Journal of Applied Econometrics

WILEY

Journal of APPLIED ECONOMETRICS

RESEARCH ARTICLE OPEN ACCESS

Unlocking New Methods to Estimate Country-Specific Effects and Trade Elasticities With the Structural Gravity Model

Rebecca Freeman[1,2] | Mario Larch[3,4,5,6,7] | Angelos Theodorakopoulos[8,9,10] | Yoto V. Yotov[5,11,12]

[1]Bank of England, London, UK | [2]Centre for Economic Performance (CEP), London School of Economics and Political Science, London, UK | [3]Department of Law, Business Administration & Economics, University of Bayreuth, Bayreuth, Germany | [4]Centre d'Etudes Prospectives et d'Informations Internationales (CEPII), Paris, France | [5]ifo Institute and CESifo Research Network, Munich, Germany | [6]Austrian Institute of Economic Research (WIFO), Vienna, Austria | [7]Nottingham Centre for Research on Globalisation and Economic Policy (GEP), Nottingham, UK | [8]Department of Economics and International Business, Aston Business School, Aston University, Birmingham, UK | [9]Centre for Business Prosperity (CBP), Aston Business School, Aston University, Birmingham, UK | [10]Department of Economics, Ghent University, Ghent, Belgium | [11]School of Economics, LeBow College of Business, Drexel University, Philadelphia, USA | [12]Center for Global Policy Analysis (CGPA), LeBow College of Business, Drexel University, Philadelphia, USA

Correspondence: Angelos Theodorakopoulos (a.theodorakopoulos2@aston.ac.uk)

Received: 7 August 2023 | **Revised:** 11 November 2024 | **Accepted:** 22 January 2025

Keywords: country-specific trade costs | elasticity of substitution | R&D and trade | services | structural gravity | trade elasticity

ABSTRACT

We propose new methods to identify the impact of country-specific characteristics, policies, and trade costs on bilateral trade flows within the structural gravity framework. We complement theory with a simple two-stage estimating procedure and offer proof of concept by quantifying the impact of country-specific research and development (R&D) expenditure on trade. Our results suggest a positive relationship overall but a larger impact of R&D on international (versus domestic) trade. Importantly, our methods deliver trade elasticity estimates without the need for price or tariff data, and we highlight this feature by obtaining aggregate and sectoral trade elasticity estimates, including for services.

JEL Classification: F10, F14, F16

1 | Introduction

Some of the most important obstacles to international trade are country-specific policies (Lamy 2012; Kasterine 2015; Grossman et al. 2021). However, the workhorse empirical model of trade — the gravity equation — has been criticized for not being able to identify the impact of country-specific determinants of trade flows, for example, "[i]n the presence of importer and exporter fixed effects, a variety of potentially interesting trade determinants can no longer be identified in a gravity equation. Notably, (1) anything that affects exporters' propensity to export to all destinations (such has having hosted the Olympics or being an island) ..." (Head and Mayer 2014, pp. 157-158). To address this challenge, we propose a simple two-stage estimating procedure based on a structural gravity model, which enables us to (i) identify the impact of any country-specific determinant of trade flows, and (ii) obtain estimates of the trade elasticity without the need for price and/or tariff data.

The theoretical model builds on influential developments in the structural gravity and economic geography literature. Most closely related are Eaton and Kortum (2002), Anderson and van Wincoop (2003), Redding and Venables (2004), Allen et al. (2020) and Anderson et al. (2020).[1] The seminal work of Arkolakis et al. (2012) shows that the structural gravity equation is representative of a wide class of trade models and can be derived from a series of different microeconomic foundations. For example, while in the paper we rely on the model on the demand side (e.g., Anderson and van Wincoop 2003), the same expression can also be obtained on the supply side (e.g., Eaton and Kortum 2002). Moreover, in line with Anderson and van Wincoop (2004) and Costinot et al. (2012), our model also applies at the sector level, and in a panel setting, as in Olivero and Yotov (2012), Eaton et al. (2016), and Anderson et al. (2020).

Guided by theory, we propose a simple two-stage estimating procedure, which is easy to implement with standard statistical tools and datasets. Following established developments in the empirical gravity literature, in Stage 1, we estimate a standard version of the structural gravity equation, which delivers estimates of the vector of direct bilateral trade costs and the multilateral resistance (MR) terms, which capture prices on the producer and consumer sides and are used in the second stage. The second-stage analysis offers our two empirical contributions. First, we can identify the impact of any country-specific determinant of bilateral trade flows without omitted variable bias due to not properly controlling for the structural MR terms (Anderson and van Wincoop 2003; Baldwin and Taglioni 2006). Second, we can obtain estimates of the trade elasticity directly from the gravity equation without the need for additional modeling or data.

Our methods complement several studies with similar objectives. For example, Head and Mayer (2014) refer to methods from labor literature (e.g., Baker and Fortin 2001) and discuss one- and two-stage procedures that allow for the estimation of country-specific effects with the gravity equation by eliminating the exporter-time and importer-time fixed effects from the econometric specification. The problem with these approaches is that they do not fully control for the structural MRs; thus, their estimates are subject to the "gold medal mistake" of Baldwin and Taglioni (2006). Baier and Bergstrand (2009) offer an alternative that is closer to the underlying theory by proxying for the MR terms using a Taylor-series expansion. The key advantage of our approach relative to the studies mentioned above is that we recover the country-specific effects from our trade estimating equation while fully controlling for the structural MRs. Finally, Beverelli et al. (2024) develop methods to identify the *differential* impact of country-specific characteristics on international relative to domestic trade within a gravity setting. Our model nests the specification of Beverelli et al. (2024) and, in addition, allows for the identification of the uniform impact of country-specific characteristics on international and domestic trade. Thus, our setting can deliver the full (differential plus uniform) effect of any country-specific variable of interest.[2] Note that we focus on the quantification of deterministic, country-specific shocks, ignoring short-run, stochastic shocks, such as trade cost shocks, demand shocks, or supply shocks. This is in line with the gravity literature we contribute to, including prominent recent papers that focus on the response of trade flows to the shock in the financial crises, for example, Eaton et al. (2016).

Motivated by significant interest in the topic,[3] we use our methods to quantify the relationship between research and development R&D and international trade. Our approach to modeling R&D is from an aggregate point of view, in the spirit of Griliches and Mairesse (1999) who treat the (stock of) R&D as an input in the production function. In effect, R&D is seen as knowledge capital that will affect output, similar to other production inputs. Alternatively, more recent studies, for example, Doraszelski and Jaumandreu (2013) and Bilir and Morales (2020), focus on firm-level analysis and model endogenously the links between R&D and productivity.[4] Importantly, even though R&D could potentially be nested structurally in our model, we do not take a strong stand on the structural links between R&D, production, and trade. The reason is that we want to highlight the general applicability of our methods to handle, within the structural gravity framework, *any* country-specific characteristic that is believed to impact trade and production, for example, R&D, corporate taxes, institutional quality, and the Olympics. Regardless of whether the effects of these characteristics can be modeled structurally or not, they can be included in a theory-consistent gravity equation.

We rely on four measures of gross R&D expenditure (total, higher education, business enterprise, and government) and decompose the impact of each type of R&D spending into (i) a uniform impact on trade regardless of whether it is domestic or international and (ii) a discriminatory effect on international relative to domestic sales. Overall, we obtain a positive and statistically significant effect of R&D expenditure on trade, but we find that it disproportionately promotes international relative to domestic trade, thus contributing to globalization. In combination, our estimates of the uniform and the discriminatory impact imply that a 10% increase in total R&D expenditure translates into roughly a 3% increase in bilateral trade. We also document significant heterogeneity in the effects of R&D by type; for example, we obtain positive and significant estimates of the effect of R&D expenditure in higher education and business enterprise but a negative estimate of the impact of government expenditure. Our results are robust to several sensitivity checks, including an instrumental variable analysis.

Our second empirical contribution is a simple approach to recover trade elasticities directly from the structural gravity model without the need for tariff and/or price data and which can be applied at any level of aggregation. Despite different methods, our aggregate trade elasticity estimates are comparable to those from the related literature.[5] In addition, our most valuable practical contribution is the estimate of the trade elasticity for services, as trade in services is not subject to tariffs, and hence, standard methods to estimate the services trade elasticity cannot be applied. The trade elasticity for services trade that we obtain is 6.8, and it is roughly 2.5 times larger than that for manufacturing, which is obtained from the same specification. We also obtain trade elasticity estimates for agriculture and mining, which are in line with those found in the literature to date.

The rest of the paper is organized as follows. Section 2 presents our structural gravity equation and translates it into an econometric model. Section 3 describes the data. Section 4 presents our benchmark estimates and applies our methods to study the impact of R&D on trade. Section 5 demonstrates how our methods can be used to obtain estimates of the trade elasticity. Section 6 includes concluding remarks and directions for future work. Finally, an online appendix includes Supporting Information.

2 | Structural Gravity With Country-Specific Effects

This section presents structural gravity methods that simultaneously allow for the identification of the impact of country-specific characteristics on bilateral trade flows and the estimation of the trade elasticity (without the need for tariffs and/or price data).

