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论文题目：Untangling the Lattice: A Multi-Stage Value-Added Gravity Model for Global Value Chain

Untangling the Lattice: A Multi-Stage Value-Added Gravity Model for Global Value Chains

Xiuqi Liu

Abstract

This essay addresses the growing complexity of global value chains by developing a fully structural, multi-stage value-added gravity model. In today's hyper-fragmented production networks, goods routinely cross borders multiple times before reaching final consumers. Standard gravity models, which measure trade in gross terms, double-count intermediate crossings and bias elasticity estimates upward. My model overcomes these limitations by explicitly mapping value-added flows through each stage of production and trade.

Methodologically, I derive the gravity equation from a Hicksian, cost-minimizing dual formulation, which isolates pure substitution effects from income changes. I embed stage-by-stage value-added contributions into a nested CES cost kernel, ensuring that each leg of the supply chain—direct, upstream, and downstream—can be identified and estimated separately. Empirically, I implement a Poisson Pseudo-Maximum Likelihood (PPML) estimator on a 2017–2023 ADB MRIO dataset covering 14 RCEP economies, controlling for multilateral resistance and zero-trade flows.

Reduced-form model estimation confirms that de-duplicating intermediate crossings and applying Hicksian compensation both attenuate distance and tariff elasticities compared to gross models. The multi-stage specification further uncovers substantial heterogeneity: border and trade-cost frictions differ markedly across production legs, and my approach sheds light on anomalies—such as negative border effects—and provide explanations of how intermediate transit hubs contribute to those counterintuitive effects.

Keywords: Gravity Model, Global Value Chains, Trade-Cost Elasticities, Intermediate Trade Frictions, Hicksian Dual

Contents

1 Introduction

In less than a generation, the growth of "Factory Asia" has transformed what used to be a simple bilateral trade landscape into a dense lattice of multi-stage production networks that span and interlink national borders. Goods assembled in one country are routinely embedded in sub-assemblies two borders away before re-entering a third market for final sale.

This era of rapid integration, however, did not prove to be linear. In the past three decades, East Asia has shifted from a regional supplier of manufactured goods into the engine of the global value chain expansion. East Asia's share of world manufactured exports increased from 18.7% in to 41.8% over the 1990s, as the so called "new Tigers"(Malaysia, Thailand, Philippines and Indonesia) rapidly industrialized and formed deeper integration with China's assembly network under the WTO-era liberalization(Lall & Albaladejo, 2004). After more than 20 years of continued growth, the increase in global value chain participation rate came to a halt with the global financial crisis in 2008, and while the recovery was fast, participation in GVCs started to decline again globally in 2011(Cigna, Gunnella, & Quaglietti, 2022). These reversals represent clear inflection points in the evolution of GVC. A key driver of structural change over the 2000s is the slowing pace of international vertical specialization, which accounts for between one-quarter and one-half of the decline in import growth from the 1990s to the 2000s. Other factors, such as the declining share of investment in GDP after the financial crisis, may have contributed, but evidence suggests that their role was less important(Constantinescu, Mattoo, & Ruta, 2020).

Against this dynamic, the China-U.S. trade war disrupted the global value chain. In 2018-2019, the U.S. imposed 10%-25% sector-wide tariffs on Chinese imports, encouraging the firms to reroute their shipments through other countries like Vietnam and Indonesia. For the average product-level tariff increase, rerouting rises by 3.6 percentage points at the country level(Iyoha, Malesky, Wen, Wu, & Feng, 2024). To add on that, Rotunno, Roy, Sakakibara, and Vezina (2023) found that Vietnamese exports to the US were around 40 % higher in 2020 relative to 2017 in sectors hit by US tariffs on Chinese products, and product-level rerouting reached 16.5% in the same period(Iyoha et al., 2024).

The COVID-19 pandemic constituted a major shock to global value chains—initially causing an estimated 9.5% drop in global trade and a steep 42% contraction in foreign direct investment in 2020, but it also acted as a catalyst for resilience strategies and subsequent structural reconfiguration in GVCs. Specifically, Lebastard and Serafini (2023) showed that while firms embedded in GVCs experienced sharper export declines—down around 42% in April 2020 in France, compared to roughly 28% for non-GVC exporters, they demonstrated stronger recovery trajectories in 2021 and later as supply chain disruptions subsided.

Furthermore, the Regional Comprehensive Economic Partnership(RCEP) entered into force in January 2022, creating the world largest free trade agreement and eliminating tariff for more than 90% of goods traded in these 15 countries. Beyond goods, the RCEP agreement, in its twenty chapters, defines means whereby investment, competition and SME participation in trade will be promoted(Stehrer & Vujanovic, 2022). This represents another policy shock that significantly increased vertical specialization and the weighted average number of stages for members for primary factors of production and final consumption, contributing to a more complex GVC(Fan, Peng, & Hu, 2023).

With the expansion of the global value chains, it becomes clear that conventional gross-trade statistics can no longer capture where value is truly created and where tariff or shock exposure exist. This is because the traditional bilateral trade statistics count every intermediate good each time it crosses a border. Johnson and Noguera (2012) estimated that double-counting can inflate measured export by up to 30-40%. This overstate of gross trade flow may distort policy conclusions regarding trade resilience and diversion in response to shocks such as tariff exposure. In response, Koopman, Wang, and Wei (2014) provides a micro-founded way to peel apart those layers of double countings. By computing the Leontief Inverse $(I - A)^{-1}$, they trace every final consumption back to its true country-industry origin, thereby eliminating potential intermediate crossings.

Noguera (2012) introduced another precise, stage-by-stage decomposition of value-added trade by exploiting the Leontief inverse expansion of the global input-output matrix and breaking down the total value-added exports into direct exports, first-round intermediates, and second-round intermediates. This method is useful to measure both direct and all tiers of indirect value-added transmissions across the global value chain.

Yet, despite these advances, most gravity frameworks still rely on gross trade flows, which is increasingly insufficient for the expanding global value chain. Most gravity frameworks are designed to measure the total value of goods flowing from one country to another. However, this approach can lose its explanatory power with the complexities of Global Value Chains, where goods cross borders multiple times as intermediate inputs. Therefore, the standard model often usually ignore the differences between gross trade and the actual domestic value-added embodied in exports.

This study's core contribution is listed as follows

- Proposes a multi-stage value-added gravity framework that decomposes trade flows into direct, upstream, and inter-hub legs.
- Allows for the estimation of trade-cost frictions and transit hub effects at different stages of the supply chain, revealing how hub routing can flip standard intuitions.
- Introduces a reduced-form model to enable a direct, side-by-side comparison of the new value-added framework with traditional gross-trade gravity models.

2 Literature Review

To contextualize this study's contribution, I first turn to the extensive literature of traditional gravity models that form the foundation of my work. Anderson and Van Wincoop (2003) established the modern structural gravity model by providing a microeconomic theoretical foundation of Tinbergen (1962) empirical law under CES preferences and fully endogenizing multilateral resistance terms(Π_i, P_j), yielding

$$x_{ij} = \frac{y_i y_j}{y^W}\left(\frac{t_{ij}}{P_i \Pi_j}\right)^{1-\sigma}$$

where x_{ij} is the bilateral trade volume, y_i and y_j are the gross domestic product of exporting country i and importing country j, t_{ij} is the trade cost, P_i and Π_j are the multilateral resistance terms of country i and j.

This framework not only modified for the third market effects through the multilateral resistance terms, but also provided a counterfactual apparatus for measuring trade cost shocks. Furthermore, Helpman, Melitz, and Rubinstein (2008) incorporated the heterogeneous firms and fixed entry costs into the gravity model, embedding firm heterogeneity to the model and releasing the symmetric trade barrier restriction proposed by Anderson and Van Wincoop (2003). Arkolakis, Costinot, and Rodríguez-Clare (2012) further enhanced the theoretical validity of the structural models by showing that any iceberg-cost and CES embedded trade model collapses to the same aggregate gains-from-trade formula, confirming the robustness of the CES backbone even when richer micro-foundations are introduced into the essay. Empirically, while many models usually use log-linear OLS model for estimation, the Poisson-Pseudo-Maximum-Likelihood(PPML) empirical framework–originally shown to be consistent for multiplicative models by Gourieroux, Monfort, and Trognon (1984)–has become another appropriate empirical model for structural measurement, with its ability to address the presence of heteroskedasticity, which simple OLS cannot deal with. To further support the use of PPML framework in gravity models, Fally (2015) demonstrated that PPML framework can be implemented as a fully structural gravity model with importer and exporter fixed effects.

Recent literature has begun to acknowledge and incorporate aspects of global value chains and value-added trade into gravity models, though often in partial, empirical, or methodological terms. Baldwin and

Taglioni (2014) empirically demonstrated that standard gravity models lose explanatory power and exhibit structural instability as parts-and-components trade rises and global value chain expands. Antràs and Chor (2013) provided the theoretical foundation for global value chain, conceptualizing it as a sequence of upstream and downstream tasks, suggesting how a cost shock at one stage might influence the entire chain. Fally (2012) further provided a theoretical improvement of gravity model by embedding the intermediate-input linkage into the model, showing how gravity fixed effect can map directly to the measurements of vertical specialization. Empirically, Greaney and Kiyota (2020) integrated Noguera (2012) decomposition of direct and indirect third-country effects into a PPML estimator. Together, these papers provide the theoretical and empirical foundation for my own extension.

Several conceptual gaps remain in the existing VA-embedded gravity literature. While many "VA-augmented" models claim a theoretical foundation, most continue to rely on standard derivation techniques from structural gravity models that omit value-added terms entirely. These approaches typically assume a one-stage CES utility or cost structure and fail to capture the multi-stage nature of global production, where value added accumulates and transmits through layered upstream and downstream linkages. For instance, Heiland and Šváb (2024) start from a structural gravity model–which may not be appropriate for global value chain context as traditional structural frameworks assume bilateral trade networks–and assign the same gravity kernel to both intermediate and final goods. From there they used the Leontief inverse to derive a general expression for VA-gravity and eventually find this reduced-form model to be misspecified and hard to interpret. The key issue here is trade costs are embedded on gross shipments, while value added is embedded on each stage. Because the standard model cannot model these stages explicitly, it cannot correctly attribute the trade costs to each leg effectively, which makes Heiland and Šváb (2024) find their gravity model inconsistent. Besides from theoretical gaps, empirical innovations also show some flaws. Hagemejer and Mućk (2025) uses OECD-TiVA flows as the left-hand-side variable in a PPML gravity with exporter-time and importer-time fixed effects, simply substituting the current gravity model and replace gross exports with domestic VA absorbed abroad. Furthermore, Zhao (2022) uses a standard PPML gravity specification to estimate how policy uncertainty affects manufacturing VA exports, bug still, the author treats VA trade as an undifferentiated flow; it thus captures only the overall elasticity and cannot tell whether direct VA shipment respond differently from inputs passing through third country nodes.

