0.010	0.012	0.374	0.439	0.418	704	631	655
NGA	ROW	138.48	0.019	0.003	0.006	0.023	0.030	0.028	1099	1091	1094
NLD	EU	389.81	0.024	0.015	0.017	0.876	0.914	0.912	140	97	99
NOR	West	160.94	0.024	0.014	0.017	0.780	0.885	0.874	248	129	142
NZL	West	74.42	0.022	0.014	0.016	0.513	0.629	0.601	548	417	449
PAK	ROW	92.58	0.023	0.009	0.013	0.028	0.078	0.073	1094	1037	1043
PER	ROW	63.56	0.013	0.005	0.007	0.061	0.107	0.094	1056	1005	1019
PHL	ESEAN	103.99	0.022	0.009	0.012	0.068	0.115	0.105	1048	996	1007
POL	EU	222.56	0.024	0.015	0.018	0.483	0.577	0.532	582	476	526
PRT	EU	102.70	0.022	0.013	0.016	0.469	0.584	0.531	597	468	528
ROU	EU	76.54	0.021	0.016	0.018	0.280	0.474	0.438	810	592	632
RUS	ROW	571.38	0.026	0.017	0.019	0.872	0.946	0.941	144	61	66
SAU	ROW	191.30	0.017	0.011	0.012	0.167	0.168	0.152	937	936	954
SEN	ROW	6.45	–	–	–	0.000	0.000	0.000	1125	1125	1125

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Table A4 (continued)

Exporter	Region	Avg. bilateral exports	Avg. ρ_{ijst} (priority)	Avg. ρ_{ijst} (publication)	Avg. ρ_{ijst} (grant)	Avg. intra-country ρ_{ijst} (priority)	Avg. intra-country ρ_{ijst} (publication)	Avg. intra-country ρ_{ijst} (grant)	Zero intra-country ρ_{ijst} (priority)	Zero intra-country ρ_{ijst} (publication)	Zero intra-country ρ_{ijst} (grant)
SGP	ESEAN	153.60	0.022	0.015	0.017	0.523	0.618	0.590	537	430	461
SVK	EU	42.85	0.020	0.013	0.015	0.446	0.593	0.557	623	458	498
SVN	EU	21.71	0.023	0.013	0.015	0.288	0.390	0.363	801	686	717
SWE	EU	230.79	0.022	0.013	0.016	0.719	0.823	0.806	316	199	218
THA	ESEAN	191.24	0.019	0.011	0.013	0.257	0.332	0.300	836	752	787
TUN	ROW	17.73	0.022	0.005	0.009	0.010	0.013	0.007	1114	1110	1117
TUR	ROW	315.03	0.019	0.009	0.013	0.304	0.334	0.319	783	749	766
TWN	ESEAN	273.34	0.022	0.014	0.015	0.691	0.774	0.770	348	254	259
UKR	ROW	64.47	0.020	0.014	0.016	0.245	0.448	0.448	849	621	621
USA	US	7,337.94	0.019	0.008	0.010	0.980	0.989	0.985	22	12	17
VNM	ESEAN	91.89	0.019	0.011	0.013	0.271	0.416	0.378	820	657	700
ZAF	ROW	168.81	0.023	0.016	0.018	0.550	0.702	0.691	506	335	348