2.1 | Theoretical Foundations

Our departing point is the standard structural gravity equation of Anderson and van Wincoop (2003), which, as famously established by Arkolakis et al. (2012), is representative of a wide class of trade models.[6]

$$X_{ij,t} = \frac{Y_{i,t}E_{j,t}}{Y_t}\left(\frac{t_{ij,t}}{\Pi_{i,t}P_{j,t}}\right)^{1-\sigma} \tag{1}$$

Here, $X_{ij,t}$ denotes bilateral trade from exporter i to importer j at time t, including domestic sales $X_{ii,t}$.[7] $Y_{i,t}$ is the value of gross output of exporter i at t, $E_{j,t}$ is the corresponding expenditure in importer j, and Y_t is the value of world output at time t. In addition, $t_{ij,t}$ denotes the direct bilateral trade costs (e.g., distance and RTAs) between the trading partners, while $\Pi_{i,t}$ and $P_{j,t}$ are the structural outward multilateral resistance (OMR) and inward multilateral resistance (IMR) terms, respectively. Finally, σ is the elasticity of substitution, and $(1-\sigma)$ can be interpreted broadly as the trade elasticity.

We also assume a Cobb–Douglas production technology with constant returns to scale, which is given by the following production value function:

$$Y_{i,t} = p_{i,t}A_{i,t}\left(L_{i,t}\right)^{1-\gamma}\left(K_{i,t}\right)^{\gamma} \tag{2}$$

where $p_{i,t}$ is the factory-gate price for exporter i at time t and $A_{i,t}$, $L_{i,t}$ and $K_{i,t}$ are the corresponding levels of technology/productivity and exogenously given endowments with labor and physical capital that are used in production, respectively.[8] As demonstrated in Anderson et al. (2020) and as we show in the Supporting Information Appendix, we can use the market-clearing condition of the gravity model and the definitions of the structural variables in the model to rewrite Equation (2) as follows:

$$Y_{i,t} = \left(\beta_i\right)^{-\frac{\sigma-1}{\sigma}}\left(A_{i,t}\right)^{\frac{\sigma-1}{\sigma}}\left(L_{i,t}\right)^{\frac{(\sigma-1)(1-\gamma)}{\sigma}}\left(K_{i,t}\right)^{\frac{(\sigma-1)\gamma}{\sigma}}\left(Y_t\right)^{\frac{1}{\sigma}}\left(\Pi_{i,t}\right)^{-\frac{\sigma-1}{\sigma}}, \tag{3}$$

where the only new term, β_i, has the alternative interpretations of a CES share parameter if the gravity model is based on Anderson and van Wincoop (2003) or a composite technology parameter if the theoretical foundations are based on Eaton and Kortum (2002). Note that our framework is a special case of Allen et al. (2020), and therefore, their proofs of the existence and uniqueness of the equilibrium apply to our setting.

Our simple extension from the existing literature is to exploit the structure of the gravity model even further by using Equation (3) to substitute $Y_{i,t}$ into Equation (1). This leads to our structural gravity model as follows:

$$X_{ij,t} = \frac{\left(A_{i,t}\right)^{\frac{\sigma-1}{\sigma}}\left(L_{i,t}\right)^{\frac{(\sigma-1)(1-\gamma)}{\sigma}}\left(K_{i,t}\right)^{\frac{(\sigma-1)\gamma}{\sigma}}E_{j,t}\left(t_{ij,t}\right)^{1-\sigma}}{\left(\beta_i\right)^{\frac{\sigma-1}{\sigma}}\left(Y_t\right)^{\frac{\sigma-1}{\sigma}}\left(\Pi_{i,t}\right)^{1-\sigma+\frac{\sigma-1}{\sigma}}\left(P_{j,t}\right)^{1-\sigma}}, \tag{4}$$

which we translate into an estimating equation next.

2.2 | From Theory to Empirics

Following Santos Silva and Tenreyro (2006), we will use the Poisson pseudo-maximum likelihood (PPML) estimator to obtain our gravity estimates. As a result, the estimating equation that corresponds to specification (4) becomes the following:

$$\begin{aligned} X_{ij,t} = \exp[&\alpha_1 ln(A_{i,t}) + \alpha_2 ln(L_{i,t}) + \alpha_3 ln(K_{i,t}) \\ &+ \alpha_4 ln(E_{j,t}) + \alpha_5 ln(t_{ij,t}) + \alpha_6 ln(\Pi_{i,t}^{1-\sigma}) \\ &+ \alpha_7 ln(P_{j,t}^{1-\sigma}) + \alpha_8 ln(\beta_i) + \alpha_9 ln(Y_t)] \times \varepsilon_{ij,t}, \end{aligned} \tag{5}$$

where the structural interpretation of the coefficients is as follows: $\alpha_1 = (\sigma-1)/\sigma$; $\alpha_2 = (\sigma-1)(1-\gamma)/\sigma$; $\alpha_3 = (\sigma-1)\gamma/\sigma$; $\alpha_4 = 1$, $\alpha_5 = 1-\sigma$; $\alpha_6 = (1-\sigma)/\sigma$;[9] $\alpha_7 = -1$, and $\alpha_8 = \alpha_9 = (1-\sigma)/\sigma$. $\varepsilon_{ij,t}$ is a stochastic error term that is assumed to not carry any systematic information about the trade costs. Hence, the error term can best be interpreted as random measurement error, reasonably because of measurement error in bilateral trade flows. This is in line with all the static gravity models that we want to contribute to and extend on.[10]

As underscored in Anderson and van Wincoop (2003), a major challenge with estimating (5) is that the MR terms are not observable. Baldwin and Taglioni (2006) refer to the omission to properly control for the MR terms as "the gold medal mistake" in gravity estimations, and to address this critique, we propose a simple two-stage estimating procedure.

Stage 1—Estimate gravity with fixed effects and recover the MR terms. We start by estimating the following gravity model, which nests specification (5):

$$X_{ij,t} = \exp[\alpha_5 ln(t_{ij,t}) + \phi_{i,t} + \psi_{j,t}] \times \varepsilon_{ij,t} \tag{6}$$

$\phi_{i,t}$ and $\psi_{j,t}$ are exporter-time and importer-time fixed effects, which will absorb and fully control for all country-specific variables in (5), including the MR terms, and we follow the gravity literature to proxy for the direct bilateral trade cost frictions as follows:

$$\begin{aligned} \alpha_5\ ln(t_{ij,t}) = &\mu_{ij} + \mu_{ij} \times t + BRDR_{ij} \times \phi_t \\ &+ \lambda_1 RTA_{ij,t} + \lambda_2 EU_{ij,t} + \lambda_3 WTO_{ij,t}. \end{aligned} \tag{7}$$

μ_{ij} denotes symmetric bilateral; that is, the same for country pair ij and ji, fixed effects, $\mu_{ij} \times t$, are symmetric bilateral linear time trends, $BRDR_{ij} \times \phi_t$ are time-varying international border effects (where $BRDR_{ij}$ is a dummy variable equal to one if countries i and j are separated by an international border and zero otherwise), and $RTA_{ij,t}$, $EU_{ij,t}$, and $WTO_{ij,t}$ are dummy variables that measure time-varying common membership between countries i and j in regional trade agreements (RTAs), the European Union (EU), and the World Trade Organization (WTO), respectively.[11]

Equation (6) will deliver estimates of the vector of bilateral trade costs, $\left(\widehat{\alpha_5 \; ln(t_{ij,t})}\right)$, which, as demonstrated by Anderson and van Wincoop (2003), can be used together with data on output and expenditure to construct the theory-consistent MR terms. More recently, however, it has been demonstrated (Arvis and Shepherd 2013; Fally 2015) that the PPML estimates of the exporter-time and the importer-time fixed effects can be used to recover the MR terms directly as follows:

$$\widehat{\Pi_{i,t}^{1-\sigma}} = \frac{Y_{i,t}}{\exp[\hat{\phi}_{i,t}]} \times \frac{E_{0,t}}{Y_t} \qquad \text{and} \qquad \widehat{P_{j,t}^{1-\sigma}} = \frac{E_{j,t}}{\exp[\hat{\psi}_{j,t}]} \times \frac{1}{E_{0,t}}, \tag{8}$$

where $E_{0,t}$ is the expenditure of the country that has been selected as a numeraire, that is, the USA in our case, whose importer fixed effects are dropped when PPML is estimated without a constant.[12] Armed with the estimates of the MR terms, we proceed to the second stage of our procedure.

Stage 2—Use the MR terms to estimate the main gravity model. We take four final steps to estimate Equation (5). First, we include exporter fixed effects, ϕ_i, to control for the unobserved exporter-specific preference parameters in our model, β_i, as well as year fixed effects, ϕ_t, to control for world output, Y_t. These fixed effects will absorb any other observable and unobservable characteristics along these dimensions. Second, we experiment with three alternatives to control for the importer time-varying variables in specification (5): (i) Our preferred option is to use the importer-time fixed effects obtained from Stage 1 ($\hat{\psi}_{j,t}$); (ii) we include importer-time fixed effects directly in our econometric model; (iii) we include expenditure and IMRs estimated from the first stage as unconstrained controls.[13] Third, our preferred option to model bilateral trade costs is to use as constraints the first-stage estimates $\left(\alpha_5\widehat{ln(t_{ij,t})}\right)$. As an alternative check, we use directly the covariates from specification (7). Finally, in addition to using data on labor and physical capital, we use a measure of total factor productivity (TFP) as a proxy for $A_{i,t}$.[14] Taking the above considerations into account, our preferred estimating equation becomes as follows:

$$\begin{aligned} X_{ij,t} = \exp[&\alpha_1 ln(A_{i,t}) + \alpha_2 ln(L_{i,t}) + \alpha_3 ln(K_{i,t}) + \alpha_5 \widehat{ln(t_{ij,t})} \\ &+ \alpha_6 ln(\widehat{\Pi_{i,t}^{1-\sigma}}) + \hat{\psi}_{j,t} + \phi_i + \phi_t] \times \varepsilon_{ij,t}. \end{aligned} \tag{9}$$