In this essay, I contributed to the limitations of the previous gravity models by formulating a value added gravity model in Hicksian cost-minimization dual, summing all the CES blocks for direct, upstream, and downstream links into a single optimization. I also embeds Noguera (2012) three-channel decomposition in the empirical model for stage-specific measurement. The PPML estimation then recovers distinct distance and tariff elasticities at each production stages.

3 Theory

3.1 Hicksian Dual and CES Nesting

Traditional Armington gravity models begin with Marshallian utility maximization. In a global value chain context, however, specifying a Marshallian utility function would be very difficult: a tariff shock alters not only relative prices but also factor incomes and tariff revenue, which in turn change the household budget Y_j. The nation therefore needs to cut its intermediate input, which transmits the shock upstream to suppliers throughout the global value chain. This ripple effect would require the Marshallian utility model to trace all the production and trade linkages to accurately track income feedback loops. Such structure will potentially forfeit the log-linear simplicity that makes gravity models so tractable. However, the Hicksian dual treats each production stage as an additional line in a single cost function. I can therefore nest constant-elasticity-of-substitution (CES) blocks for direct, upstream, and downstream links, yet still solve one optimization problem. This framework not only solves the multi-stage simulation bottleneck, but also keeps the simplicity of gravity model and the convenience of log-linearization. It should be noted that Hicksian derivation is not a new method for gravity modeling. For instance, Costinot and Rodríguez-Clare (2014) used Shephard's Lemma for welfare changes, but the gravity itself follows the standard Armington model. My essay, however, begins from the Hicksian dual and builds the cost kernel itself, placing Hicksian cost minimization at the center of my model.

Another consequence of using Hicksian cost minimization is that Hicksian demand holds real utility constant, so the response to tariff or other policy shock is a compensated elasticity that only shows the substitution effect and is not contaminated by the income feedback. In a Marshallian set-up, however, a rise in tariff raises the import prices but also reduces the real incomes, causing consumers and firms buy less of all normal goods. As a result, the observed decline in trade flows reflect both substitution across suppliers and overall demand contraction. Since gravity-model elasticities are meant to capture only the pure resistance effect, mixing in income-driven market-size shocks inflate the coefficient and therefore overstate trade's sensitivity to cost. This characteristic of the Hicksian model has mixed effects to gravity model. For gravity models isolating structural elasticities, for instance, those that aim to estimate pure trade-cost responsiveness, the Hicksian model is considered to be preferable than traditional Marshallian approach because it yields cleaner, more interpretable estimates of how trade patterns reallocate across partners in response to marginal policy changes. However, for gravity models intended for general-equilibrium counterfactuals or welfare analysis, this approach would need further refinement. In those contexts, endogenizing expenditure and price indices are necessary. However, this study's primary purpose is to derive and estimate stage-specific value-added cost elasticities and illuminate their structural interpretation, so that a model incorporating both substitution and income effects is not necessary.

3.2 Assumptions

I begin by laying out the key assumptions in this model.

- The representative customer in each nation has a constant-elasticity-of-substitution(CES) utility function, which implies a constant elasticity of substitution across all pairs of variaties and ensure the tractability of the dual cost of the function.
- In each origin i, gross output is produced by combining a country-specific value-added factor (e.g. labor and capital) one-for-one with a composite of imported intermediates. Production exhibits constant returns to scale and takes place under perfect competition.
- Shipping one unit from i to j requires iceberg cost $\hat{\tau}_{ij} \geq 1$ units at origin.
- Let $A = [a_{ki}]$ be the industry-level input-output coefficient matrix, with

  $$v_i \;=\; 1 - \sum_{k=1}^{G} a_{ki}$$

  denoting the share of gross output in country i that accrues to domestic value added. We assume the Leontief inverse $B = (I - A)^{-1}$ exists (i.e. the spectral radius of A is below one), so that multi-stage production linkages are well-defined.
- World markets clear: total world factor income equals total world expenditure,

  $$\sum_{i=1}^{G} v_i = \sum_{j=1}^{G} E_j.$$

  Each country's expenditure E_j finances its bundle of imports and home-produced goods at prices determined endogenously by the CES price index P_j.

- Firm heterogeneity, proposed by Melitz (2003), is not considered in this model, because our focus on industry-level value added data makes it inappropriate to derive firm-level micro analysis.

3.3 Theoretical Model

Consider a world of G countries indexed by $i = 1, \ldots, G$, where each country both produces and consumes a differentiated good. Each destination $j \in \{1, \ldots, G\}$ is inhabited by a representative consumer with CES utility function

$$U_j = \left(\sum_i q_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma \in \{1, \infty\} \tag{1}$$

where q_{ij} is the quantity of differentiated products that destination country j sources from origin country i, and σ is the elasticity of substitution.

As mentioned, in a global value chain context, production crosses borders multiple times. In a Hicksian dual I can collapse the entire value chain into one nested cost function. Every time an intermediate crosses a border I multiply its delivery price by the iceberg cost of that link and by the domestic value-added share of the origin, which is the product's total cost that stays in the production country, such as labor wages, and domestic inputs.

Now I derive the cost function. Recall that iceberg cost assumption suggests that the supplier must ship $\hat{\tau}$ units to guarantee one unit of the good to survive the journey. Equivalently, only a fraction

$$\tau_{ij} = \frac{1}{\hat{\tau}_{ij}} \in (0, 1)$$

of any shipments arrive. Because the Hicksian problem is written in terms of goods available for consumption in j, we express feasibility in arrivals. Therefore, I will use the delivered share τ_{ij} instead of $\hat{\tau}_{ij}$, putting iceberg costs directly into resource constraint.

Each unit of gross output produced in country i pays a fixed value-added share v_i representing wages, profits, and other domestic factor costs. That payment is made only once at each stage, and happens at the moment of the production, so the shipment cost doesn't affect this term.

A unit demand in j can come directly from i, or via one upstream hop k, or two hops l, and so on. The cost function is therefore constructed to capture the complexity of the multi-stage global value chain.

$$C_j(q) = \sum_i \underbrace{\tau_{ij} v_i}_{\text{direct}} q_{ij} + \sum_{i,k} \underbrace{\tau_{kj} \tau_{ik} v_i}_{\text{one upstream hop}} q_{ij} + \sum_{i,k,l} \underbrace{\tau_{lj} \tau_{kl} \tau_{ik} v_i}_{\text{two upstream hop}} q_{ij} + \ldots \tag{2}$$

$$= \sum_i \sum_{n=1}^{\infty} \sum_{h_1, h_2, \ldots, h_{n-1}} (v_i \tau_{ih_1} \tau_{h_1 h_2} \ldots \tau_{h_{n-1} j}) q_{ij} \tag{3}$$

where h represents the dummy index for intermediate nodes on a path from origin i to destination j. The cost function C_j can be interpreted as a decomposition of final products into their constituent value-added components from different countries. Traditional trade models treat a product like a single, solid, undifferentiated good. In contrast, this model recognizes that a product is a bundle of value-added contributions from a chain of countries. Each term in (2) represents a unique path a good takes through the global value chain. The reason that each term only contains a single value added quantity(v_i) is because I decomposed each final product's value into several value-added terms, and I eventually collected all the elements together, forming (3), so that I am not assuming quantity shipped on along a given route is the same across all routes, no matter their complexity

A potential objection here is that, as Antràs and De Gortari (2020) point out, shipping costs(or more generally trade costs) are a function of the gross value of a shipped good, not a function of the value added. Likewise, Koopman et al. (2014) also suggests that multi-stage production magnifies the trade costs as goods move through stages on gross flows. A clarification is therefore necessary. While the terms are written as the product of the trade cost τ and value added share v_i, the economic logic here is sequential rather than commutative. Iceberg costs attach to the gross physical shipment at each leg of the journey, then the value added share is used to decompose and allocate the correct portion of that final, friction-laden cost back to the country of origin i. The algebra here is simply a compact way to trace this value, though it may cause some confusion. Therefore, the economic interpretation of the cost function is valid.

While (3) groups the terms by paths, I can apply Tonelli's theorem to this discrete case to collect the coefficients on each q_{ij} by changing the order and regrouping the summation, pulling the q_{ij} outside the inner sums and then summing over all paths that start at i and end at j.

$$C_j(q) = \sum_i \left[v_i \sum_{n=1}^{\infty} \sum_{h_1,\dots,h_{n-1}} \tau_{ih_1} \dots \tau_{h_n-1j} \right] q_{ij} \tag{4}$$

I define two matrices, let T be the $G \times G$ dimension matrix representing all iceberg cost factors

$$T = \begin{pmatrix} \tau_{11} & \tau_{12} & \cdots & \tau_{1G} \\ \tau_{21} & \tau_{22} & \cdots & \tau_{2G} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{G1} & \tau_{G2} & \cdots & \tau_{GG} \end{pmatrix}$$

and $V := \operatorname{diag}(v_1, \dots, v_G)$ is $G \times G$ dimension matrix for all the value added shares.

Since

$$\sum_{h_1,\dots,h_{n-1}} \tau_{ih_1 \dots \tau_{h_{n-1}j}} = (T^n)_{ij}$$

the coefficient on q_{ij} in (4) equals

$$v_i \sum_{n=1}^{\infty} (T^n)_{ij}$$

Stacking all destinations at once and collecting the (i, j) coefficients into a matrix yields

$$C(q) = V\left(T + T^2 + T^3 + \dots\right) q. \tag{5}$$

The parenthesis is the familiar matrix geometric series.

Recall that for any square matrix M the Neumann series

$$I + M + M^2 + \cdots$$

converges if the spectral radius $\rho(M) := \max |\lambda_i(M)|$ is strictly below one. When it converges,

$$\sum_{n=0}^{\infty} M^n = (I - M)^{-1}. \tag{6}$$

Back to my model, since one unit of final demand is composed by domestic contribution v_j and imported contribution, weighted by other countries' value added, and the pass-through iceberg factors τ_{ij}, so

$$1 = v_j + \sum_i \tau_{ij} v_i$$

, and destination j's value-added share is

$$v_j = 1 - \sum_i \tau_{ij}\, v_i \implies \sum_i \tau_{ij}\, v_i < 1.$$

I have the even stronger bound$\sum_i \tau_{ij} < 1$ for each column j, according to the definition of τ_{ij}. That implies the induced 1-norm

$$\|T\|_1 := \max_j \sum_i |\tau_{ij}| < 1;$$

every induced norm dominates $\rho(T)$, so $\rho(T) < 1$. Consequently the series in (5) is absolutely convergent and (6) applies with $M = T$.

Insert (6) (with $M = T$) into (4) and subtract the I term I have:

$$T + T^2 + \cdots = (I - T)^{-1} - I.$$

Define

$$B := V\big[(I - T)^{-1} - I\big]. \tag{7}$$

Then (2) simplifies to the Hicksian dual

$$C(q) = B\, q.$$

Finally, making the formula ij-specific I have

$$C_j(q) \;=\; \sum_{i=1}^{G} B_{ij}\, q_{ij}, \quad B_{ij} = v_i[(I - T)^{-1} - I]_{ij} \tag{8}$$

where B_{ij} is the Leontief-style cost kernel that automatically adds a new line for every intermediate pass. In this way I encode all stages in one closed-form object.