Table A5: Descriptive statistics by exporter in 2020: trade-policy variables

Exporter	Region	Total exports	Avg. bilateral exports	Avg. share positive flows	Avg. tariff faced	Avg. tariff imposed	Avg. TBT stock	Avg. SPS stock	Avg. TBT distance	Avg. SPS distance	Avg. GVC tariff	Avg. GVC TBT distance	Avg. GVC SPS distance
ARG	ROW	237489.26	148.80	0.06	5.01	10.10	27.04	8.53	0.16	0.05	0.000031	0.000121	0.000055
AUS	West	595645.09	373.21	0.22	4.94	1.51	19.74	26.83	0.12	0.05	0.000046	0.000291	0.000099
AUT	EU	221913.61	139.04	0.34	3.54	1.83	26.05	10.61	0.11	0.05	0.000028	0.000117	0.000040
BEL	EU	263408.18	165.04	0.41	3.54	1.83	27.16	10.72	0.12	0.05	0.000042	0.000178	0.000074
BGD	ROW	280894.38	176.00	0.04	4.07	12.78	16.49	7.85	0.12	0.06	0.000004	0.000008	0.000003
BGR	EU	43095.93	27.00	0.16	3.55	1.83	26.01	10.78	0.11	0.05	0.000006	0.000026	0.000011
BLR	ROW	60002.52	37.60	0.08	5.20	5.86	16.39	7.84	0.12	0.06	0.000025	0.000107	0.000045
BRA	ROW	877000.66	549.50	0.22	5.19	10.59	29.07	26.17	0.15	0.07	0.000108	0.000484	0.000208
BRN	ESEAN	12413.47	7.78	0.02	4.70	0.23	16.51	7.85	0.12	0.06	0.000001	0.000010	0.000001
CAN	West	695348.74	435.68	0.26	4.11	0.90	30.38	78.94	0.13	0.06	0.000049	0.000355	0.000148
CHE	West	408545.72	255.98	0.32	4.02	3.64	21.53	9.70	0.13	0.06	0.000054	0.000431	0.000148
CHL	ROW	147649.42	92.51	0.07	4.05	2.09	25.17	10.91	0.12	0.06	0.000019	0.000098	0.000036
CHN	CN	19722873.31	12357.69	0.57	4.78	5.23	31.71	34.97	0.15	0.07	0.001473	0.006074	0.000972
CIV	ROW	36388.26	22.80	0.03	4.87	10.42	16.80	8.16	0.11	0.05	0.000008	0.000018	0.000019
CMR	ROW	20801.06	13.03	0.02	5.07	17.67	16.53	7.84	0.12	0.06	0.000007	0.000012	0.000009
COL	ROW	153566.11	96.22	0.07	4.38	3.18	19.81	10.36	0.15	0.06	0.000007	0.000066	0.000018
CRI	ROW	22861.35	14.32	0.04	4.85	3.20	20.58	9.53	0.13	0.05	0.000004	0.000010	0.000007
CYP	EU	4746.80	2.97	0.05	3.56	1.83	26.02	10.64	0.11	0.05	0.000001	0.000003	0.000002
CZE	EU	199418.76	124.95	0.32	3.53	1.83	27.81	10.87	0.12	0.05	0.000018	0.000100	0.000023
DEU	EU	2153439.62	1349.27	0.56	3.54	1.83	26.29	10.95	0.11	0.05	0.000213	0.001161	0.000400
DNK	EU	137776.90	86.33	0.31	3.54	1.83	37.90	10.64	0.17	0.05	0.000023	0.000182	0.000055
EGY	ROW	247283.72	154.94	0.08	4.60	0.00	20.68	10.54	0.12	0.10	0.000017	0.000096	0.000070
ESP	EU	588187.89	368.54	0.44	3.55	1.83	27.56	10.65	0.13	0.06	0.000082	0.000439	0.000141
EST	EU	17567.43	11.01	0.14	3.54	1.83	26.10	10.61	0.11	0.05	0.000004	0.000016	0.000008
FIN	EU	142601.18	89.35	0.23	3.53	1.83	26.54	10.61	0.11	0.05	0.000024	0.000098	0.000035
FRA	EU	898717.46	563.11	0.49	3.54	1.83	26.77	10.64	0.12	0.05	0.000138	0.000596	0.000202
GBR	EU	697348.30	436.94	0.48	3.92	3.29	16.62	7.85	0.12	0.06	0.000083	0.000741	0.000255
GRC	EU	65444.23	41.01	0.18	3.56	1.83	26.01	10.61	0.11	0.05	0.000007	0.000035	0.000011
HKG	ESEAN	33657.27	21.09	0.23	5.39	0.00	17.20	9.00	0.11	0.05	0.000026	0.000054	0.000006
HRV	EU	23852.43	14.95	0.13	3.53	1.83	26.07	10.61	0.11	0.05	0.000001	0.000006	0.000003
HUN	EU	122235.80	76.59	0.24	3.55	1.83	26.35	10.68	0.12	0.05	0.000014	0.000075	0.000021
IDN	ESEAN	806139.47	505.10	0.21	4.36	5.91	18.65	11.09	0.11	0.06	0.000070	0.000208	0.000092