Similar to the first stage, we rely on the PPML estimator to estimate Equation (9) and all of its variants. For consistent parameter estimates of pseudo-maximum likelihood estimators, we need to ensure a correctly specified conditional mean of the estimating equation (Gourieroux et al. 1984a, 1984b). As such, the underlying assumption is that the theoretical model delivers a correctly specified estimating equation when unpacking the exporter-time fixed effects and that we properly control for variables that are unobserved or generated from Stage 1. To the extent that we properly control for unobserved bilateral trade costs through Equation (7), we retrieve from Stage 1 consistent estimates of the scaled log of bilateral trade costs $\left(\alpha_5\widehat{ln(t_{ij,t})}\right)$ and exporter-time ($\hat{\phi}_{j,t}$) and importer-time ($\hat{\psi}_{j,t}$) fixed effects. In the same vein, based on the additive property of PPML (Arvis and Shepherd 2013; Fally 2015), the log of scaled OMR $\left(ln(\widehat{\Pi_{i,t}^{1-\sigma}})\right)$ is also consistently computed since it is an exact transformation of the consistently estimated exporter-time fixed effects in combination with data on output and expenditure (see Equation (8)). Furthermore, an additional assumption is that the variable used to proxy for $A_{i,t}$ properly controls for unobserved TFP variation in the model. Finally, to the extent of errors arising from the theoretical model or generated regressors from Stage 1, we assume that such errors enter the estimating equation in a way that still delivers a correctly specified conditional mean and thus consistent estimates.

Three final considerations should be taken into account when estimating Equation (9). First, given the two-stage nature of our estimating approach and the potential uncertainty introduced in Stage 2 by the generated regressors from Stage 1, closed-form solutions for the variance-covariance matrices are not apparent. To ensure precision in our standard error estimates, we implement a Bayesian cluster (at the country-pair) bootstrap method, introduced by Rubin (1981).[15] This method assigns bootstrap replication weights to the original sample points—country-pair clusters in our case—with strictly positive, noninteger weights drawn from an exponential distribution with a unit mean.[16] For each of the 100 bootstrap replication samples we consider, we use the resampling weights to estimate the parameters of interest through weighted regressions in both estimation stages. This process allows us to obtain the parameter distributions and compute cluster bootstrap standard errors that we can use for statistical inference.

The Bayesian bootstrap offers a key advantage over the classic bootstrap that resamples with replacement. This is due to its continuous weighting scheme that ensures all observations/clusters contribute to each resample, albeit with possibly small weights. Thus, this approach prevents the problem of missing observations/clusters in resamples that can lead to unusual estimates or collinearity issues. Overall, this method is particularly beneficial for models relying on the original data structure, like structural gravity models and in particular our two-stage estimation procedure where the construction of the MR terms from Equation (8) would fail to hold in bootstrap samples with corner cases, that is, country-pair clusters not drawn in a bootstrap replication sample.

Second, the MRs are potentially endogenous by construction. To address this issue, in Section 4, we will capitalize on and extend the methods of Feyrer (2019), Feyrer (2021), and Anderson et al. (2020) by constructing a series of instruments for the OMRs. Third, the estimation of Equation (9) relies upon the need for information on production inputs ($K_{i,t}$ and $L_{i,t}$). While in our analysis we draw upon standard sources, alternative datasets with a broad set of countries and/or more disaggregated sectors can be challenging to come across.

In sum, Equation (9) has two main advantages relative to standard gravity equations. First, consistent with our main objective, it enables us to obtain estimates of country-specific determinants of trade flows. We demonstrate this in the next section, where we apply our methods to study the impact of country-specific

R&D expenditure on international trade. However, the estimating equation can accommodate any country-specific variable. Second, Equation (9) can deliver estimates of the trade elasticity directly from bilateral trade data. We demonstrate this in Section 5, where we obtain elasticity estimates from aggregate data and from sectoral data, including agriculture, mining, manufacturing, and services.

3 | Data Description and Sources

To conduct our empirical analysis, we combine data from several standard sources. First, the data on trade, output, and expenditure come from the World Input-Output Tables (WIOTs) of the World Input-Output Database (WIOD). WIOTs are available for 43 countries,[17] cover years 2000–2014, and provide consistent and harmonized information, in USD, on bilateral (intermediate and final) international and domestic trade flows for 56 disaggregate goods and services industries (see Supporting Information Appendix Table B.1 for a detailed breakdown).[18]

We match the WIOTs for each year with country-specific data on factors of production (capital and labor compensation) from the WIOD Socio Economic Accounts (SEA), which cover the same countries, period, and sector disaggregation. To ensure consistency across datasets, we convert the capital and labor compensation variables, available in national currency, to USD using the same exchange rates used in the production of the WIOTs.

The main advantages of using WIOD for our analysis are threefold. First, the WIOTs allow for consistency with our structural model insofar as they include information on both domestic and international trade flows. Second, we can obtain disaggregate results and provide sector-specific trade elasticities. This is particularly important for services and is a novel contribution of our analysis. Finally, combining information from WIOT and SEA allows us to obtain data on the country-specific factors of production at a disaggregate level, which is important for our analysis at the sectoral level.

Subsequently, we match all WIOD data at the aggregate level with information on TFP at current PPPs and population from version 10.0 of the Penn World Table (PWT), dummy variables for common bilateral EU and WTO membership from CEPII, and bilateral RTA membership from the RTAs Database from Egger and Larch (2008). Finally, we source country-specific data on gross domestic expenditure on R&D at current PPPs per capita from the Organisation for Economic Co-Operation and Development Main Science and Technology Indicators Database (OECD 2024). We include four variables in our country-specific analysis: total gross domestic expenditure on R&D at current PPPs per capita, which is then broken down into three subcategories for higher education expenditure, business enterprise expenditure, and total government intramural expenditure. Due to missing information on R&D spending for Brazil (BRA), Cyprus (CYP), Indonesia (IDN), India (IND), and Malta (MLT), we exclude those countries from the respective analysis that explores the links between R&D and trade. For the remaining 37 countries in our sample, there are missings for some years on total, higher education, business enterprise, and government intramural R&D expenditure which represent, 5.1%, 4.1%, 4.3%, and 4% of the sample, respectively. To fill in those missings, we apply a forward (and where still needed a backward) linear interpolation using the known values for each variable available in the original sample during 1981–2023.

4 | Estimating Country-Specific Trade Costs

We start this section by applying our two-stage procedure to obtain benchmark results. Next, we perform a series of sensitivity checks to demonstrate the robustness of our methods and findings. Finally, we provide proof of concept by examining the links between country-specific R&D expenditure and bilateral trade.

4.1 | Benchmark Estimates

Table 1 presents the empirical results from various ways of estimating our baseline specification (9). The two panels of Table 1 are based on different approaches to proxy bilateral trade costs. The estimates in Panel A are obtained with fully flexible bilateral trade costs as specified in Equation (7), while the estimates in Panel B are obtained after constraining the vector of bilateral trade costs in the second-stage analysis to be the vector of corresponding estimates we obtain from the first stage.

Column (1) presents our most flexible specification, whereby we include importer-time fixed effects directly instead of using their estimates from Stage 1. We note that the estimates of the effects of RTA, EU, and WTO membership exhibit expected signs and magnitudes in line with the literature. Further, the point estimates on labor and capital fall within the theoretical bounds of zero to one and with a ratio of roughly 2/3 and 1/3, respectively, have plausible magnitudes. Our point estimate of the power transformation of the OMR term, $ln(\widehat{\Pi_{i,t}^{1-\sigma}})$, is equal to −0.755 and is statistically significant at the 1% level.

In the next two columns of Panel A, we gradually constrain the specification from Column (1) given estimates from the first stage and guided by theory. Specifically, we vary the degree to which we constrain the importer-time fixed effects. In Column (2), we include expenditure and estimates of the power transformation of the IMR term from the first stage, corresponding to Equation (8) instead of importer-time fixed effects. The estimates on both new variables are statistically significant and with signs as predicted by theory. Moreover, in line with our priors based on theory, the estimates for expenditure and IMR are close to unity. Importantly, the estimates on all other variables are very close to those in Column (1). Next, in Column (3), we directly include the computed vector of importer-time fixed effects from the first stage, with its parameter constrained to unity. Once again, results remain comparable to those from Column (1).