The representative agent in j therefore solves

$$\arg\min_{q_{ij}} C_j = \sum_i B_{ij} q_{ij} \quad s.t. \quad U_j = \left(\sum_i q_{ij}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = 1 \tag{9}$$

Therefore, the Lagragian equation is

$$\mathcal{L} = \sum_i B_{ij} q_{ij} - \lambda_j \left[\left(\sum_i q_{ij}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} - 1\right]$$

At optimum, the marginal dual cost of importing one more unit from i equals the shadow value of a unit of utility in j.

The first-order condition is

$$q_{ij} = \left(\frac{\lambda_j}{B_{ij}}\right)^{\sigma} \tag{10}$$

and the constraint pins down

$$\lambda_j \equiv P_j = \left(\sum_i B_{ij}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{11}$$

Recall from Shephard's lemma, the Hicksian demand is expressed as

$$h_i(p,u) = \frac{\partial E(p,u)}{\partial p_i}$$

where h_i is the hicksian demand, E is the total expenditure, and p is the product price.

Plugging this equation back to the model, while the total expenditure is originally $E_j = P_j U_j$, since I set utility level to 1 in (9), the total expenditure is therefore expressed as

$$E_j = P_j \tag{12}$$

Therefore, with the perfect competition assumption, price equals marginal cost

$$p_{ij} = B_{ij} \tag{13}$$

the hicksian demand should be

$$q_{ij}^H = \frac{\partial P_j}{\partial p_i} = \frac{\partial P_j}{\partial B_{ij}} = B_{ij}^{-\sigma} P_j^{\sigma} \tag{14}$$

For the value added export, recall from Koopman et al. (2014) definition that

$$VA = VLF \tag{15}$$

where, assuming G countries, V is the $G \times G$ dimension matrix representing the value added share,

$$V = \mathrm{diag}\big(v_1 \; v_2 \; \cdots \; v_G\big),$$

L is the $G \times G$ dimension Leontief inverse matrix

$$L = \begin{pmatrix} L_{1,1} & L_{1,2} & \cdots & L_{1,G} \\ L_{2,1} & L_{2,2} & \cdots & L_{2,G} \\ \vdots & \vdots & \ddots & \vdots \\ L_{G,1} & L_{G,2} & \cdots & L_{G,G} \end{pmatrix},$$

and F is the $GN \times G$ dimension matrix representing final demand

$$F = \begin{pmatrix} F_{1,1} & F_{1,2} & \cdots & F_{1,G} \\ F_{2,1} & F_{2,2} & \cdots & F_{2,G} \\ \vdots & \vdots & \ddots & \vdots \\ F_{G,1} & F_{G,2} & \cdots & F_{G,G} \end{pmatrix}.$$

Following the simplification of Miernyk (1965) to the original Leontief (1941) model, the gross output X can be defined as

$$X = LF$$

Therefore, the value added export term can further be simplified as

$$VA = VX \tag{16}$$

I further defined the bilateral gross output term X_{ij} as

$$X_i = p_{ij} q_{ij}^H \tag{17}$$

where p_{ij} is the price of the product and is shown to be equal to $B(\tau, v)$ from (13), and q_{ij}^H is the compensated demand quantity.

Since $p_{ij} q_{ij}^H$ is commonly interpreted as the expenditure of a single consumer, a natural objection is that using this equation as the definition of gross output might be ignoring the multiple intermediate-use rounds. In truth, no such gap exists, and the reason is that each element $B(\tau, v)$ of the Leontief inverse already embodies the complete sequence of direct and indirect input requirements. Consequently, multiplying this "all-inclusive" cost kernel by the Hicksian quantity q_{ij}^H reproduces the full gross-output revenue generated in origin i by destination j's purchase.

Plugging(17) into (16), I have

$$VA_{ij} = v_i p_{ij} q_{ij}^H$$

Further incorporating (14) and (13), I can rewrite the formula as

$$VA_{ij} = v_i P_j^\sigma B_{ij}^{1-\sigma} \tag{18}$$

3.4 Empirical Framework

Value added from i can be shipped to k, used there as an input, shipped on to ℓ, and eventually show up in j. Let $T = [\tau_{ab}]$ collect the bilateral trade cost (iceberg) factors on every link $a \to b$. The total "route cost" that takes i's value added to j, counting all possible routes, is

$$B_{ij} = v_i \Big[(I - T)^{-1} - I\Big]_{ij} = v_i \sum_{n=1}^{\infty} (T^n)_{ij} = v_i \sum_{p \in \mathcal{P}_{i \rightsquigarrow j}} \prod_{(a \to b) \in p} \tau_{ab}, \tag{19}$$

where $\mathcal{P}_{i \rightsquigarrow j}$ is the set of all directed routes from i to j with length $1, 2, \ldots$. The last expression just expands the geometric series: direct $i \to j$ routes, $i \to k \to j$ routes, $i \to k \to \ell \to j$ routes, and so on.

Plugging (19) back into the Hicksian demand for value added developed in (18) gives

$$VA_{ij} = v_i \, P_j^\sigma \, B_{ij}^{1-\sigma}. \tag{20}$$

Take logs and totally differentiate:

$$d \ln VA_{ij} = d \ln v_i \; + \; \sigma \, d \ln P_j \; + \; (1 - \sigma) \, d \ln B_{ij}. \tag{21}$$

In the empirical regression I include exporter-time and importer-time fixed effects, so the first two differentials are absorbed. The action comes through $d \ln B_{ij}$.

Because B_{ij} is a positive sum of route terms, its log change is a share-weighted sum of the log changes of those terms. Write $B_{ij} = \sum_p q_p$, where $q_p = v_i \prod_{(a\to b)\in p} \tau_{ab}$ is the contribution of route p. Then

$$d\ln B_{ij} = \sum_p \omega_{ij}(p)\, d\ln q_p, \qquad \omega_{ij}(p) = \frac{q_p}{B_{ij}}, \quad \sum_p \omega_{ij}(p) = 1.$$

Every route p is a product of links, so $d\ln q_p = \sum_{(a\to b)\in p} d\ln \tau_{ab}$. Swap the sums and collect by link:

$$d\ln B_{ij} = \sum_{a,b} \lambda_{ij}^{ab}\, d\ln \tau_{ab}, \qquad \lambda_{ij}^{ab} \equiv \sum_{p\in(a\to b)} \omega_{ij}(p). \tag{22}$$

where λ_{ij}^{ab} is the fraction of all $i\to j$ routes (weighted by their importance) that pass through link $a\to b$.

I do not observe every microscopic route p that value added takes from country i to its final absorber j. Nevertheless, the world input–output (IO) tables tell me how value added must traverse each bilateral link in equilibrium. The theoretical object that governs this traversal in our model is the route elasticity weight

$$\lambda_{ij}^{a\to b} \;\equiv\; \sum_{p\ni(a\to b)} \omega_{ij}(p) \;=\; \frac{\partial \ln B_{ij}}{\partial \ln \tau_{ab}}, \tag{23}$$

where B_{ij} is the Hicksian cost kernel and $\omega_{ij}(p)$ is the share of value added travelling along route p. $\lambda_{ij}^{a\to b}$ is the structural share of VA $(i\to j)$ that crosses the single link $a\to b$ somewhere along the chain.

I do not observe the trade cost at every route, but to make the model empirically estimatable, I can decompose the value-added flows.

Let $A = (\alpha_{k\ell})$ be the input-coefficient matrix and $B = (I-A)^{-1} = (b_{ik})$ the Leontief inverse. Denote by f_{kj} final goods from k to j, and by $y_{\ell j}$ the gross absorption of ℓ's output in j, implicitly defined by $y_{\cdot j} = (I-A)^{-1} f_{\cdot j}$. Because the Hicksian cost kernel B_{ij} rolls all upstream traversal from i to k into b_{ik}, the value added from i ultimately absorbed in j admits the exact partition

$$VA_{ij} = (1-\alpha_i)\sum_k b_{ik}\, x_{k\to j}, \tag{24}$$

$$x_{k\to j} = f_{kj} + \sum_\ell \alpha_{k\ell}\, y_{\ell j}, \qquad y_{\cdot j} = (I-A)^{-1} f_{\cdot j}, \tag{25}$$

$$\Rightarrow\; VA_{ij} = (1-\alpha_i)\sum_k b_{ik} f_{kj} \;+\; (1-\alpha_i)\sum_{k,\ell} b_{ik}\alpha_{k\ell} y_{\ell j}. \tag{26}$$

Using the exact IO partition in (26), the numerators of the shares are observable in the MRIO, so the proxies in (27) follow directly. (Equivalently, these numerators coincide with the s_{ikj} and $\phi_{ik\ell j}$ constructs of Noguera (2012); here we derive them from the Hicksian kernel rather than taking them as primitives.)

$$\widehat{\lambda}_{ij}^{i\to k} = \frac{(1-\alpha_i) b_{ik} f_{kj}}{VA_{ij}}, \qquad \widehat{\lambda}_{ij}^{k\to \ell} = \frac{(1-\alpha_i) b_{ik}\alpha_{k\ell} y_{\ell j}}{VA_{ij}}. \tag{27}$$

By construction, $\sum_k \widehat{\lambda}_{ij}^{i\to k} + \sum_{k,\ell} \widehat{\lambda}_{ij}^{k\to\ell} = 1$,
Since

$$\sum_k \hat{\lambda}_{ij}^{i\to k} + \sum_{k,\ell} \hat{\lambda}_{ij}^{k\to\ell} = \frac{(1-\alpha_i)\sum_k b_{ik} f_{kj} + (1-\alpha_i)\sum_{k,\ell} b_{ik}\alpha_{k\ell} y_{\ell j}}{VA_{ij}} = \frac{VA_{ij}}{VA_{ij}} = 1.$$

the proxy inherits the partition property of the true weights.

Define four stage aggregates (all endogenous to the Hicksian model):

$$
\begin{aligned}
s_{ij}^{(d)} &:= \lambda_{ij}^{i\to j}, \\
s_{ij}^{(ik)} &:= \sum_{k\neq j} \lambda_{ij}^{i\to k}, \\
s_{ij}^{(kj)} &:= \sum_{k\neq i} \lambda_{ij}^{k\to j}, \\
s_{ij}^{(kl)} &:= \sum_{k\neq i} \sum_{\ell\neq j} \lambda_{ij}^{k\to \ell}.
\end{aligned}
\tag{28}
$$

They sum to one and pinpoint where a trade-cost shock bites: directly on $i \to j$, upstream out of i, downstream into j, or on other links of the network.