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Table A5 (continued)

Exporter	Region	Total exports	Avg. bilateral exports	Avg. share positive flows	Avg. tariff faced	Avg. tariff imposed	Avg. TBT stock	Avg. SPS stock	Avg. TBT distance	Avg. SPS distance	Avg. GVC tariff	Avg. GVC TBT distance	Avg. GVC SPS distance
IND	ROW	2106737.15	1320.01	0.36	4.56	11.66	21.20	12.35	0.14	0.06	0.000188	0.000507	0.000155
IRL	EU	283678.90	177.74	0.17	3.58	1.83	26.02	10.61	0.11	0.05	0.000044	0.000203	0.000106
ISL	West	8660.65	5.43	0.04	4.17	2.14	16.39	7.89	0.12	0.06	0.000006	0.000016	0.000011
ISR	ROW	161764.25	101.36	0.14	4.45	3.29	22.50	7.86	0.13	0.06	0.000017	0.000124	0.000033
ITA	EU	1056390.84	661.90	0.50	3.54	1.83	26.15	10.61	0.11	0.05	0.000103	0.000480	0.000164
JOR	ROW	27840.17	17.44	0.03	4.72	6.44	17.20	7.93	0.12	0.05	0.000004	0.000009	0.000004
JPN	ESEAN	2741275.75	1717.59	0.34	4.31	1.59	31.04	27.41	0.19	0.05	0.000246	0.001329	0.000151
KAZ	ROW	189524.48	118.75	0.04	5.13	4.96	17.00	8.83	0.13	0.07	0.000007	0.000138	0.000097
KHM	ESEAN	21117.21	13.23	0.04	3.89	9.82	16.65	7.88	0.12	0.06	0.000005	0.000007	0.000004
KOR	ESEAN	1491831.44	934.73	0.30	3.86	6.20	46.60	44.66	0.17	0.07	0.000169	0.001124	0.000267
LAO	ESEAN	11021.99	6.91	0.02	4.19	7.37	16.39	8.08	0.12	0.05	0.000002	0.000012	0.000002
LTU	EU	33141.99	20.77	0.19	3.55	1.83	26.87	10.61	0.11	0.05	0.000007	0.000036	0.000012
LUX	EU	20385.57	12.77	0.13	3.57	1.83	26.01	10.61	0.11	0.05	0.000007	0.000016	0.000010
LVA	EU	14985.72	9.39	0.14	3.59	1.83	26.15	10.83	0.11	0.05	0.000003	0.000010	0.000007
MAR	ROW	85446.96	53.54	0.08	4.53	6.33	16.65	8.89	0.12	0.05	0.000026	0.000081	0.000029
MEX	ROW	748659.47	469.08	0.17	4.16	5.56	22.53	9.42	0.13	0.06	0.000036	0.000295	0.000089
MLT	EU	5146.75	3.22	0.05	3.54	1.83	26.01	10.61	0.11	0.05	0.000000	0.000002	0.000001
MMR	ESEAN	110896.24	69.48	0.04	4.09	4.80	16.39	8.02	0.12	0.05	0.000005	0.000033	0.000012
MYS	ESEAN	412842.85	258.67	0.21	4.53	6.35	20.77	8.60	0.12	0.05	0.000042	0.000284	0.000069
NGA	ROW	273254.30	171.21	0.04	4.79	10.43	16.69	8.67	0.12	0.05	0.000007	0.000102	0.000005
NLD	EU	409825.45	256.78	0.49	3.54	1.83	27.30	10.97	0.12	0.06	0.000064	0.000270	0.000127
NOR	West	168005.54	105.27	0.17	4.04	5.79	17.80	8.06	0.16	0.05	0.000029	0.000511	0.000113
NZL	West	109485.97	68.60	0.11	4.91	1.24	19.46	11.05	0.11	0.16	0.000016	0.000028	0.000055
PAK	ROW	263239.73	164.94	0.08	4.62	11.45	17.63	7.86	0.12	0.06	0.000010	0.000016	0.000007
PER	ROW	123100.91	77.13	0.06	4.21	0.99	17.50	9.47	0.12	0.05	0.000008	0.000056	0.000017
PHL	ESEAN	286061.16	179.24	0.11	4.15	4.53	19.67	10.17	0.13	0.05	0.000017	0.000076	0.000015
POL	EU	411255.78	257.68	0.38	3.54	1.83	26.02	10.68	0.11	0.05	0.000052	0.000228	0.000081
PRT	EU	111209.49	69.68	0.23	3.57	1.83	26.01	10.61	0.11	0.05	0.000013	0.000052	0.000018
ROU	EU	139262.86	87.26	0.21	3.60	1.83	26.55	10.65	0.12	0.05	0.000010	0.000054	0.000024
RUS	ROW	929035.54	582.10	0.22	5.35	5.71	18.29	10.15	0.12	0.06	0.000186	0.001027	0.000238
SAU	ROW	385092.96	241.29	0.06	5.33	4.79	35.65	12.10	0.15	0.05	0.000074	0.000337	0.000064
SEN	ROW	15318.06	9.60	0.02	4.14	10.43	16.43	7.87	0.12	0.06	0.000002	0.000009	0.000005
SGP	ESEAN	238527.13	149.45	0.24	3.78	0.03	17.40	9.66	0.11	0.05	0.000045	0.000239	0.000062