The estimates in Panel B are obtained after constraining the vector of bilateral trade costs in the second-stage estimation to be the vector of corresponding estimates that we obtain from the first stage. Results in Columns (4)–(6) are obtained following the same steps for the specification of the importer-time fixed effects that we used in Columns (1)–(3). Specifically, in Column (4), we include importer-time fixed effects. Then, in Column (5), we include the structural covariates for expenditure and the IMR

TABLE 1 | Baseline results with country-level data.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A			Panel B		
	Flexible bilateral trade costs			Constrained bilateral trade costs		
	with constrained importer-time FEs:			with constrained importer-time FEs:		
	None	**Partial**	**Full**	**None**	**Partial**	**Full**
$ln(A_{i,t})$	0.224***	0.248***	0.259***	0.226***	0.246***	0.256***
	(0.063)	(0.067)	(0.068)	(0.067)	(0.069)	(0.069)
$ln(L_{i,t})$	0.517***	0.532***	0.566***	0.518***	0.532***	0.563***
	(0.075)	(0.066)	(0.067)	(0.083)	(0.070)	(0.071)
$ln(K_{i,t})$	0.279***	0.242***	0.254***	0.277***	0.245***	0.255***
	(0.061)	(0.067)	(0.067)	(0.069)	(0.070)	(0.071)
$ln(\widehat{\Pi_{i,t}^{1-\sigma}})$	−0.755***	−0.709***	−0.798***	−0.752***	−0.711***	−0.796***
	(0.106)	(0.069)	(0.070)	(0.118)	(0.078)	(0.079)
$RTA_{ij,t}$	0.067**	0.077**	0.078**			
	(0.032)	(0.035)	(0.035)			
$EU_{ij,t}$	0.172***	0.168***	0.140***			
	(0.042)	(0.043)	(0.042)			
$WTO_{ij,t}$	0.328***	0.320***	0.322***			
	(0.060)	(0.067)	(0.067)			
$ln(E_{j,t})$		0.952***			0.954***	
		(0.006)			(0.005)	
$ln(\widehat{P_{j,t}^{1-\sigma}})$		−0.890***			−0.896***	
		(0.010)			(0.007)	
Observations	26,460	26,460	26,460	26,460	26,460	26,460

Note: This table presents results for Equation (9) using country-level data following the two-stage approach. Estimates in Panel A are obtained with fully flexible bilateral trade costs. Column (1) includes importer-time FEs directly. Column (2) includes expenditure and estimates of the power transformation of the IMR term from Equation (8) instead of importer-time fixed effects. Further, Column (3) includes the computed vector of importer-time FEs from the first stage, with its parameter constrained to unity. Estimates in Panel B are obtained after constraining the vector of bilateral trade costs to be the vector of corresponding estimates that we obtain from the first stage. Results in Columns (4)–(6) are obtained following the same steps for Columns (1)–(3). Column (6) represents our preferred baseline specification. Standard errors in each column are computed using a Bayesian country-pair (ij) cluster bootstrap with 100 replications over the two-stage estimation procedure and reported in parentheses below point estimates. For further details see text.
*$p < 0.10$.
** $p < .05$.
*** $p < .01$.

term from the first stage. Finally, in Column (6), we constrain to unity the computed vector of importer-time fixed effects from the first stage. Column (6) represents our preferred specification as it aligns most closely with the theory. Overall, the estimates in Column (6) are as expected and are strikingly similar to all other results in Table 1.

4.2 | Endogeneity Concerns and Robustness Analysis

There are at least three potential reasons for endogeneity concerns with the key structural OMR covariate, $ln(\Pi_{i,t}^{1-\sigma})$, in Equation (9). First, it is endogenous by construction because it includes own-country national income. Second, in addition to the direct link to own size, it could be endogenous due to indirect links between own national income and the national incomes of all other countries. Finally, there could also be an indirect relationship between own national income and the IMRs of all other countries. To mitigate these concerns, we follow and extend the existing literature to construct three different IVs.

Specifically, we rely on the generalized method of moments (GMM) estimation technique for panel count data models with endogenous regressors, discussed in detail in Windmeijer and Santos Silva (1997) and Windmeijer (2008).[19] We estimate a set of exactly identified models, that is, the number of instruments is the same as the number of endogenous variables, based on the following unconditional sample moment conditions: $\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}\boldsymbol{Z}_{ij,t}\varepsilon_{ij,t}=0$; $\sum_{i=1}^{I}\varepsilon_{ij,t}=0$; $\sum_{t=1}^{T}\varepsilon_{ij,t}=0$, where $\boldsymbol{Z}_{ij,t}=\left\{ln(A_{i,t}), ln(L_{i,t}), ln(K_{i,t}), ln\left(\left(\Pi_{i,t}^{\mathrm{IV}-\kappa}\right)^{1-\sigma}\right)\right\}$ is the matrix of IVs and where $\kappa=(1,2,3)$ represents the respective approach used to construct the instrumental variable

TABLE 2 | Baseline results with IVs for OMR terms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		No. employees weights			Population weights		
	Baseline	**IV-1**	**IV-2**	**IV-3**	**IV-1**	**IV-2**	**IV-3**
$ln(A_{i,t})$	0.256***	0.233***	0.257***	0.255***	0.237***	0.257***	0.255***
	(0.069)	(0.080)	(0.072)	(0.073)	(0.081)	(0.072)	(0.074)
$ln(L_{i,t})$	0.563***	0.565***	0.572***	0.576***	0.574***	0.570***	0.574***
	(0.071)	(0.090)	(0.087)	(0.087)	(0.090)	(0.086)	(0.086)
$ln(K_{i,t})$	0.255***	0.246***	0.243***	0.239***	0.235***	0.246***	0.242***
	(0.071)	(0.080)	(0.076)	(0.075)	(0.081)	(0.074)	(0.074)
$ln(\widehat{\Pi_{i,t}^{1-\sigma}})$	−0.796***	−0.785***	−0.788***	−0.787***	−0.781***	−0.788***	−0.788***
	(0.079)	(0.123)	(0.114)	(0.112)	(0.121)	(0.115)	(0.113)
F-effective		188.0	22.2	11.1	106.1	6.0	4.5
observations	26,460	26,460	26,460	26,460	26,460	26,460	26,460

Note: This table presents results using country-level data. Column (1) presents baseline results for Equation (9). In all subsequent columns, we correct for potential endogeneity from the OMR term in Equation (9) through different instruments. Column (2) solves for IMR and OMR terms using base-year weights and $t_{ij,t}$ estimated from the first stage. Column (3) solves for IMR and OMR terms using base-year weights and $t_{ij,t}$ estimated following Feyrer (2019). Column (4) uses a base-year weighted average of t_{ij} estimated following Feyrer (2019). Columns (2)–(4) use the number of employees in the year 2000 for base-year weights. Columns (5)–(7) correct for potential endogeneity in Equation (9) following the same procedure as Columns (2)–(4), but use population in the year 2000 as base-year weights. Within-country values ($i = j$) are excluded when constructing all instruments. Standard errors in each column are computed using a Bayesian country-pair (ij) cluster bootstrap with 100 replications over the two-stage estimation procedure and reported in parentheses below point estimates.

*$p < 0.10$.

** $p < .05$.

*** $p < .01$.

$ln\left(\left(\Pi_{i,t}^{\text{IV}-\kappa}\right)^{1-\sigma}\right)$ to account for the potential endogeneity of the OMR term.[20]

In what follows, we describe each IV and discuss the corresponding estimates in turn.

Table 2 presents our findings, where, to ease comparison, Column (1) reproduces results from our preferred specification from Column (6) of Table 1. In our first IV, IV-1, we follow Anderson et al. (2020) and reconstruct the OMR term using base-year weights. Mechanically, we compute the following: $\left(\Pi_{i,t}^{\text{IV-1}}\right)^{1-\sigma} = \sum_{j\neq i}\left(\frac{t_{ij,t}}{P_{j,t}^{\text{IV-1}}}\right)^{1-\sigma}\frac{W_{j,2000}}{W_{2000}}$, where W represents base-year weights either using number of employees from SEA or base-year population from PWT.[21] Thus, we simultaneously eliminate the direct own-size links by construction as well as residual endogeneity due to links between national income and incomes of other countries. Results under this IV strategy, when using the number of employees as weights, are presented in Column (2), and they are very similar to our baseline estimates in Column (1).

Our second IV, IV-2, extends the methods in IV-1 to account for potential additional higher order endogeneity introduced by the bilateral fixed effects in our trade cost vector. Following the recommendations of Feyrer (2019), we build upon the approach taken in IV-1 but now compute $\tilde{t}_{ij,t}$ from a complementary first-stage regression where we regress international bilateral gross exports on time-varying distance ($dist_{ij,t} \equiv dist_{ij} \times \phi_t$) and use this trade cost vector to recompute MR terms as $\left(\Pi_{i,t}^{\text{IV-2}}\right)^{1-\sigma} = \sum_{j\neq i}\left(\frac{\tilde{t}_{ij,t}}{P_{j,t}^{\text{IV-2}}}\right)^{1-\sigma}\frac{W_{j,2000}}{W_{2000}}$, using employee weights. The results in Column (3) remain in line with our baseline estimates.

Finally, our third IV, IV-3, uses the recomputed trade cost vector from IV-2 and takes a weighted average for each exporter across all importers, using base-year employee weights; that is, we compute $\left(\Pi_{i,t}^{\text{IV-3}}\right)^{1-\sigma} = \sum_{j\neq i}\left(\tilde{t}_{ij,t}\right)^{1-\sigma}\frac{W_{j,2000}}{W_{2000}}$. The new results from Column (4) remain similar to our baseline specification. Columns (5)–(7) of Table 2 follow the same estimation approach as Columns (2)–(4), except employ population weights. Results are almost identical under the two alternative weighting schemes for the IVs.