Totally differentiating $VA_{ij} = (1-\sigma)B_{ij}$ with respect to all bilateral costs and inserting (28) yields

$$
\begin{aligned}
\widehat{VA}_{ij} \;=\; (1-\sigma)\Big[& s_{ij}^{(d)}\,\widehat{\tau}_{ij} + \sum_{k\neq j} \lambda_{ij}^{i\to k}\,\widehat{\tau}_{ik} + \sum_{k\neq i} \lambda_{ij}^{k\to j}\,\widehat{\tau}_{kj} \\
& + \sum_{k\neq i} \sum_{\ell\neq j} \lambda_{ij}^{k\to \ell}\,\widehat{\tau}_{k\ell}\Big] + (\phi_{i,t} + \psi_{j,t})
\end{aligned}
\tag{29}
$$

Collect the four cost channels in levels:

$$
\begin{aligned}
\Gamma_{ij} := s_{ij}^{(d)} \ln \tau_{ij} + \sum_{k\neq j} \lambda_{ij}^{i\to k} \ln \tau_{ik} + \sum_{k\neq i} \lambda_{ij}^{k\to j} \ln \tau_{kj} \\
+ \sum_{k\neq i} \sum_{\ell\neq j} \lambda_{ij}^{k\to \ell} \ln \tau_{k\ell}.
\end{aligned}
\tag{30}
$$

Substituting Γ_{ij} in place of $\ln \tau_{ij}$ gives the multistage Hicksian gravity

$$
\ln VA_{ij,t} = \phi_{i,t} + \psi_{j,t} + (1-\sigma)\,\Gamma_{ij,t} + \varepsilon_{ij,t}. \tag{31}
$$

To estimate each pathway separately, construct

$$
\begin{aligned}
Z_{ij}^{(d)} &:= Z_{ij}, \\
Z_{ij}^{(u_i)} &:= \sum_{k\neq j} \lambda_{ij}^{i\to k}\, Z_{ik}, \\
Z_{ij}^{(u_j)} &:= \sum_{k\neq i} \lambda_{ij}^{k\to j}\, Z_{kj}, \\
Z_{ij}^{(net)} &:= \sum_{k\neq i} \sum_{\ell\neq j} \lambda_{ij}^{k\to \ell}\, Z_{k\ell},
\end{aligned}
\tag{32}
$$

for any bilateral cost proxy Z_{ab} (tariff, log distance, …). Stack them in a PPML:

$$
\mathbb{E}[VA_{ij,t} \mid X] = \exp\Big(\phi_{i,t} + \psi_{j,t} + \beta_d\, Z_{ij,t}^{(d)} + \beta_{u_i}\, Z_{ij,t}^{(u_i)} + \beta_{u_j}\, Z_{ij,t}^{(u_j)} + \beta_{net}\, Z_{ij,t}^{(net)}\Big). \tag{33}
$$

3.5 Reduced-Form Theoretical Model

While the multistage model is much more realistic and yields a richer, more credible interpretation, its coefficients, compared to the traditional model, are jointly shaped by three factors: the data concept(gross vs.

value added), demand system(Marshallian vs. Hicksian), and the network architecture(upstream/downstream links vs. bilateral flows). Here I present a simplified model by collapsing it to a simplified one-border reduced form model. Specifically, I assume that all trade flows happen between bilateral countries and transit does not happen.

$$B_{ij} = v_i \tau_{ij} \tag{34}$$

This assumption is clearly counterfactual: The entire reason for using value added trade flows is to avoid the double counting in the global value chain, but the one-border assumption denies the existence of the multi-stage reality.

However, this simplification can be beneficial. It can deliberately switch off the impact of network architecture by collapsing the production network to simple dyad, thereby eliminating the network's influences on the trade frictions. At the same time, it can also provide a clean theoretical contrast to Marshallian estimates, clarifying the role of compensated versus uncompensated responses. While empirically separating the income effect from the de-duplication effect is not attained in this study, the reduced form model is still a powerful analytical tool.

I now derive the reduced gravity model based on (34)'s one-border restriction. Define

$$VA_i = \sum_j VA_{ij}, \quad VA_W = \sum_i VA_i, \quad w_i = \frac{VA_i}{VA_W} \tag{35}$$

where VA_i represents the total value-added exports originating in country i, VA_W is the world total value-added exports, and w_i is the origin i's share of world value-added exports.

Plugging (34) and into (18), I have

$$VA_{ij} = v_i^{2-\sigma} P_j^{\sigma} \tau_{ij}^{1-\sigma} \tag{36}$$

Plug (12) and (35) into (36), I have

$$VA_{ij} = w_i E_j \left[\tau_{ij}^{1-\sigma} P_j^{\sigma-1} v_i^{2-\sigma} w_i^{-1}\right] \tag{37}$$

Solving for the bracket:

$$\tau_{ij}^{1-\sigma} P_j^{\sigma-1} v_i^{2-\sigma} w_i^{-1} = \tau_{ij}^{1-\sigma} (P_j/v_i)^{\sigma-1} \frac{v_i}{w_i} \tag{38}$$

Define $\Psi_i = \frac{v_i}{w_i}$ and plug it back to the gravity equation, I have

$$\tau_{ij}^{1-\sigma} (P_j/v_i)^{\sigma-1} \frac{v_i}{w_i} = \tau_{ij}^{1-\sigma} (P_j/v_i)^{\sigma-1} \Psi_i \tag{39}$$

Plugging (39) into (37), I have

$$VA_{ij} = w_i E_j \Psi_i \left(\frac{\tau_{ij}}{P_j/v_i}\right)^{1-\sigma}$$

Rearrange the formula, I have

$$VA_{ij} = \frac{VA_i}{VA_W} E_j \left(\frac{\tau_{ij}}{P_j/v_i}\right)^{1-\sigma} \Psi_i, \quad \Psi_i = \frac{v_i}{w_i} \tag{40}$$

The final gravity equation can be interpreted through intuition. The $\frac{VA_i}{VA_w}$ term and E_j shows that the bigger the export's global footprint or the importer's compensating spending, the larger the bilateral flow. However, trade diminishes with higher bilateral cost τ_{ij}, but the effect is moderated by how costly all other sources are to $j(P_j)$ and how costly it is for i to reach anybody(v_i). The Ψ term further distinguishes a technologically efficient but small country from an equally efficient giant. It preserves the possibility that two origins with identical w_i but different v_i ship different amounts of VA.

This model marks a clear departure from traditional gravity models, which usually incorporate the gross output terms Y_i and Y_j. In my model, however, these terms no longer explicitly appear, as all revenue flows are captured by the minimized expenditure E_j, which, according to (12), coincides with the CES price index P_j when the utility is normalized to 1. Instead of summing the gross exports as traditional gravity models do, I aggregate the value-added shipments across infinitely many production stages via the Leontief-inverse cost kernel $B = (I - T)^{-1} - I$, where each element B_{ij} reflects direct, one-hop, two-hop and higher-order iceberg trade costs weighted by domestic VA shares v_i.

As previously discussed, this model's departure from the traditioanl model stems from the combined effect using value-added data to eliminate double-counting and adopting a Hicksian foundation to isolate pure substitution effects. While it is empirically challenging to separate the two effects, it is possible to theoretically quantify the impact of eliminating the income effect.

Under the one-border restriction $B_{ij} = v_i\tau_{ij}$, consider a uniform proportional increase in iceberg costs,

$$d \ln \tau_{ij} = \delta > 0 \quad \forall i, j.$$

The Hicksian value-added flow satisfies

$$VA_{ij}^H = \frac{VA_i\, E_j}{VA^W}\Big(\frac{\tau_{ij}}{P_j/v_i}\Big)^{1-\sigma}\Psi_i,$$

where E_j is the compensating expenditure (utility held constant), so

$$d^H \ln E_j \;=\; 0.$$

Taking logarithms and totally differentiating gives

$$\begin{aligned} d^H \ln VA_{ij} &= (1-\sigma)\, d\ln\tau_{ij} - (1-\sigma)\, d\ln\Big(\tfrac{P_j}{v_i}\Big) + d^H \ln E_j \\ &= (1-\sigma)\, d\ln\tau_{ij} + (\sigma-1)\, d\ln P_j + \underbrace{d^H \ln E_j}_{=0} \\ &= -(\sigma-1)\,\delta \;+\; (\sigma-1)\, d\ln P_j. \end{aligned} \tag{41}$$

Hence the Hicksian elasticity is

$$\epsilon_{ij}^H \;=\; \frac{d^H \ln VA_{ij}}{\delta} \;=\; -(\sigma-1) \;+\; (\sigma-1)\,\frac{d\ln P_j}{\delta}.$$

Under $B_{ij} = v_i\tau_{ij}$ the CES price index $P_j = [\sum_i (\frac{VA_i}{VA_W})\, v_i^{1-\sigma}\, \tau_{ij}^{1-\sigma}]^{\frac{1}{1-\sigma}}$ satisfies Anderson and Van Wincoop (2003)

$$d\ln P_j \;=\; \tfrac{1}{2}\,(1-w_j)\,\delta, \qquad w_j \equiv \frac{VA_j}{VA^W}.$$

Substituting into (41) yields

$$\epsilon_{ij}^{H} = -(\sigma - 1)\Big[1 - \tfrac{1}{2}(1 - w_j)\Big] = -\frac{\sigma - 1}{2}\,(1 + w_j).$$

By the Slutsky identity for any normal good,

$$\epsilon_{ij}^{M} = \epsilon_{ij}^{H} \ + \ \frac{d \ln E_j}{\delta},$$

where the *income effect* $\frac{d \ln E_j}{\delta}$ has the same sign as the substitution effect.

A uniform cost shock also implies

$$d \ln E_j \ = \ d \ln P_j \ = \ \tfrac{1}{2}(1 - w_j)\,\delta > 0.$$

Hence

$$\epsilon_{ij}^{M} = \epsilon_{ij}^{H} + \tfrac{1}{2}(1 - w_j)\,\delta,$$

showing the uncompensated elasticity is strictly more negative by $\frac{1}{2}(1 - w_j)\,\delta$

Crucially, this gap gives a clear measure of how much standard gravity elasticities are inflated by omitted income effects. The empirical results will confirm that the Hicksian approach indeed lowers estimated elasticities, demonstrating its necessity for bias correction. However, because using VA flows inherently eliminate double-counting, the "de-duplication" channel and the Hicksian income-effect channel operate simultaneously in my regression and cannot be separated. Consequently, although the results can offer suggestive support for the model's completeness, rigorously establishing the sufficiency requires decomposition of these two effects.

3.6 Reduced-form Empirical Model

I now construct the poisson pseudo maximum likelihood empirical framework for my reduced-form gravity model

The observed VA flow deviates from theoretical predictions because of measurement error, sectoral aggregation noise, and omitted bilateral frictions. I capture all this iwth a multiplicative error $u_{ij,t} > 0$ Therefore

$$VA_{ij,t} = VA_{ij,t}^{T} \times u_{ij,t} \tag{42}$$

where $VA_{ij,t}^{T}$ represents the theoretical VA flows without the measurement errors errors, and is equal to the VA term in the theoretical model.