Continued on next page

Table A5 (continued)

Exporter	Region	Total exports	Avg. bilateral exports	Avg. share positive flows	Avg. tariff faced	Avg. tariff imposed	Avg. TBT stock	Avg. SPS stock	Avg. TBT distance	Avg. SPS distance	Avg. GVC tariff	Avg. GVC TBT distance	Avg. GVC SPS distance
SVK	EU	86474.97	54.18	0.20	3.54	1.83	26.75	10.63	0.12	0.05	0.000009	0.000044	0.000010
SVN	EU	33687.41	21.11	0.19	3.55	1.83	27.62	10.86	0.12	0.05	0.000004	0.000022	0.000008
SWE	EU	235375.64	147.48	0.31	3.55	1.83	27.73	10.61	0.12	0.05	0.000038	0.000196	0.000062
THA	ESEAN	567102.02	355.33	0.28	4.56	10.13	26.45	13.65	0.17	0.06	0.000121	0.000787	0.000120
TUN	ROW	31967.07	20.03	0.06	4.63	0.00	16.61	7.85	0.12	0.06	0.000007	0.000034	0.000016
TUR	ROW	534470.51	334.88	0.34	4.35	5.63	18.80	10.51	0.12	0.05	0.000082	0.000390	0.000098
TWN	ESEAN	715620.26	448.38	0.29	5.54	5.12	26.95	21.55	0.15	0.06	0.000165	0.000607	0.000079
UKR	ROW	121404.83	76.07	0.14	4.60	2.32	21.47	9.79	0.16	0.06	0.000030	0.000153	0.000060
USA	0US	6310580.46	3954.00	0.52	4.98	1.67	46.05	69.56	0.19	0.14	0.000456	0.002987	0.002137
VNM	ESEAN	612411.19	383.72	0.21	4.01	7.60	20.70	10.45	0.12	0.06	0.000100	0.000344	0.000097
ZAF	ROW	201371.57	126.17	0.15	4.80	4.02	20.03	8.77	0.12	0.05	0.000053	0.000111	0.000030

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