To our knowledge, for such nonlinear models, there is no formal first-stage statistic to test for weak instruments similar to what is available in log-linear models (see, for instance, the dynamic reduced form income equations in Anderson et al. 2020). However, for a heuristic indication of the instrument's strength, we perform a test for weak instruments in linear instrumental variables regression that is robust to heteroscedasticity, autocorrelation, and clustering by Montiel Olea and Pflueger (2013). Specifically, at the bottom of each column in Table 2, we report the first-stage effective F statistic for weak instruments after estimating our baseline model in logs instead of in levels.[22]

Following the rule of thumb approach that instruments are weak if the effective F statistic is less than 10, we find for the first set of instruments in Columns (2)–(4) that the tests reject the null hypothesis of weak instruments. However, when moving from IV-1 to IV-2 and IV-3, the tests suggest that the instruments become progressively weaker. This is expected since, by construction, compared to IV-1, we rely on increasingly less variation to construct IV-2 and in turn IV-3. Interestingly, the effective F statistics in Columns (5)–(7) of Table 2 suggest that when using population weights, the instruments are weaker compared to the respective ones with employment weights in Columns (2)–(5). In particular, in Columns (6) and (7), we fail to reject the null hypothesis of weak instruments. One could try to construct "stronger" instruments similar to those in Columns (3), (4), (6), and (7) but following more closely Feyrer (2019) to exploit richer heterogeneity from improvements in aircraft and maritime technology over time. However, this is beyond the scope of this paper given that there is no real formal test for weak instruments in these estimators and point estimates remain robust across specifications.

We conclude this section with a summary of some robustness experiments.[23] First, we use as dependent variable total exports corrected for the error term from the first-stage estimation ($\hat{X}_{ij,t} = X_{ij,t}/\hat{\epsilon}_{ij,t}$). Second, instead of offsetting in the estimation procedure the estimates from the first-stage regressions, we net them out directly from gross exports, that is, $X_{ij,t}/\left(\widehat{t_{ij,t}^{1-\sigma}} \exp[\hat{\psi}_{j,t}]\hat{\epsilon}_{ij,t}\right)$. Third, we exploit the fact that the SEA database provides additional measures of capital and labor, that is, capital compensation and compensation of employees, respectively. Fourth, we use alternative ways to calculate standard errors, including (i) classic country-pair cluster bootstrap methods by drawing samples with replacement only in Stage 2 and (ii) analytical country-pair cluster robust standard errors from the Stage 2 PPML regression without accounting for any potential first-stage estimation/model uncertainty. Fifth, we estimate a weighted PPML in Stage 2 using as weights the inverse of the standard errors from the estimated exporter-time fixed effects in Stage 1, attaching smaller weights to less precisely estimated OMRs from Stage 1. Finally, we employ an alternative method to control for productivity by assuming that productivity follows a Markov (first-order autoregressive) process, which allows us to estimate a version of Equation (9) without the need to first estimate TFP.[24] In sum, while we observe some quantitative changes in our estimates across the sensitivity experiments, our main conclusions and results, especially those of the OMRs, are robust.

4.3 | Proof of Concept: Links Between R&D and Trade

This section demonstrates how the structural gravity model can deliver estimates of the full effects of country-specific determinants of international trade, focusing on the impact of R&D expenditure as an example.[25] To highlight our methods, we decompose the impact of R&D into two components: (i) a uniform impact on sales regardless of destination and (ii) a discriminatory effect on international relative to domestic sales. We explore four R&D measures as follows: (i) total gross domestic expenditure on R&D at current PPPs per capita (Total), which is then broken down into subcategories for (ii) higher education (H. Edu.), (iii) business enterprise (Business), and (iv) government intramural (Govt.).[26] Finally, we show that our methods deliver results that can be very different from those produced when applying alternative procedures that the literature has proposed to obtain estimates of the effects of country-specific variables. Table 3 presents our findings, where Columns (1)–(4) offer results for each of the four R&D variables, respectively. The four panels, A–D, report estimates from alternative approaches to obtain estimates of R&D effects on bilateral trade flows. For brevity, Table 3 only reports results related to our country-specific R&D variables of interest. Full results are relegated to Appendix D in the Supporting Information.

Panel A of Table 3 implements our two-stage estimation procedure, but in the first-stage estimating equation, we now also include the interaction of R&D with international borders, $ln(R\&D_{i,t}) \times BRDR_{ij}$, as in Beverelli et al. (2024). This allows us to obtain an estimate of the partial effect of R&D expenditure on international trade relative to domestic sales. Overall, we find a positive and statistically significant effect of R&D expenditure on international relative to domestic trade, suggesting that innovation in R&D promotes international trade disproportionately, thus contributing to globalization. However, these effects vary by R&D type. Specifically, we obtain positive and significant estimates of the impact of higher education and business enterprise R&D expenditure (Columns (2) and (3), respectively) but a negative, sizable, and statistically significant estimate of the impact of government expenditure (Column (4)). One possible explanation for the latter result is "home bias" in government spending. As such, we find this result not only intuitive but also interesting and provoking.

We next incorporate the log of $R\&D_{i,t}$ into our second-stage estimation, that is, by adding this extra term into our baseline estimating equation (corresponding to Table 1, Column (6)). The estimates in "Stage 2" of Panel A reveal that the impact of each type of R&D expenditure on sales is positive and statistically significant. This is another intuitive finding, as we would expect that innovation in R&D should promote efficiency. Furthermore, we note that the estimates of the effects of the different types of R&D expenditures are similar in magnitude.

In combination, the estimates from "Stage 1" and "Stage 2" of Panel A enable us to obtain the total impact of each type of R&D on international trade; we report these estimates in the last row of Panel A. Two main findings stand out. First, the total impact of R&D expenditure in higher education is the strongest, closely followed by the effects of business enterprise expenditure, albeit more volatile. Specifically, our estimates suggest that a 10% increase in R&D expenditure in higher education translates into about a 1.8% increase in international trade, while the corresponding estimate for business enterprise expenditure is 1.5%. Second, while the positive uniform effect of government R&D expenditure works in the opposite direction of its negative discriminatory impact on international trade, the former is not enough to outweigh the latter. Therefore, according to our calculations, the net impact of government R&D expenditures on international trade is negative and statistically significant with an estimated elasticity of −0.08.

We next break from our two-stage procedure and experiment with alternative estimation techniques of country-specific variables from the literature. In this vein, Panel B presents results from a "naïve" one-stage gravity specification, whereby we exclude the exporter-time fixed effect such that we can include time-varying country-specific characteristics. As noted above,

TABLE 3 | Country-specific results—R&D.

	(1) Total	(2) H. Edu.	(3) Business	(4) Govt.
Panel A: Stage 1				
$ln(R\&D_{i,t}) \times BRDR_{ij}$	0.217***	0.135***	0.114**	−0.116**
	(0.078)	(0.051)	(0.054)	(0.047)
Stage 2				
$ln(R\&D_{i,t})$	0.067**	0.044**	0.038*	0.040*
	(0.032)	(0.022)	(0.022)	(0.021)
Total effect	0.283***	0.179***	0.152***	−0.076*
	(0.077)	(0.052)	(0.057)	(0.045)
Panel B: Naïve gravity				
$ln(R\&D_{i,t}) \times BRDR_{ij}$	0.215**	0.145***	0.111*	−0.102**
	(0.086)	(0.053)	(0.059)	(0.049)
$ln(R\&D_{i,t})$	0.016	−0.038	−0.006	0.056
	(0.055)	(0.036)	(0.039)	(0.037)
Total effect	0.231***	0.107***	0.105***	-0.046
	(0.046)	(0.029)	(0.033)	(0.030)
Panel C: FE PPML, Stage 2				
$ln(R\&D_{i,t})$	0.065*	0.033	0.026	0.038*
	(0.035)	(0.022)	(0.022)	(0.022)
Total effect	0.282***	0.168***	0.140**	−0.078*
	(0.078)	(0.049)	(0.055)	(0.046)
Panel D: FE OLS, Stage 2				
$ln(R\&D_{i,t})$	0.003	0.019	−0.010	0.034
	(0.035)	(0.019)	(0.022)	(0.021)
Total effect	0.220***	0.155***	0.105**	−0.082*
	(0.075)	(0.047)	(0.051)	(0.047)

Note: The country-specific variable we include is gross domestic expenditure on R&D at current PPPs per capita (Column (1)), broken down into subcategories for higher education (H. Edu., Column (2)), business enterprise expenditure (Business, Column (3)), and total government expenditure (Govt., Column (4)). For brevity, only country-specific variables and their interactions with the border dummy are included. See Supporting Information Appendix D for full results. Standard errors in each column are computed using a Bayesian country-pair (ij) cluster bootstrap with 100 replications over all stages involved in each estimation procedure and reported in parentheses below point estimates. The number of observations is 20,535 in Panels A and B and 555 in Panels C and D. For further details, see the text and tables in the Supporting Information Appendix Section D.

*$p < 0.10$.

**$p < .05$.

***$p < .01$.

this estimation procedure does not properly account for the structural OMR of Anderson and van Wincoop (2003). As such, results are bound to be biased for this reason, also known as the "gold medal mistake" critique of Baldwin and Taglioni (2006). Nonetheless, we explore this naïve setup since it has been frequently employed in the literature to obtain estimates of various country-specific characteristics.

Concretely, the econometric model that we employ includes all bilateral covariates in the trade cost specification (7) as well as the full set of importer-time fixed effects which fully accounts for IMRs. However, instead of using exporter-time fixed effects, we naïvely include exporter fixed effects, year fixed effects, GDP as a proxy for exporter size, and an a-theoretical remoteness index, which, following the vast gravity literature, we construct as importer GDP-weighted bilateral distance. Consistent with our main specification and due to the use of domestic trade flows, we can obtain estimates of the differential effect of R&D on international relative to domestic trade (through the interaction of $ln(R\&D_{i,t}) \times BRDR_{ij}$) as well as its uniform impact by directly including the $ln(R\&D_{i,t})$ covariate.