Log linearize the original theoretical framework and plugging (42), I have

$$\ln VA_{ij,t} = \ln \frac{VA_{i,t}\,E_{j,t}}{VA_{W,t}} + (1 - \sigma)\big[\ln \tau_{ij,t} - \ln P_{j,t} + \ln v_{i,t}\big] + \ln \Psi_{i,t} + \varepsilon_{ij,t}.$$

I now group the origin-specific time-varying terms:

$$\phi_{i,t} \equiv \ln VA_{i,t} + \ln \Psi_{i,t} + (1 - \sigma) \ln v_{i,t} - \ln VA_{W,t}$$

and destination-specific time-varying terms:

$$\psi_{j,t} \equiv \ln E_{j,t} - (1 - \sigma) \ln P_{j,t}$$

Plugging these terms back to the log-linear equation, I have

$$\ln VA_{ij,t} = \phi_{i,t} + \psi_{j,t} + (1-\sigma)\ln \tau_{ij,t} + \varepsilon_{ij,t} \tag{43}$$

Given

$$VA_{ij,t} \sim \text{Poisson}\big(\mu_{ijt}\big)$$

I have

$$\mu_{ijt} = \exp\left(\phi_{i,t} + \psi_{j,t} + (1-\sigma)\ln \tau_{ij,t}\right)$$

Now I impose the mean-independence normalization, which delivers consistent quasi-maximum-likelihood estimates even when the true error distribution is unknown(Gourieroux et al., 1984) and avoids the heteroskedasticity bias of log-OLS highlighted by Silva and Tenreyro (2006).

$$\mathbb{E}[\exp(\varepsilon_{ij,t}) \mid X_{ij,t}] = 1 \tag{44}$$

where $X_{ij,t}$ are all the regressors and fixed-effect dummies.

Given (44) and (42), I can derive

$$\mu_{ij,t} = \mathbb{E}\big[VA_{ij,t} \mid X_{ij,t}\big] = \exp\Big(\phi_{i,t} + \psi_{j,t} + (1-\sigma)\ln \tau_{ij,t}\Big). \tag{45}$$

Incorporating (47) into (45) to replace the iceberg trade cost term, I have

$$\mathbb{E}\big[VA_{ij,t} \mid X_{ij,t}\big] = \exp\Big(\phi_{i,t} + \psi_{j,t} + \sum_k \underbrace{(1-\sigma)\delta_k}_{\tilde{\delta_k}} D^k + \underbrace{(1-\sigma)\gamma}_{\tilde{\gamma}} \ln d_{ij} + \underbrace{(1-\sigma)\lambda}_{\tilde{\lambda}} T_{ij}\Big).$$

Therefore, the final PPML empirical model is

$$\mathbb{E}\big[VA_{ij,t} \mid X_{ij,t}\big] = \exp\Big(\phi_{i,t} + \psi_{j,t} + \sum_k \tilde{\delta_k} D^k + \tilde{\gamma}\ln d_{ij} + \tilde{\lambda} T_{ij}\big) \tag{46}$$

Because PPML with high-dimensional fixed effects automatically enforces the multilateral-resistance structure, it is fully consistent with the underlying theory while remaining robust to zeros and heteroskedasticity(Fally, 2015).

If intermediate use is absent ($\alpha_i = 0\,\forall i$) then $\lambda_{ij}^{i\mapsto j} = 1$ and all other λ's vanish; (31) collapses exactly to the one-border benchmark in Eq. (46). Hence the multistage specification *nests* the baseline both theoretically and empirically.

4 Empirical Results

4.1 Data

For the value-added component, I draw on the Asian Development Bank's Multiregional Input-Output(MRIO) tables, which provides final demand and intermediate-use data for 72 countries at current price through 2017 to 2023. My sample is restricted to the 14 Asian economies that ultimately became the RCEP members: China, Japan, Korea, Australia, New Zealand and the ten ASEAN signatories. I excluded Myanmar because Asian Development Bank's MRIO tables omitted Myanmar, and no alternative IO dataset reconciles both the full 2017-2023 period and our sectoral breakdown. For instance, OECD's ICIO only extends to 2020, and has a different ISIC-Rev.4 Classification that would misalign with Asian Development Bank's categories. However, Myanmar's own trade footprint is minimal: in 2019 its combined exports and imports of goods and services totaled just U.S. $41.7 billion, only about 1.8 percent of roughly U.S. $2.3 trillion in intra-RCEP merchandise trade that year. Therefore, omitting MMR has a negligible effect on our gravity estimation.

I selected trade data from RCEP countries because it provides a suitable, theory-driven test bed for empirical estimation. While the RCEP agreement entered into force on January 1, 2022, in fact, these fourteen economies had already woven a dense web of trade and investment linkages long before 2022. Since the late 1990s, ASEAN drove five "ASEAN + 1" FTAs—ACFTA (2005), AJCEP (2008), AKFTA (2010), AANZFTA (2010) and AICECA (2010)—and by November 2021 each RCEP member had on average signed over 14 bilateral RTAs and six plurilateral RTAs with fellow ASEAN + 6 partners. These successive agreements helped push intra-regional imports to 50 percent of total imports by 2018—an increase of ten percentage points since 1990. Moreover, intra-RCEP merchandise flows reached about US$2.3 trillion in 2019, with manufactured goods (electrical machinery, chemicals, metals) and minerals dominating the value of cross-border shipments, a clear signal of mature, integrated supply chains and deep value-added networks well before RCEP's entry into force. Therefore, the bloc sits at the epicenter of Factory Asia, spans the full income spectrum, and entered a landmark mega-FTA midway through the sample, offering a natural experiment in tariff simplification and rules-of-origin harmonization. These features make RCEP both representative of modern global value chains and rich enough to stress-test the new model's capacity to handle zeros, heterogeneous partners and shifting policy regimes.

The estimation of trade cost in the one-border assumption model follows Anderson and Van Wincoop (2003) framework, specifying

$$\ln\tau_{ij} = \sum_k \delta_k D^k + \gamma \ln d_{ij} + \lambda \ln T_{ij} \tag{47}$$

where D^k are the dummy variables capturing geographic and cultural adjacency such as contiguity, common language, and colony history, d_{ij} is the geographical distance between countries i and j, and T_{ij} is the bilateral tariff term, δ_k, γ, and λ are all parameters of estimation.

The binary indicators are sourced from CEPII's GeoDist database. For tariffs, we are mindful that RCEP preferential rates are not universally utilized. Accordingly, at the HS-6 level we construct an "effectively applied" tariff as the minimum of the MFN applied rate and the RCEP preferential rate for each product–dyad–year.

4.2 Summary Statistics

Using annual dyad level data for the fourteen RCEP economies from 2017 to 2023, I initially collected 1372 observations. After excluding observations with missing or negative values, the final sample contains 1282 observations. To illustrate the structure of the panel data used in this study, the table below shows a random five-row excerpt of the bilateral value-added trade flows between RCEP member economies from 2017 to 2023.

Year	Exporter	Importer	Distance (km)	Contiguity	Common_Language	Colony	Tariff (%)	VA_flow (USD mn)
2019	CHN	PHL	2850.32	0	0	0	2.01	26237.96
2020	AUS	AUS	1042.82	0	0	0	–	1044713.00
2018	LAO	CHN	2778.65	1	0	0	8.51	2062.80
2017	VNM	CHN	2330.80	1	0	0	5.97	11070.29
2018	IDN	KOR	5291.68	0	0	0	7.16	6717.49

Table 1: Random 5-row Sample (Long Form) of RCEP Panel Data

Each observation corresponds to a unique exporter–importer–year triple and includes both trade-cost variables (distance and tariffs) and standard gravity dummies (contiguity, common language, and colonial ties).

To complement this structural snapshot, the following table reports the summary statistics for the key quantitative variables used in this empirical estimation: value added flows, bilateral distance, and applied tariff rates.

Variable	Mean	SD	Min	Max	Between SD	Within SD
VA_flow_total (USD mn)	128 992	1 064 286	-5 259	16 227 479	1 056 993	142 693
Distance (km)	3 792	2 943	9.56	11 041	2 949	0
Tariff_rate (%)	5.01	4.85	0	38.6	4.62	1.53

Table 2: Descriptive Statistics (RCEP dyads, 2017–2023)

The standard deviation of VA flow(1064286) is significantly larger than the mean of VA flow(128992), showing that the data is extremely skewed. The minimum value of the VA flow is negative, which is caused by statistical error: when estimating the technical coefficients and then enforcing exact row/column totals via least-squares or entropy-based balancing, random estimation errors and the imposition of marginal constraints can "push" some cells below zero(Ten Raa & Van Der Ploeg, 1989). However, considering that these negative values merely occupy 0.6% of the total VA flow data, I simply drop them in the following empirical estimation. The distance variable has a within-group standard deviation of 0, and a between-group standard deviation of 2949, implying that geography doesn't change over time, so my distance-elasticity identification comes purely from cross-sectional variation. The tariff variable has a mean of 5.01%, standard deviation of 4.85%, minimum value being 0,and maximum value being 38.6%, implying that average protection is modest but with some spikes. The between-group standard deviation and within-group standard deviation further shows that most tariff variation is cross-sectional, but there is non-trivial time variation which I can exploit under my exporter-year/importer-year FE setup. Overall the descriptive statistics shows the variation in tariff protection levels skewness in value added flows, further motivating the use of PPML estimation in the following sections.

Before turning to the empirical results, the table below summarizes the interpretation of all model coefficients used in both the baseline and decomposed gravity specifications.

Coefficient	Interpretation
ln(dist)	Elasticity of value-added trade flows with respect to bilateral distance between exporter and importer.
dist_{ik}	Effect of geographic distance on the first-stage leg of the GVC from the exporter (i) to intermediate country (k).
dist_{kj}	Effect of geographic distance on the second-stage leg of the GVC from intermediate node (k) to the final importer (j).
dist_{kl}	Effect of geographic distance on intermediate-to-intermediate trade flows within the GVC, from k to l.
tariff	Impact of overall applied tariff rates on total value-added trade flows.
tariff_{ik}	Effect of tariff rates on the upstream leg of the value chain from exporter (i) to intermediate node (k).
tariff_{kj}	Effect of tariff rates on the mid-chain leg from intermediate node (k) to final destination (j).
tariff_{kl}	Effect of tariffs applied between two intermediate nodes ($k \to l$) on VA trade flows through that path.
contig	Captures whether the exporter and importer share a contiguous land border.
comlang	Indicates whether the trading partners share an official or primary language.
colony	Reflects whether a historical colonial relationship exists between trading partners.

Table 3: Conceptual Interpretation of Estimated Coefficients

This table serves to clarify the economic meaning of each regressor and its expected directional effect on value-added trade flows.

4.3 Baseline Estimation

Before estimating the full multi-stage framework, I first establish a baseline using the reduced-form model. In this way I can conduct a direct sidfe-by-side comparison with the traditioanl gross-trade gravity model, showing the impact of isolating the combined impact of two major innovations: eliminating the double-counting by using value-added flows, and removing income effects by using a Hicksian dual.

To be more specific, I conducted a regression based on the reduced form empirical model developed in (46), and another regression based on traditioanl PPML gravity model, like the one used by Fally (2015), so that I can directly compare the elasticities with dozens of prior studies. The results are shown below.

	(1) Value-Added	(2) Traditional
ln(dist)	-1.689^{***}	-1.895^{***}
	(0.088)	(0.100)
Contiguity	-1.611^{***}	-1.771^{***}
	(0.233)	(0.273)
Common language	-0.067	-0.119
	(0.280)	(0.320)
Colonial tie	0.866	1.169
	(0.533)	(0.764)
Tariff rate	-0.166^{**}	-0.260^{***}
	(0.052)	(0.057)
Adj. Pseudo-R^2	0.9885	0.9909
Squared Corr.	0.9996	0.9999

Notes: Poisson Pseudo-MLE (PPML) estimated with exporter-year and importer-year fixed effects; standard errors clustered by `pair_id` in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$.

Table 4: PPML Estimates: Value-Added Absorption vs. Gross Trade Volume

Shown by the results, the distance is highly significant and negative in both models. In my VA-embedded reduced-form PPML model, the coefficient is -1.689, yet the traditional PPML estimation gives -1.859. This discrepancy can be partly explained by the double-counting issue raised by Koopman et al. (2014). Specifically, official trade statistics are measured in gross terms, including both intermediate and final products, so they double count the value of intermediate goods that cross international borders more than once. Because the gross flows record "origin to third country", "third country to destination" as two separate crossings, the distance cost gets applied twice or more times, so the distance elasticity is overestimated. The value added absorption, however, only credits the final destination once, effectively de-deuplicating those multi-stage legs.

Another resistance coefficient, tariff, also shows similar differences between the value-added estimation and traditional estimation. While the tariff coefficient in both models are negative and significant, the tariff elasticity in my value-added model is -0.166, much smaller than that in the traditional model, which is -0.26. This discrepancy can also be explained by the previous reason, that when intermediate inputs cross borders multiple times, each crossing incurs a tariff charge, so the tariff cost is magnified. Gross trade PPML therefore picks up these stacked tariff hits, whereas the value-added model eliminates intermediate duplications and retains only the final-stage tariff, resulting in a smaller estimated coefficient. Another potential explanation is the difference in the model derivation method. Traditional models use a Marshallian method, which produces an uncompensated price shock, including both substitution and income effects. A Hicksian approach, as shown in the theoretical development, nets out the income effect, and isolates pure substitution effect at constant purchasing power, therefore having a less negative coefficient.

The contiguity coefficients are highly significant but negative(-1.611 for VA model, and -1.77 for traditional model), implying that sharing a border actually reduces bilateral trade. This contrasts the usual gravity prediction a positive border effect as neighbors face lower transport costs, fewer information frictions, and more cultural affinity. However, this counterintuitive outcome is not unprecedented: Greaney and Kiyota (2020) also found similar empirical result, and they attributed it to statistical artifacts. However, I can offer a more compelling explanation that lies in the structure of the global value chain. Specifically, many neighbor-to-neighbor shipments are not consumed locally but instead pass through regional transit and re-export hubs that provide services to facilitate the movement of intermediate goods within the region and across the regions where international production network is intense(Jones, Kobza, Lowery, & Peters, 2020).

These hubs, often countries with favorable trade policies like free zones and robust infrastructure, act as central nodes. Specifically, raw materials or intermediate goods from an origin country are first shipped to transit hub, and from there, they are re-exported to all over the world. In a gross trade model, the trade flows between the origin country and transit hubs seem to be significant, and trade flows between neighboring countries become minimal. Since major transit hubs build strong connections with countries across large geographical regions, significant trade flows between an origin country and transit hub usually happen in countries that are not contiguous. The negative contiguity effect in the Va-gravity arises because only part of the value added is recorded when intermediate products are shift from origin to transit hubs, and the model ultimately attributes the final value added to the country of final consumption, which, after being re-exported by the transit hubs, are often countries not contiguous to origin country. To provide a real world example for better illustration, Indonesia is the world's largest palm oil producer and exporter, generating over 47 million tonnes in 2023. However, more than 50% of Indonesia's crude palm oil(CPO) is exported in unprocessed formObidzinski (2013), and a key destination is Pasir Gudang in Johor, Malaysia, where it is refined. After refining, Malaysia re-exports the palm oil to other countries like India, Kenya, and Netherland. This case provides a real-world example that supports the theoretical argument.

Common-language and colonial-tie dummies turn out statistically indistinct mainly because exporter-year and importer-year fixed effect have already soak up almost all variations those cultural links would explain. Moreover, in RCEP< there also little time-varying bilateral variation in shared language or colonial history. The adjusted pseudo-R^2 and R^2 of both models exceed 0.98, indicating high explanatory power of high dimensional fixed effect.

4.4 Multistage Estimation

Building on the multistage structural-gravity framework, I estimated an augmented PPML regression that explicitly decomposes each trade-cost variable into its sequential legs—$dist_i k$, $dist_k j$, $dist_k l$ and $tariff_i k$, $tariff_k j$, $tariff_k l$—while retaining the standard controls (contiguity, common language, colonial ties) and high-dimensional exporter-year and importer-year fixed effects. The full set of coefficient estimates, standard errors, significance levels, and goodness-of-fit statistics for this multistage specification are presented in the table below.

	Estimate	Std. Error	z value	Pr(> |z|)
ln(dist)	−0.5035*	0.2059	−2.4451	0.0145
dist_{ik}	0.3140**	0.1212	2.5906	0.0096
dist_{kj}	−0.2962*	0.1272	−2.3294	0.0198
dist_{kl}	−0.6042***	0.0439	−13.7512	$< 2.2 \times 10^{-16}$
tariff	−0.0433*	0.0210	−2.0552	0.0399
tariff_{ik}	−0.0097	0.0180	−0.5414	0.5882
tariff_{kj}	0.1114**	0.0376	2.9662	0.0030
tariff_{kl}	−0.1393**	0.0435	−3.2032	0.0014
contig	−0.2642*	0.1056	−2.5025	0.0123
comlang	−0.1867	0.1390	−1.3427	0.1794
colony	−0.0055	0.2761	−0.0199	0.9841
Adj. Pseudo-R^2				0.9973
Squared Corr.				0.9988

Notes: Poisson Pseudo-MLE estimated with exporter-year and importer-year fixed effects; standard errors clustered by `pair_id`. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 5: PPML Regression with Distance–Tariff Interactions and Contiguity

Accoding to the results, the overall distance coefficient is significant and negative(-0.5035), capturing the aggregate transport cost and time-delay across all legs of the journey. The $dist_{kl}$ oefficient, reflecting the cumulative multi-border costs, has the largest negative value. The $k \to l$ link often involves two border crossings(exit and entry), extra handling, time delays and regulatory checks. These compounded frictions make the inter-hub leg the most distance-sensitive coefficient, therefore showing steepest negative value. The $dist_{kj}$ has a coefficient of -0.296, representing the standard delivery friction. Once goods leave the first hub k for the final market j, there is no further value-adding stage, so it's pure transportation. Thus the usual distance-decay effect dominates. A counterintuitive coefficient here is $dist_{ik}$, which is positive. It may reflect the quality-upgrading at distant hubs. When the first-leg haul from exporter i to hub k is longer, it often means k is a high-end processing center with advanced machinery or skilled labour. Shippers are willing to bear extra transport costs because they obtain a larger value-added upgrade at k. That boost in product value more than offset the extra miles, yielding a net positive elasticity.

For the tariff coefficients, it can be noticed that $tariff_{kl}$ has the most negative value. This is because the $k \to l$ sits in the middle of a multi-leg chain. duties here compound with handling and transportation frictions. Higher tariff therefore disproportionately discourage firms from using this shipment point. Another potential explanation is that many free trade agreements offer preferential rates only for final imports, not for intermediate transfer between hubs. So when $k \to l$ rises, there's no easy way for firms to reroute or claim origin benefits, and they simply cut shipments on that route. The $tariff_{ik}$ term has a minimal and non-significant coefficient. This occurs because origin-to-hub tariffs are frequently low. Specifically, duties charged on imports into k are later rebated when goods are re-exported. That mechanism neutralizes the direct tariff pull on this leg, rendering the coefficient statistically not significant in my model. A counterintuitive coefficient is $tariff_{kj}$, which is significant and has a positive value(0.111). This can be explained by re-export avoidance and rerouting effect. When the tariff between the first hub k and the final market j rises, firms respond by increasing shipments, doing additional assembly, finishing, or transformation in k—so that the good "originates" in k and qualifies for lower or zero duties under regional rules. That extra work in k shows up as higher VA absorption in k (and hence in my VA measure for the i→k chain), yielding a positive $tariff_{kj}$ elasticity

5 Robustness Check

For comparibility, I also report a conventional log-linear OLS specification as a benchmark robustness check. Running OLS allows me to verify that the headline distance and tariff elasticities are not artifacts of the Poisson quasi-likelihood, while making transparent the distortions introduced when zeros are dropped and heteroskedasticity is ignored. The divergence can clearly show the instability under the OLS model are mitigated by the PPML.

	(1) Value-Added (OLS)	(2) Gross Trade (OLS)
ln(dist)	-1.209^{***}	-1.408^{***}
	(0.148)	(0.187)
Contiguity	0.080	$0.755^{\dagger}$
	(0.281)	(0.419)
Common language	0.043	-0.034
	(0.212)	(0.278)
Colonial tie	-1.594^{***}	-2.180^{***}
	(0.404)	(0.600)
Tariff rate	-0.021	-0.012
	(0.014)	(0.018)
Adj. R^2	0.9079	0.8681
Within R^2	0.5661	0.4665
RMSE	0.716	1.091

Notes: Ordinary Least Squares on ln of the dependent variable. Exporter and importer fixed effects (and year fixed effects if included). Robust (clustered) standard errors in parentheses.
Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$, $^{\dagger}p < 0.15$.

Table 6: Log-Linear OLS Estimates: Value-Added vs. Gross Trade

In the log-linear OLS models, the core directional results line up with my PPML baseline: distance remains strongly negative(-1.21 in the VA model, and -1.41 in the traditional model). The difference in the distance coefficient of the two models mirrors the "double counting" bias in gross flows, as mentioned before. However, several differences between log-linear estimation and PPML estimation emerges. Under log-linear OLS, the border dummy is small and positive(0.08 in VA model and 0.76 in traditional model), but is statistically not significant in my model. This contrasts with my two PPML estimation results, where contiguity coefficient is large, negative and significant. The tariff effect is attenuated further and lost significant effect. Both OLS estimations also show significant, but large and negative coefficients for colonial dummy, which counters to gravity intuition because historical colonial relationships are generally expected to strengthen trade links through shared institutions, language, and established economic networks. The divergence between PPML and log-linear OLS estimates stems primarily from heteroskedasticity. Additionally, excluding zero flows in the log specification further contributes to this discrepancy.

To test the heteroskedasticity of the data, I employ two complementary diagnostics. First I inspect a scale-location plot, which graphs the square root of absolute residuals against fitted $\log(VA)$. This stabilizes the vertical scale and makes systematic changes in residual dispersion easier to detect.