We draw two conclusions from the results in Panel B. First, the estimates of the differential effect of R&D on trade are similar to the corresponding estimates in Panel A. To some extent, this is not surprising. While estimated in a "naïve" one-stage gravity setting, we nonetheless have included all bilateral covariates (except exporter-time fixed effects) that are grounded in structural gravity theory as well as domestic trade flows. In a true nal¨ive setting, one might instead omit importer-time and country-pair controls in favor of variables such as importer-time GDP and bilateral distance and only include international trade flows.

Second, all estimates of the uniform effects of R&D are statistically insignificant, with those on higher education and business turning negative. Thus, we do not find evidence of any uniform effect of R&D on aggregate sales. This is in contrast with expectations as well as the main findings from Panel A, thus casting doubt on this specification. Based on this, we conclude that the naïve one-stage gravity specification may result in biases in the country-specific estimates of interest. Note that while the differences between the R&D estimates in our application are small, they could be significant in other applications. Furthermore, this approach cannot deliver estimates of trade elasticities, a potentially significant drawback.

The specification that we employ in Panel C aims at comparing our two-stage procedure with the common practice to regress fixed effects recovered from the first-stage regression on explanatory variables (including country-specific variables) in a second stage. To do so, motivated by our theory, we implement the following two-stage procedure. The first-stage estimating equation is identical to that in Panel A. As before, this equation will deliver estimates of the differential effects of R&D on international relative to domestic trade. Then, the second-stage estimating equation uses the exponent of the fitted values of the exporter-time fixed effects from the first stage ($\exp[\hat{\phi}_{i,t}]$) and regresses them on all exporter-specific variables in our second-stage specification from Panel A, including R&D expenditure. As the exporter-time fixed effects are a multiplicative function of output and OMRs (see Equation (8)), we estimate the second stage using PPML.

Based on the new estimates, we conclude that the procedures we employ in Panels A and C deliver similar estimates, albeit slightly smaller in magnitude which renders some of the estimates insignificant in Panel C. Since the two procedures are closely related by design, we found the similarity between the estimates in Panels A and C reassuring. The implication is that as long as the structural properties of the gravity model are preserved, researchers may select their preferred method. We prefer the model in Panel A because it uses bilateral trade flows (our outcome of interest) as the dependent variable in the second stage in a theoretically founded way. Hence, it does not rely on fixed effects to simultaneously decompose the effects of R&D and to estimate its full impact. Moreover, given that Panel C relies upon fixed effects as a dependent variable, assumptions about the pattern of heteroscedasticity and error term variance inherently deviate from those in Panel A. Overall, the results in Panel C reinforce our main contribution, which is to demonstrate that it is possible to obtain estimates of the full impact of country-specific variables within a properly specified structural gravity model.

We conclude with an analysis of results in Panel D, where we employ the same two-stage procedure used in Panel C; however, instead of using the PPML estimator in Stage 2, we rely on OLS to estimate Stage 2 in logs, that is, the dependent variable is the fitted values of the exporter-time fixed effects from Stage 1 ($\hat{\phi}_{i,t}$). The use of OLS for the second-stage analysis is consistent with the standard two-stage approach from the related literature (Head and Mayer 2014). Interestingly, the estimated effect of $ln(R\&D_{i,t})$ is no longer comparable to those from Panels A–C: The point estimate on total R&D expenditure per capita (Column (1)) is both economically small and statistically insignificant, while the estimate on Business (Column (3)) switches sign altogether. That on H. Edu. and Govt. remain positive but insignificant (Columns (2) and (4)) and, however, are smaller in magnitude. Based on this, we conclude that consistent with the use of PPML for standard gravity regressions, it is probably preferable to also rely on it for the second-stage analysis of the type of analysis that we describe here.

5 | Estimating the Trade Elasticity

This section shows how our estimating framework can be used to recover estimates of the trade elasticity, which is a crucial parameter in international economics, both in the trade literature (e.g., Arkolakis et al. 2012; Feenstra et al. 2018) and in the macro literature (e.g., Lisack et al. 2023). As summarized in Footnote 5, there are a plethora of estimates at various levels of aggregation that have been computed through a range of methods. We believe that our approach adds value to the related literature because (i) it is straightforward to implement, (ii) it does not require tariff and/or price data, and (iii) subject to data availability, it can be implemented directly at the same level of aggregation that is required for counterfactual analysis with the structural gravity model.

As discussed when describing the structural parameters of Equation (5), one can directly recover the elasticity of substitution from the estimated parameter on the OMR, that is, $\alpha_6 = (1-\sigma)/\sigma$.[27] When doing this for aggregate trade, based on results from our baseline specification in Column (6) of Table 1, we obtain an elasticity of substitution $\sigma = 1/(1-0.796) = 4.9$, which is readily comparable to estimates from the related literature. However, this specification does not fully exploit the structure of the parameters imposed by our model, which might prove useful in better identifying the elasticity. Therefore, in what follows, we exploit the full structure of the parameters when estimating our baseline specification. Specifically, as discussed in Section 2.2, the structural interpretation of the parameters under constant returns to scale (CRS) is as follows: $\alpha_6 = (1-\sigma)/\sigma$, $\alpha_1 = -\alpha_6$, $\alpha_2 = -(1-\gamma)\alpha_6$, and $\alpha_3 = -\gamma\alpha_6$, where γ is the output elasticity of capital.[28] However, since our model also holds in the absence of the CRS assumption, we estimate a more flexible version as well by defining $\alpha_2 = -\delta\alpha_6$, where δ is the output elasticity of labor (and keeping all other constraints the same). When relaxing the CRS assumption, we also provide a test of whether it holds, that is, we test the null hypothesis that $\gamma + \delta = 1$. For estimation, similar to the IV specifications in Section 4, we rely on the GMM technique where we now impose in our baseline specification (9) the parameter constraints discussed above and use the following unconditional sample moment conditions: $\sum_{i=1}^{I} \varepsilon_{ij,t} = 0$, $\sum_{t=1}^{T} \varepsilon_{ij,t} = 0$, and $\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} \boldsymbol{Z}_{ij,t}\varepsilon_{ij,t} = 0$, where $\boldsymbol{Z}_{ij,t}$ is the matrix of IVs.

Table 4 reports estimates of the trade elasticities of substitution for aggregate trade. Columns (1) and (2) show elasticities for our baseline model under CRS and non-CRS, respectively (where $\tilde{\alpha} \equiv \alpha_6$). Several observations are in order. First, the results in both columns are very similar, albeit with smaller but not statistically different OMR estimates and thus elasticities of substitution in

TABLE 4 | Aggregate trade elasticities.

	(1)	(2)	(3)	(4)
	Baseline		Alternative procedure	
	CRS	no CRS	CRS	no CRS
$\tilde{\alpha}$	-0.717^{***}	-0.744^{***}	-0.815^{***}	-0.830^{***}
	(0.036)	(0.091)	(0.041)	(0.074)
γ	0.385^{***}	0.370^{***}	0.307^{***}	0.288^{***}
	(0.111)	(0.105)	(0.066)	(0.096)
δ		0.602^{***}		0.697^{***}
		(0.112)		(0.065)
ρ			0.795^{***}	0.807^{***}
			(0.048)	(0.073)
$\sigma = 1/(1+\tilde{\alpha})$	3.531^{***}	3.906^{***}	5.393^{***}	5.891^{**}
	(0.444)	(1.386)	(1.191)	(2.557)
$\gamma + \delta$		0.972^{***}		0.985^{***}
		(0.088)		(0.056)
$H_0 : \gamma + \delta = 1$ (p-value)	n/a	0.750	n/a	0.792
Observations	26,460	26,460	588	588

Note: $\tilde{\alpha} = (1-\sigma)/\sigma$ where σ is the elasticity of substitution. γ is the output elasticity of capital, δ is the output elasticity of labor which is only estimated in the models which do not impose constant return to scale (CRS), and ρ is the autoregressive parameter of productivity (see Supporting Information Appendix C). "n/a" stands for not applicable. Standard errors in each column are computed using a Bayesian country-pair (ij) cluster bootstrap with 100 replications over the two-stage estimation procedure and reported in parentheses below point estimates. For further details, see the text and the Supporting Information Appendix.
$^{*}p < 0.10$.
$^{**}p < .05$.
$^{***}p < .01$.

Column (1). This is expected, since in Column (2), we fail to reject the null hypothesis of CRS. Second, compared to our baseline results in Column (6) of Table 1, the point estimate on the OMR term, $\tilde{\alpha}$, is smaller resulting in elasticities of substitution which are lower by roughly one unit, that is, 3.5 and 3.9 compared to 4.9, which puts them on the lower end of the elasticities of substitution in the trade literature but in the upper end of the elasticities of substitution from the macro literature (Ruhl 2008).

Third, the IV matrix used for identification in both columns is $\boldsymbol{Z}_{ij,t} = \{ln\left(\Pi_{i,t}^{1-\sigma}\right), ln(K_{i,t}),\ ln(L_{i,t})\}$. Interestingly, when we repeat the analysis after adding productivity ($ln(A_{i,t})$) as an overidentifying instrument to strengthen identification, the estimates paint a different picture.[29] For example, the elasticity of substitution becomes even smaller, that is, 3.2 with CRS and 1.8 without CRS, while the model without CRS delivers capital and labor elasticities around 0.7 and rejects the null hypothesis of CRS (with p-value 0.001). This analysis points to potential difficulties in identifying the parameters in this constrained version of the model when proxying for unobserved productivity with generated variables that might be imperfect.