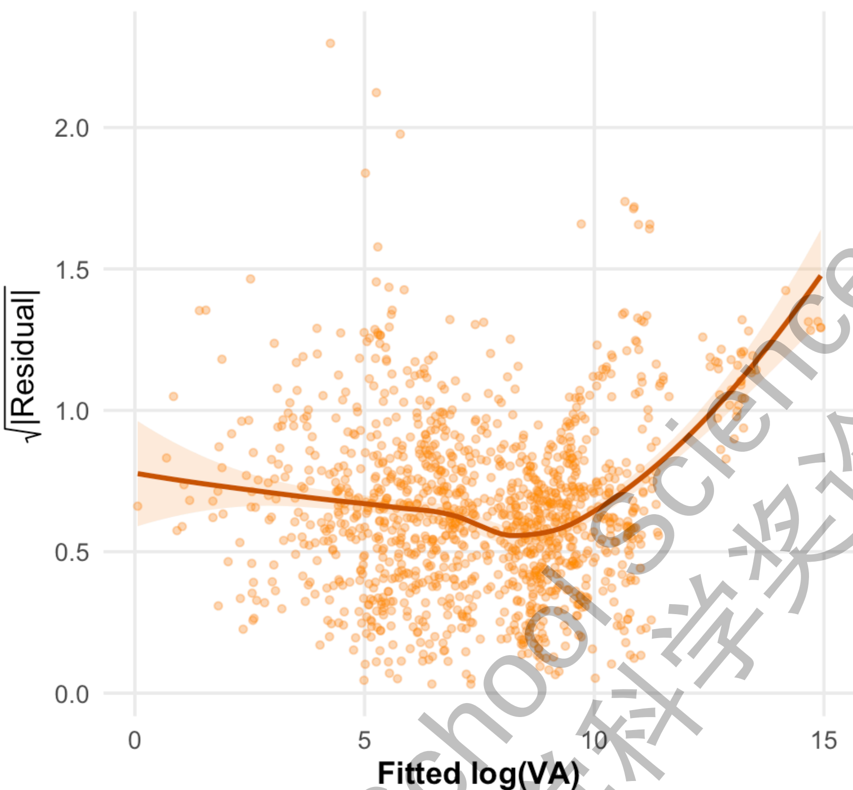

Figure 1: scale-location plot

Under homoskedasticity the smoothed trend should be approximately flat and the cloud of points roughly horizontal. However, according to figure ?? for fitted $\log(VA)$ below about 9 the square root of residual values cluster around modest, nearly fat band, but starting near 10 the smooth curve turns shaprly upward and vertical spread widens. This monotonic rise in residual dispersion at higher fitted values signals that large bilateral flows exhibit disproportionately greater variance.

Furthermore, I run the Breusch-Pagan test, a formal Lagrange-Multiplier test that regresses the squared residuals on the fitted values to evaluate whether error variance depends on the explanatory variables. With a p-value of 9.3×10^{-22}, the test rejects homoskedasticity, confirming that the variance of the log-errors is not constant.

The heteroskedastic environment explains the anomalies I observe in the OLS robustness estimate. The contiguity coefficient flips from negative to positive, showing that small, low-variance flows are overweighted once zeros are dropped and logs compress large flows. The colonial tie coefficient becomes implausibly large and negative because high-variance influential dyads derive unstable estimates. Tariff elasticities attenuate toward zero as the model under-penalizes misfit for high-variance, high-volume observations.

PPML directly models trade in levels, keeps zero flows, and remains consistent under general forms of heteroskedasticity; as a result it avoids the mis-weighting, sign flips, and attenuation problems that afflict the log-OLS estimates, hence I adopt PPML as my primary estimation approach.

I now support my explanation of the negative value of contiguity coefficients. As mentioned, the counterintuitive sign of contiguity dummy can be explained by the transit/re-export mechanism. Among the 14

RCEP economies, Singapore's container port set a record 2023 throughput of about 39.0 million TEUs, an all-time high and a 4.6% year-on-year increase, indicating sustained expansion of transshipment capacity. Furthermore, Malaysia's principal gateway Port Klang handled 14.64 million TEUs in 2024 (after 2023), aiming for further growth and representing nearly half of Malaysia's total container volume, signalling Malaysia's own role as a complementary distribution hub across the Strait. To isolate the influence of these corridors I re-estimate the PPML model after excluding all Singapore-Malaysia dyads.

	Baseline	Excluding Transit Hub
Contiguity coefficient	-1.611^{***}	-1.325^{***}
Standard error	(0.233)	(0.254)

Table 7: Effect of Dropping Transit Hub on Contiguity Coefficient

Comparing the results, it is clear that dropping the Singapore-Malaysia attenuate the negative coefficient by approximately 20%, despite the coefficient remaining negative. This economically meaningful shift is precisely the transit hub explanation predicts: eliminating the region's principal re-export corridors diminishes the understatement of neighbor value-added absorptions. But considering that other transit or staging routes still exist, the coefficient still remains negative even after removing two big transit hubs.

To support my explanation of the positive $dist_{ik}$coefficient in the multi-stage model, I refine my PPML multistage model by allowing that distance elasticity to differ with exporter technological intensity. Specifically, I introduced a binary indicator $hightech_i$ that equals 1 for origin countries whose R&D efforts and innovation capacity exceed the region's median. Of the fourteen countries I chose, I classify China, Japan, Korea, Singapore, Australia, and New Zealand as high-tech because their $\frac{R\&D}{GDP}$ ratio is well above the approximate RCEP median of about 1.5%, and the remaining eight countries (Brunei, Cambodia, Indonesia, Laos, Malaysia, Philippines, Thailand, Vietnam) as lower-tech. I therefore estimate

$$\mathbb{E}[VA] = \exp(\ldots + \beta_{ik} dist_{ik} + \omega\,(dist_{ik} \times hightech_i) + \ldots)$$

The results are shown below

Variable	Estimate	Std. Error	z value	$\Pr(>\lvert z \rvert)$
ln(dist) (aggregate)	-0.5197^{***}	0.1427	-3.6415	0.00027
$dist_{ik}$	0.2904^{**}	0.0917	3.1678	0.00154
$dist_{kj}$	-0.1774^{*}	0.0874	-2.0296	0.04240
$dist_{kl}$	-0.6403^{***}	0.0318	-20.1481	$< 2.2 \times 10^{-16}$
$dist_{ik} \times hightech_i$	0.1098^{*}	0.0525	2.0918	0.03646

Notes: Poisson Pseudo-Maximum Likelihood estimates with exporter-year and importer-year fixed effects; standard errors clustered by country pair. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 8: PPML Regression: Distance Segments with High-Tech Interaction

The interaction coefficient on $dist_{ik} \times hightech_i$ is positive and statistically significant($\beta = 0.110, p < 0.05$). Economically, this supports an "upstream value densification" mechanism mentioned early: high-tech exporters can embed more value per unit before goods enter the hub network (through advanced component fabrication, design, testing), so a longer initial route does not proportionally deter shipments and may coincide with consolidating higher value content. On the other hand, lower-tech origins lack the same capacity to offset additional first-leg frictions, leaving them with the baseline (smaller) effect.

Finally, I present robustness check to support the rerouting and re-export avoidance mechanism used to explain the counterintuitive result if $tariff_{kj}$. In the multistage setup, any $i \to j$ flow is a share-weighted sum of routes, so I can use IO-based proxies for the route weights, which are already explained in the multistage model part, to identify the countries that most intensively act as intermediates across all pairs. I therefore construct an intermediate-share index H_k that endogenously ranks the hubs:

$$H_k = \frac{\sum_{(i,j):\,(i,k,j)\in\mathcal{T}} s_{ikj}}{\sum_{k'\in\mathcal{K}} \sum_{(i,j):\,(i,k',j)\in\mathcal{T}} s_{ik'j}}.$$

where $\mathcal{K}$ is the set of all candidate intermediate countries, $\mathcal{T}$ is the set of admissible ordered triples(i,k,j) with $i \neq k$, $k \neq j$, $i \neq j$, k is the summation index ranging over all potential intermediates in $\mathcal{K}$.

Transit	H$_k$
SGP	0.2105
THA	0.1799
MYS	0.1794

Table 9: Top three transit coefficients by H_share

After ranking all the countries based on H_k. I take the top three countries, which are Malaysia, Singapore and Thailand, as the major transit hubs and remove them from my datasets.

With the reduced data, I run the multistage regression, where the results are shown below

	Estimate	Std. Error	z	Pr($>|z|$)
ln(dist)	-0.5699^{*}	0.2455	-2.3213	0.0203
dist$_{ik}$	0.3680^{**}	0.1273	2.8920	0.0038
dist$_{kj}$	-0.1633	0.1506	-1.0843	0.2785
dist$_{kl}$	-0.6717^{***}	0.0565	-11.8942	$< 2.2 \times 10^{-16}$
tariff	-0.0263^{*}	0.0161	-1.6351	0.1022
tariff$_{ik}$	0.0013	0.0120	0.1061	0.9155
tariff$_{kj}$	0.0566^{*}	0.0343	1.6494	0.0991
tariff$_{kl}$	-0.0872^{**}	0.0425	-2.0486	0.0405
contig	-0.1856^{*}	0.0949	-1.9556	0.0501
comlang	-0.0461	0.1489	-0.3096	0.7569
colony	-0.0910	0.2039	-0.4465	0.6553
Adj. Pseudo-R^2				0.9968
Squared Corr.				0.9985

Table 10: Multistage PPML after Hub-Filtering

Notes: Poisson Pseudo–Maximum Likelihood with exporter–year and importer–year fixed effects; standard errors clustered by country pair. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Recall that the original $tariff_{kj}$ coefficient is about +0.11, reflecting that many observed "kj" legs run through a small set of high-end transit / upgrading hubs where recorded (or nominal) tariffs coexist with value-adding processing, bonded-warehouse regimes, or duty-drawback arrangements. This produces a compositional, apparent positive association rather than a genuine pro-trade tariff effect. After dropping the top three transit hubs, the coefficient falls by roughly half to about +0.05 and is only marginally significant at 10% level, indicating that most of the earlier positive signal was concentrated in those hub routes. In other words, the attenuation from 0.11 to 0.05 shows that the positive $tariff_{kj}$ coefficient is a hub-specific routing/upgrade artifact

6 Conclusion

This study provides a robust theoretical foundation for a multi-stage, value added gravity model. Using a Hicksian approach, direct, upstream, and downstream links are successfully nested in a single CES cost function. This method provides a less biased measure of trade frictions by eliminating the potential inflation of the coefficients caused by shifts in domestic income. Furthermore, it addresses stage heterogeneity by incorporating Noguera (2012)'s decomposition method and developing a multi-stage empirical model.

Empirical estimations using data from 14 RCEP countries also present several important findings. First, the comparison between the reduced form value-added model and the traditional trade-volume model confirms that using value-added flows eliminate the redundancy and provides a more reliable map for economic activities. This correction significantly attenuate the negative effects of distance and tariff on trade suggested by the traditional model.

I also found that while the reduced-form model is tractable and elegant, its functions are limited to providing rough estimations and comparison. The main disadvantage of this model is that it still treats trade friction as a single, monolithic bilateral cost. While it successfully shows that the overall resistance is lower in the VA-Hicksian model, it cannot explain why or where in the supply chain do these frictions operate differently.