To address this challenge, Columns (3) and (4) of Table 4 present results when implementing the alternative procedure to control for productivity, which we describe in detail in the Supporting Information Appendix. The advantage of this method is that instead of using an ex-ante estimate of TFP as in Columns (1) and (2), we can directly account for unobserved productivity within our estimation. Hence, implementing this alternative procedure controls for TFP without the need for productivity data but with the need to estimate the additional parameter ρ that reflects the persistence in the autoregressive process that productivity is assumed to follow. As can be observed, irrespective of whether or not the CRS assumption is imposed, we recover comparable estimates for the output elasticity of capital, γ, and $\tilde{\alpha}$. The latter implies an aggregate elasticity of substitution, $\sigma = 5.9$, in Column (4), which is a bit larger than some recent trade elasticity estimates, for example, Simonovska and Waugh (2014) and Caliendo and Parro (2015), but readily comparable to the majority of estimates from the trade literature, for example, Anderson and van Wincoop (2003), Egger et al. (2012), Head and Mayer (2014), and Fontagné et al. (2022).

Interestingly, we fail to reject the null hypothesis of CRS in Column (4), which lends support to the robustness of this approach. When comparing with Column (7) of the Supporting Information Appendix Table C.1—whereby we also implement the alternative procedure but do not impose constraints on the parameters of our baseline specification—we note that the point estimate on the OMR term is strikingly similar. Finally, the estimated output elasticities of capital and labor are within the expected range. We, therefore, conclude that the alternative estimation approach (i) delivers robust results and (ii) consistently controls for unobserved productivity.[30] As we shall see below, this is particularly important when taking results to the sectoral level due to the paucity of disaggregate TFP estimates.

TABLE 5 | Sectoral trade elasticities.

	(1) Aggregate	(2) Manufacturing	(3) Services	(4) Agriculture	(5) Mining
Panel A: CRS					
$\tilde{\alpha}$	-0.815^{***}	-0.603^{***}	-0.827^{***}	-0.704^{***}	-0.765^{***}
	(0.041)	(0.074)	(0.047)	(0.111)	(0.080)
γ	0.307^{***}	0.349^{***}	0.284^{***}	0.493^{***}	0.539^{**}
	(0.066)	(0.123)	(0.073)	(0.132)	(0.211)
ρ	0.795^{***}	0.928^{***}	0.709^{***}	0.703^{***}	0.715^{***}
	(0.048)	(0.049)	(0.081)	(0.128)	(0.212)
$\sigma = 1/(1+\tilde{\alpha})$	5.393^{***}	2.517^{***}	5.773^{***}	3.380^{***}	4.248^{***}
	(1.191)	(0.466)	(1.566)	(1.265)	(1.436)
Panel B: no CRS					
$\tilde{\alpha}$	-0.830^{***}	-0.659^{***}	-0.872^{***}	-0.754^{***}	-0.908^{***}
	(0.074)	(0.128)	(0.066)	(0.091)	(0.121)
γ	0.288^{***}	0.304^{*}	0.256^{***}	0.308^{**}	0.278
	(0.096)	(0.167)	(0.062)	(0.136)	(0.207)
δ	0.697^{***}	0.629^{***}	0.685^{***}	0.457^{***}	0.340
	(0.065)	(0.128)	(0.058)	(0.105)	(0.218)
ρ	0.807^{***}	0.937^{***}	0.721^{***}	0.611^{***}	0.924^{***}
	(0.073)	(0.056)	(0.111)	(0.084)	(0.213)
$\sigma = 1/(1+\tilde{\alpha})$	5.891^{**}	2.935^{***}	7.827^{*}	4.066^{***}	10.864
	(2.557)	(1.101)	(4.051)	(1.500)	(14.319)
$\gamma+\delta$	0.985^{***}	0.933^{***}	0.942^{***}	0.765^{***}	0.618^{***}
	(0.056)	(0.144)	(0.031)	(0.076)	(0.205)
$H_0: \gamma+\delta=1$ (p-value)	0.792	0.643	0.056	0.002	0.063
Observations	588	588	588	588	588

Note: $\tilde{\alpha} = (1-\sigma)/\sigma$ where σ is the elasticity of substitution, γ is the output elasticity of capital, δ is the output elasticity of labor which is only estimated in the models which do not impose constant return to scale (CRS), and ρ is the autoregressive parameter of productivity (see Supporting Information Appendix C). Standard errors are clustered by country-pair in parentheses. Standard errors in each column are computed using a Bayesian country-pair (ij) cluster bootstrap with 100 replications over the two-stage estimation procedure and reported in parentheses below point estimates. For further details, see the text and Supporting Information Appendix.
$^{*}p < 0.10$.
$^{**}p < .05$.
$^{***}p < .01$.

Next, in Table 5, we bring our analysis to the sectoral level using the preferred alternative estimating procedure. Specifically, we offer results for Manufacturing, Services, Mining, and Agriculture.[31] Panel A presents results when imposing CRS, while Panel B relaxes this assumption. For ease of comparison, in Column (1), we reproduce aggregate results from the last two columns of Table 4. The point estimates of $\tilde{\alpha}$ and γ in Panels A and B are similar, except for Columns (4) and (5), where the differences seem to be driven by the fact that the CRS assumption imposed in Panel A fails to hold with decreasing returns to scale, as also suggested when testing the null hypothesis (H_0) of CRS at the bottom of Panel B. We, therefore, rely upon Panel B when interpreting our estimates.

For Manufacturing, we estimate an elasticity of substitution $\hat{\sigma}_{Manufacturing} = 2.94$ (Column (2)), which is in line with the estimates of Broda and Weinstein (2006) using data at similar levels of aggregation and smaller but still closely related to those in Simonovska and Waugh (2014) who use a sample with more developing countries. Of course, when focusing on more disaggregated sectors, we expect the estimated elasticities to be quite heterogeneous (Fontagné et al. 2022). Overall, we view the close alignment of our results as a reassuring verification of our methods and validation that our approach can be extended to other sectors for which tariff data are not readily available.

Column (3) presents our results for Services. Overall, we find an elasticity of substitution $\hat{\sigma}_{Services} = 7.83$, which is roughly 2.5 times larger than $\hat{\sigma}_{Manufacturing}$. We find this result intuitive given the nature of services trade. Importantly, this estimate is higher than what previous literature which has attempted to estimate the services elasticity suggests. For instance, Egger et al. (2012) obtain an elasticity estimate $\hat{\sigma}_{Services} = 5.96$ after developing a structural model of goods and services trade and production and implementing a systems estimation strategy to identify all parameters. Thus, our novel results for services hint that this sector might be even more substitutable than we previously thought. However, we expect to see more heterogeneous estimates when we look into more disaggregated services sectors (Francois and Hoekman 2010).

Finally, in Columns (4) and (5) of Table 5, we examine two additional sectors in the economy by estimating elasticities of substitution for the Agriculture and Mining sectors. In line with our priors that agricultural products should be less substitutable across countries (e.g., due to pronounced home bias in this sector) while goods in the mining sector should be more homogeneous, we find an Agriculture elasticity $\hat{\sigma}_{Agriculture} = 4.07$, while that for Mining is $\hat{\sigma}_{Mining} = 10.86$, albeit statistically insignificant possibly due to large measurement error in Mining production and trade data.

In sum, the results in this section demonstrate the validity of our proposed methods to identify the elasticity of substitution (σ), and hence the trade elasticity ($1 - \sigma$), at the aggregate and sectoral level within a structural gravity setting. One large merit of this approach is that, provided availability of the necessary production and trade data, researchers can directly implement our methods to estimate their own elasticities at their preferred levels of (dis-)aggregation and for their relevant country and time samples without the need for tariff and/or price data.

6 | Conclusion

Guided by theory, we propose a simple two-stage procedure to estimate structural gravity models with two important implications. First, our methods allow the estimation of the effects of any country-specific variable on trade, and we offer a proof of concept by estimating the impact of research and development (R&D) expenditure on bilateral trade flows. Second, the proposed methods deliver estimates of the trade elasticity without the need for price and/or tariff data. We highlight this feature by obtaining both aggregate and sectoral trade elasticity estimates, including estimates of the trade elasticity for services trade.

While our theoretical insights offer a marginal contribution to the gravity literature, the empirical possibilities they unlock are large. From an application point of view, our methods can be used to obtain estimates of any country-specific determinant of trade flows, including revisiting existing applications that do not properly control for the MR terms and new applications that consider the effects of variables that have not been studied before. In addition, from a general equilibrium perspective, our methods enable researchers to recover their own trade elasticities while using the same data applied in their counterfactual exercises which correspond to the exact level of (dis-)aggregation required. Finally, from a methods perspective, decomposing the structural IMR term would allow isolating the impact of international versus domestic links and incorporate a structural estimating framework that simultaneously accounts for sectors and intermediates. This would naturally open the door to further apply our methods to the fast-moving literature that addresses global value chains, structural gravity, and policy-induced GE/welfare effects.

While we focus on the quantification of deterministic, country-specific shocks, trade flows may also be subject to short-run, stochastic shocks, such as trade cost shocks, demand shocks, or supply shocks. Extending the standard trade framework to account for stochastic short-run demand, supply, and/or trade cost shocks, to capture short-run fluctuations, is a very valuable endeavor, which we leave for future research. Additionally, allowing for endogenous capital and labor and utilizing the framework for counterfactual analysis are fruitful extensions for the future.

Acknowledgments

Special thanks are extended to Richard Baldwin, Ruben Dewitte, Bruno Merlevede, and João Santos Silva for useful suggestions and feedback. We also thank the handling editor, Michael McCracken, and two anonymous referees for their guidance and comments. We remain responsible for any remaining errors.