Moreover, the aggregate distance elasticity in the reduced-form model is larger than the specific elasticity for the direct $i \to j$ leg in the multi-stage model. This comparison reveals that the reduced-form model is more like a weighted "average" of all possible paths(it is not the real weighted average since that would require an empirical estimation using (18)). Because some of these indirect legs are extremely sensitive to distance, they pull the "average" friction in the reduced-form model upward. These findings further support my previous claim that the reduced-form model cannot provide a precise estimation, and that simply substituting the trade volume to value added flows in traditional gravity models is not an appropriate method.

Empirical estimation using data from the 14-economy RCEP bloc confirms that once value-added flows are used to correct for the double-counting, the negative effects of distances and tariffs on trade are significantly attenuated. Moreover, the multi-stage model reveals that these aggregate frictions are heterogeneous along the supply chain. This insight further helps to explain puzzles revealed by traditional models, such as the negative contiguity effect, which I show arises from neighboring economies acting as transit hubs that pass value downstream rather than absorbing it.

Finally, the study help to resolve puzzles remained in some gravity studies, such as the negative contiguity effect. I have demonstrated that this is because many neighboring countries are usually treated as transit hubs rather than trading partners, where values of the products are passed downstream to third markets, rather than being absorbed by the neighboring countries. This dynamic, overlooked by traditional bilateral gravity models, leads to a systematic understatement of value-added absorpotions and offers a reasonable explanation for the negative contiguity effects.

7 Discussion

In a world of escalating trade wars, such as the one happened between the U.S. and China in 2018-2019 and again in 2025, the Hicksian value-added model is a more appropriate tool for analysis. Instead of seeing the magnified effect from gross trade using traditional models, my framework provides a less biased estimate of the true tariff impact on a product's final value. This help policymakers understand the real consequences of their tariff policies, rather than being misled by inflated gross trade figures. The model is also particularly useful for analyzing how firms respond to tariff. For instance, the counterintuitive positive elasticity for $tariff_{kj}$ shows that firms engage in "re-export avoidance" by performing additional assembly or transformation in a hub country to qualify the product for lower tariffs as a new good. This provides insights for trade negotiators who need to anticipate how companies will react to new tariffs and how to prevent unintended consequences. The negative contiguity effect further supports that neighboring countries serve as transit hubs for goods that are ultimately destined for a third market. This insight can inform infrastructure planning and trade agreements, reinforcing the efficiency of transit corridors and customs procedures in major export hubs like Singapore and Malaysia.

The multi-stage model's ability to decompose trade-cost variables into different legs of the supply chain allows for more precise policy interventions. Instead of a one-size-fits-all approach, policymakers can identify and address the specific frictions that are most detrimental to trade at different stages of production. This study finds that both $dist_{kl}$ and $tariff_{kl}$ show the most negative impact on trade flows, which is likely because these legs often involve multiple border crossings, handling fees, and regulatory checks. This finding suggests that trade facilitation efforts should prioritize for goods moving between major transit hubs to maximize efficiency gains.

However, limitations exist in the study. The primary purpose of the empirical estimation of this study is to test the model's internal effectiveness and mechanics, so that using the 14 RCEP countries, which is a highly-integrated GVC sample, can be appropriate. However, it should be notice that choosing this sample can limit the generalizability of the findings as the unique characteristics of this trade bloc may not be applicable for other regions. The necessity for a larger and more generalized sample countries arises when future researches want to apply this model to study global trade policies.

The current framework operates on industry-level IO data, and therefore fails to identify firm-level dynamics, such as entry, exit, quality, and upgrading, which were emphasized by Melitz (2003). A potential research direction is to incorporate firm heterogeneity, which is already standard in traditional gravity models.

Furthermore, Hicksian foundation is a key theoretical strength of this study, as it isolates the pure substitution responses. Empirically, however, this behavioural adjustment is blended with the accounting adjustment of the "de-duplication" of intermediate crossings. Because both channels push elasticities in the same direction, the regression cannot tell how much of the coefficient drop comes from behavioral substitution and how much from the deduplication. Finer decomposition will be required to decompose the two effects.

Finally, the 2017–2023 sample period was characterized by extraordinary economic volatility, including the U.S.-China trade war, the COVID-19 pandemic, and the implementation of the RCEP agreement. While this turbulent environment offers a valuable opportunity to stress-test the model against major shocks, it also suggests that the estimated cost elasticities could be period-specific. To produce more meaningful insights, a powerful future research direction would be to leverage the multi-stage value-added gravity framework within a Difference-in-Difference methodology to rigorously evaluate the impacts of these economic shocks.

Overall, the study demonstrates that how we measure the trade fundamentally alters what we can learn from it–and, by extension, the levers policymakers choose to pull. The Hicksian value-added gravity model thus offers a more faithful, policy relevant map of the world economy in an era where goods routinely cross borders multiple times before reaching end consumers.

References

Anderson, J. E., & Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American economic review*, *93*(1), 170–192.

Antràs, P., & Chor, D. (2013). Organizing the global value chain. *Econometrica*, *81*(6), 2127–2204.

Antràs, P., & De Gortari, A. (2020). On the geography of global value chains. *Econometrica*, *88*(4), 1553–1598.

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

Baldwin, R. E., & Taglioni, D. (2014). Gravity chains: Estimating bilateral trade flows when parts and components trade is important. *Journal of Banking & Financial Economics*, *2*(2).

Cigna, S., Gunnella, V., & Quaglietti, L. (2022). Global value chains: measurement, trends and drivers. *ECB occasional paper*(2022/289).

Constantinescu, C., Mattoo, A., & Ruta, M. (2020). The global trade slowdown: cyclical or structural? *The World Bank Economic Review*, *34*(1), 121–142.

Costinot, A., & Rodríguez-Clare, A. (2014). Trade theory with numbers: Quantifying the consequences of globalization. In *Handbook of international economics* (Vol. 4, pp. 197–261). Elsevier.

Fally, T. (2012). Production staging: Measurement and facts. *Boulder, Colorado, University of Colorado Boulder, May*, 155–168.

Fally, T. (2015). Structural gravity and fixed effects. *Journal of international economics*, *97*(1), 76–85.

Fan, Z., Peng, S., & Hu, W. (2023). How does the regional comprehensive economic partnership affect the restructuring of global value chains? *China & World Economy*, *31*(3), 140–172.

Gourieroux, C., Monfort, A., & Trognon, A. (1984). Pseudo maximum likelihood methods: Theory. *Econometrica: journal of the Econometric Society*, 681–700.

Greaney, T. M., & Kiyota, K. (2020). The gravity model and trade in intermediate inputs. *The World Economy*, *43*(8), 2034–2049.

Hagemejer, J., & Mućk, J. (2025). Eu enlargements, brexit and value-added trade: A structural gravity approach. *PloS one*, *20*(4), e0299738.

Heiland, I., & Šváb, P. (2024). *Estimating gravity equations for trade in value added: A structural perspective* (Tech. Rep.). CESifo Working Paper.

Helpman, E., Melitz, M., & Rubinstein, Y. (2008). Estimating trade flows: Trading partners and trading volumes. *The quarterly journal of economics*, *123*(2), 441–487.

Iyoha, E., Malesky, E., Wen, J., Wu, S.-J., & Feng, B. (2024). *Exports in disguise?: Trade rerouting during the us-china trade war.* Harvard Business School.

Johnson, R. C., & Noguera, G. (2012). Accounting for intermediates: Production sharing and trade in value added. *Journal of international Economics*, *86*(2), 224–236.

Jones, L., Kobza, C., Lowery, F., & Peters, C. (2020). The rising role of re-exporting hubs in global value chains. *J. Int'l Com. & Econ.*, 1.

Koopman, R., Wang, Z., & Wei, S.-J. (2014). Tracing value-added and double counting in gross exports. *American economic review*, *104*(2), 459–494.

Lall, S., & Albaladejo, M. (2004). China's competitive performance: a threat to east asian manufactured exports? *World development*, *32*(9), 1441–1466.

Lebastard, L., & Serafini, R. (2023). Understanding the impact of covid-19 supply disruptions on exporters in global value chains. *Research Bulletin*, *105*.

Leontief, W. (1941). The structure of the american economy, 1919–1929 harvard university press. *Cambridge (new, enlarged edition, Oxford University Press, New York, 1951)*, *181*.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, *71*(6), 1695–1725.

Miernyk, W. H. (1965). The elements of input-output analysis. *Wholbk*.

Noguera, G. (2012). Trade costs and gravity for gross and value added trade. *Job Market Paper, Columbia University*, *4*.

Obidzinski, K. (2013, Jul). *Fact file – indonesia world leader in palm oil production.* Retrieved from https://forestsnews.cifor.org/17798/fact-file-indonesia-world-leader-in-palm-oil-production/#.Uj8Sbz82XLk

Rotunno, L., Roy, S., Sakakibara, A., & Vezina, P.-L. (2023). Trade policy and jobs in vietnam: The unintended consequences of trump's trade war.

Silva, J. S., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and statistics*, 641–658.

Stehrer, R., & Vujanovic, N. (2022). *The regional comprehensive economic partnership (rcep) agreement: economic implications for the eu27 and austria* (Tech. Rep.). FIW-Kurzbericht.

Ten Raa, T., & Van Der Ploeg, R. (1989). A statistical approach to the problem of negatives in input-output analysis. *Economic Modelling*, *6*(1), 2–19.

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

Zhao, T. (2022). Economic policy uncertainty and manufacturing value-added exports. *Engineering Economics*, *33*(1), 103–114.

Acknowledgment

My interest in the field of international economics was ignited by the global discussion of Trump's 2025 trade policies. At that time, the posts on the internet about tariff, trade balances, and economic nationalism were impossible to ignore, and these discussions inspired me to delve in the academic research about international economics. Initially, I was impressed by the complex trade networks of the world, but then I stumbled upon a theoretical framework that incorporates simplicity and elegance: the gravity model.

What attracted me most about gravity model is its beautiful theoretical structure and its resemblance to one of the fundamental law of physics. The straightforward yet powerful concept helped me to view the chaos of the world economy with a simple lens. It was the initial encounter that set me on to the path of studying gravity model, and eventually contributing to this field.

I would like to also sincerely thank my economics teacher, Ms. Yaxin He, who provided me with guidance and professional instruction during the research. Her guidance were unpaid. When I was struggling with the conceptualization of the foundation for my model, she suggested me to use a Hicksian approach rather than the traditional Marshallian utility maximization, because she believes linear functions would be far more simpler to deal with rather than exponential functions. This crucial shift in methodological foundation helped me to build the model with greater clarity and precision. Beyond that, Ms. He also helped me in my practical development of becoming a researcher. She taught me the basic grammar structure of R language, and also provided guidance on the general structure of the essay, such as how to present empirical results and robustness check.

Since I participated this competition alone, without any other team members, I did the entire research including finding a research question, reviewing the literature, building theoretical models, analyzing the data, interpreting results, drawing conclusion, and writing the paper on my own. Thus, it is unnecessary to present the detailed explanation of the work division among the group members.