Data Availability Statement

The data is publicly available. Specifically, all necessary information and instructions for obtaining and managing the data, as well as the step-by-step procedures used to replicate all results presented in both the manuscript and the supporting information appendix, are publicly available at: https://journaldata.zbw.eu/dataset/new-methods-to-estimate-country-specific-effects-and-trade-elasticities-with-the-structural-gravity.

Open Research Badges

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at https://doi.org/10.15456/jae.2025058.1704592316.

Endnotes

[1] Anderson and van Wincoop (2004), Baldwin and Taglioni (2006), Head and Mayer (2014), Yotov et al. (2016), and Yotov (2024) offer surveys of the related empirical literature.

[2] There are two other methodological differences between our study and Beverelli et al. (2024). First, their setup requires the availability of data on domestic trade flows, while our methods can be applied to international data only. Second, their setting does not allow for the identification of directional effects, that is, effects on exports versus imports, while our model allows for such effects.

[3] See, for example, Haaland and Kind (2008), Aw et al. (2011), Akcigit et al. (2018), Cai et al. (2022), and Peters and Roberts (2022). Griliches (1998) reviews the literature on the impact of R&D on output.

[4] We complement these firm-level analyses from both methodological and empirical angles. From a methodological perspective, we obtain estimates of the impact of R&D expenditure on trade within a theoretically motivated multicountry empirical model, which naturally lends itself to extending the analysis to study the GE implications of the relationship between R&D and trade. From an empirical and policy point of view, we quantify the full partial equilibrium impact of R&D expenditure on trade and decompose it into uniform versus discriminatory effects.

[5] See, for example, Broda and Weinstein (2006), Egger et al. (2012), Hillberry and Hummels (2013), Simonovska and Waugh (2014), Soderbery (2015), Caliendo and Parro (2015), Feenstra et al. (2018), and Fontagné et al. (2022) among others.

[6] Our theoretical presentation is for a generic sector. However, for example, as demonstrated by Anderson and van Wincoop (2004), the analysis applies at any level of aggregation. Please see Section A of

the Supporting Information Appendix for detailed derivations of the equations in this section.

[7] Domestic trade flows are consistent with gravity theory, and there are significant benefits from using them in gravity estimations (Yotov 2022). However, unlike Beverelli et al. (2024), our methods do not require the use of domestic trade flows; that is, they can be implemented with international trade data only.

[8] We decided to explicitly model production as a function of labor and capital instead of assuming an endowment economy, as data for labor and capital are available, which more clearly highlights our extension of substituting for output in the trade gravity equation in the second step. Anderson et al. (2020) derive a gravity model after allowing for capital dynamics, that is, endogenous capital. They demonstrate that this extension does not change the estimation of the gravity equation. Moreover, the property that the MRs can be perfectly recovered from the fixed effects remains valid. The transition function for capital in their framework is only a function of lagged, endogenous variables, such as prices. This is consistent with our treatment of capital as predetermined and thus uncorrelated with the contemporaneous error term. However, as the estimation stage is all we care about in this paper, we stick to the assumption of exogenous capital and labor.

[9] As we recover the MRs to the power of $1-\sigma$ from the fixed effects, we express the power of the corresponding variable as follows: $1-\sigma+(\sigma-1)/\sigma=-(1-\sigma)(1-\sigma)/\sigma$, which implies that $\alpha_6=(1-\sigma)/\sigma$.

[10] In addition to long-run, deterministic country-specific policy changes that we focus on, trade flows may be subject to short-run shocks, like trade cost shocks, demand shocks, or supply shocks. Thus, we see significant value in introducing stochastics in the standard trade gravity framework, and we expect that such a contribution would be very impactful. However, we also recognize that this is a formidable task, which is beyond the scope of our paper.

[11] Due to the use of domestic trade flows, we could also add country-specific variables that are interacted with the international border dummy, as in Beverelli et al. (2024). We demonstrate this in Section 4.

[12] See Fally (2015) and Anderson et al. (2018) for further details on the calculation of the structural MRs from the estimates of the PPML fixed effects.

[13] Note that, in principle, we also could unpack the importer-time fixed effects. This would allow us to investigate the drivers of the importer-time fixed effects and to investigate country-specific effects on the importer and on the exporter side, for example. We see this as a fruitful area for future research.

[14] We are keenly aware that the TFP measures are estimates of an unobservable term and might not perfectly capture true productivity differences across countries and over time. The fixed effects in our model mitigate this limitation as the exporter fixed effects account for any country-specific productivity differences, while the time fixed effects control for any global productivity trends and changes over time. Moreover, for robustness, we assume a first-order autoregressive process for productivity and use the structure of our model to replace technology with explanatory variables. Details are provided in the Supporting Information Appendix.

[15] This method is also known as the exchangeable weighted cluster bootstrap. For more details, see Lo (1987); Præstgaard and Wellner (1993); Cheng et al. (2013).

[16] All observations within a cluster have the same weight and weights are scaled to sum to the number of clusters. We cluster standard errors by country-pair to allow for correlation in the error term at this level. There are 1764 clusters for the baseline sample. For a complete review on cluster robust inference, see Cameron and Miller (2015).

[17] See Supporting Information Appendix Table B.2 for a full list of countries included in our analysis. Beyond the countries listed in Table B.2, the WIOTs contain information on a "rest of world" (RoW) aggregate. We exclude from our analysis the RoW due to the paucity of data on various aggregates, for example, trade agreements, and Russia (RUS) due to scarcity and incompleteness of sectoral data on production factors and production/trade.

[18] At this stage, we also clean the data by setting negative trade flow values to zero, if and when they occur. This affects only final goods/services trade and represents only 0.08% of the data in final goods trade.

[19] As discussed in this literature, when controlling for unobserved heterogeneity, panel count data models might suffer from incidental parameter problems with inconsistent estimates. While Jochmans and Verardi (2022) provide a solution to this problem for exponential regression models that feature two-way fixed effects in cross-sectional data, we are not aware of a solution for this problem in panel data. Note, however, that we expect this to be less of a concern in our estimation setting since our variable of interest varies at the exporter–importer–year (ij,t) level, and thus, we have a relatively large number of observations to identify the exporter (i) and time (t) fixed effects.

[20] For the estimation, given the specified moment conditions, we assume that the error term $\varepsilon_{ij,t}$ in Equation (9) enters additively in the model specification. However, equivalently, if $\boldsymbol{Z}_{ij,t}$ are valid instruments in the additive model, there are appropriate transformations of $\boldsymbol{Z}_{ij,t}$ to also create valid instruments in the multiplicative model in Equation (9), giving the same estimation results for the two model specifications (Windmeijer and Santos Silva 1997).

[21] Specifically, given the trade cost vector and the base-year weights, we solve for the system of equations that come from the OMR and IMR terms, the latter being $\left(P_{j,t}^{\text{IV-1}}\right)^{1-\sigma}=\sum_{i\neq j}\left(\frac{t_{ij,t}}{\Pi_{i,t}^{\text{IV-1}}}\right)^{1-\sigma}\frac{W_{i,2000}}{W_{2000}}$.

[22] Specifically, we regress the endogenous variable $ln\widehat{(\Pi_{i,t}^{1-\sigma})}$ on the respective instrument used in each column in Table 2, $ln\left(\left(\Pi_{i,t}^{\text{IV}-\kappa}\right)^{1-\sigma}\right)$, and all other exogenous control variables, that is, $ln(A_{i,t})$, $ln(L_{i,t})$, $ln(K_{i,t})$, ϕ_i, ϕ_t, and the combined vector of bilateral trade costs and importer-time fixed effects $\left(\alpha_5\widehat{ln(t_{ij,t})}+\hat{\psi}_{j,t}\right)$ estimated from the first stage. Then we look at the effective F statistic for $ln\left(\left(\Pi_{i,t}^{\text{IV}-\kappa}\right)^{1-\sigma}\right)$ calculated following Montiel Olea and Pflueger (2013).

[23] Details on each of them are included in Section C of the Supporting Information Appendix.

[24] This approach is in the same spirit as both dynamic panel (Blundell and Bond 2000) and proxy variable methods (Olley and Pakes 1996) for estimating production functions.

[25] However, as noted previously, our methods and analysis apply to any country-specific variable.

[26] As discussed earlier, by quantifying the impact of R&D on trade with our methods, we complement a series of excellent studies, for example, Haaland and Kind (2008), Aw et al. (2011), Akcigit et al. (2018), and Peters and Roberts (2022), which study this relationship from the perspective of the firm.

[27] Recall from Section 2.1 that the trade elasticity, $1-\sigma$, is directly linked to the elasticity of substitution, σ. For convenience, in what follows, our discussion focuses on σ.

[28] By definition, $1-\gamma$ is the output elasticity of labor.

[29] For the model with CRS similar to the one in Column (1), the estimated parameters become as follows: $\tilde{\alpha}=-0.684$, $\sigma=3.164$, and $\gamma=0.418$, while for the model without CRS similar to the one in Column (2): $\tilde{\alpha}=-0.457$, $\sigma=1.84$, $\gamma=0.681$, and $\delta=0.672$. For brevity, we do not present the full table.

[30] The autoregressive parameter of productivity ρ is roughly 0.8 in both Columns (3) and (4) in Table 4, in line with most studies on productivity using both aggregate and disaggregate data.

[31] See Supporting Information Appendix Table B.1 for a detailed breakdown of all WIOD industries. The Agriculture, Mining and Quarrying, Manufacturing, and Services sector encompasses WIOD industries 13, 4, 5-23, and 28-50, respectively.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.