Geo-Spatial Proximity and Cross Border Effects on Location Choice in a Globalised Economy

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Abstract

Global Value Chain (GVC) activities are often found to be clustered geographically, suggesting that participation in global production networks may exhibit spatial interdependence. This paper examines whether a country's engagement in GVCs depends on the participation of its neighbours and whether productivity gains generate cross-border spillovers that enhance GVC integration through firms' location and sourcing decisions. Building on a theoretical framework, we show that GVC participation is spatially dependent on the engagement of geographically proximate countries and that productivity improvements can have ambiguous effects on another country's integration into global production networks. Nonetheless, spatial proximity emerges as a necessary condition for positive cross-border spillovers in GVC participation.

Using bilateral value-added trade data for 76 countries over 2000–2019, we provide empirical evidence of strong spatial dependence in GVC engagement, indicating that the benefits of GVC integration diffuse across borders through path-dependent location choices in the presence of trade frictions. Employing a two-stage empirical strategy, we combine structural gravity estimation with a spatial autoregressive specification to quantify interdependencies in GVC participation and value-added exports. Our analysis reveal significant positive spillovers among spatially proximate economies arising from productivity shocks, underscoring the spatial complexity of global production networks. By explicitly incorporating geospatial interdependencies, this study contributes to the trade literature and offers new insights into the cross-border implications of technological change.

Keywords: *Geographical Proximity, Spatial Dependence, Global Value Chain, Productivity Spillovers, Location Choice*

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1 Introduction

Economic activities often cluster around a particular region. Such spatial clustering drives a cycle of economic agglomeration and higher productivity. This pattern of spatial concentration supplements income inequality and raises concerns for the trailing regions[1]. Amidst the conditions presented in the contemporary globalised world[2], the Global Production Network (GPN)[3] could provide opportunities to these trailing regions for mitigating such spatial inequality by allowing them to participate in various stages of the production process. Participation in production activities within a GPN enables countries to realise the benefits of global trade integration and diversify their export baskets. It has led to significant improvements in firm-level productivity, driven by knowledge spillovers and technology transfers. As a result, countries involved in GPNs have witnessed increases in per capita income, reflecting the broader economic benefits of such participation.

In recent decades, technological improvements, particularly in the domain of ICT and transportation, enabled coordination among distant firms and fragmentation of the production process. Falling trade barriers could also be attributed as a significant contributor to augmenting the fragmentation of the production process. These factors have allowed firms aiming to minimise the overall cost of production to situate production nodes across the globe, leveraging the differential in factor costs and retaining only a subset of the production within their economic boundaries. The likelihood of a country's participation in global production networks depends on its geography, climate, and resource endowments, while market size, infrastructure, institutions, and factor mobility enhance its overall attractiveness. Moreover, as trade is costly, the spatial configuration of the production network that internalises these frictions must consider the geographic proximity of other production nodes and of the final market[4] Consequently, cross-border production networks tend to form among spatially proximate countries, consistent with the argument that reductions in trade costs encourage the relocation of production stages towards neighbouring economies (Johnson & Noguera, 2012b)[5].

This paper argues that an improvement in a country's Comparative Cost Advantage (CCA; for instance through higher productivity), can reshape the geography of production network by attracting a greater share of value-chain activities to that economy. Spatially Proximate regions/countries in turn, may become preferred locations for intermediate stages that benefit from proximity to the newly expanded production base. This mechanism gives rise to spatial spillover effects, whereby productivity gains in one country

[1] See,Rodríguez-Pose (2018).

[2] By a globalised world, we refer to an economy that is not solely interconnected through Ricardian trade but also through the integration of production processes across borders.

[3] We alternatively use Global Value Chain (GVC) in place of GPN.

[4] See Antràs and Gortari (2020), Tyazhelnikov (2022).

[5] See section 2, where we provide statistical evidence to motivate our discussion.

propagate across borders through the reallocation of production stages and the deepening of regional GVC linkages, while potentially displacing incumbent producers elsewhere. This paper therefore, addresses two central questions. *First*, does participation in GVCs exhibit spatial dependence? i.e., does a country's engagement in GPN depend on the participation of its geographically proximate partners *Second*, can such productivity gains generate spatial spillovers that enhance GVC participation in neighbouring economies via firms' location and sourcing decisions? Building on these questions, the paper contributes to the existing literature in two main ways:

First, this study underscores that, beyond country-specific attributes, a country's integration into the GPN is systematically associated with, and reinforced by, the level of economic integration and attractiveness of its spatially proximate economies. Although an extensive body of research has examined the determinants of GVC participation, comparatively limited attention has been devoted to analysing the repercussions of offshoring on economies in close geographical proximity to the offshored destination. As a result, the literature has largely overlooked the complex intra-regional interdependencies that shape production network dynamics and has provided only limited causal evidence on the interrelationship between offshoring activities and the regional diffusion of economic integration.

Second, the study also contributes by explaining how productivity spillover effects influence the real income of other countries within a general equilibrium framework through a rather novel mechanism. Beyond the broad scholarship emphasising productivity spillovers arising from trade, foreign direct investment, technological diffusion, and human and capital mobility that indirectly affect income, existing research has also examined direct trade-based mechanisms operating through terms-of-trade effects and firm or market restructuring. This study advances the literature by uncovering a distinct channel through which productivity gains are transmitted internationally via the location-optimising behaviour of firms within GPNs.

For our analysis, in section 3 we build on the theoretical framework described in Antràs and Gortari (2020), whose multistage production network model closely aligns with the sequential value addition approach that has also been widely considered in recent scholarship on GVCs. Consistent with the decentralised network framework in Antràs and Gortari (2020); Johnson and Moxnes (2019), firms at each stage of the production process minimise costs by sourcing inputs from the cheapest available suppliers. Trade costs are assumed to reflect the spatial configuration of countries, proximate countries face lower trade costs relative to distant ones. Our analysis reveals that the effect of an increase in a country's technology parameter on a neighbouring country's value-added within the production network is ambiguous, and can be intuitively decomposed into three key channels: the location effect, the substitution effect, and the scale effect. The Location Effect is positive, and is argued to grow with geographical proximity between countries. The Substitution Effect reduces participation by reallocating production away from certain firms or locations. In contrast, the Scale Effect enhances the value-added for incumbent firms or countries, expanding their role within the production network. In summary, we find that geographic proximity systematically increases the likelihood of positive spillovers through greater participation in GVCs.

The empirical analyses to substantiate our theoretical findings are two pronged. We begin by empirically establishing spatial dependence in GVC participation. This is a novel attempt to understand spatial dependence in GPN participation in a causal framework.

A substantial body of scholarship in international trade has established the use of structural gravity models, and some function of bilateral distance between the exporter and importer country to account for the spatial dependence to capture the role of distance in shaping bilateral trade flows. However, this approach has been challenged. As Behrens, Ertur, and Koch (2012); LeSage and Pace (2008) emphasise, that spatial dependence, which reveal correlation owing to some underlying economic relationship, is a broader concept which is not captured simply by a measure of bilateral distance. Our analysis in section 4 builds on the structural gravity framework (Fally, 2015; Yotov, Piermartini, Larch, et al., 2016), extending it to the context of GVC trade. We use data for 76 countries over 2000–2019 and exploit exporter-time fixed effects (FEs) as the primary source of identifying variation. The measure of GVC related value added follows Wang, Wei, Yu, and Zhu (2022), which addresses the double-counting issue inherent in other participation measures, and is computed using the Inter Country Input Output (ICIO) table. These estimated FEs enable a consistent assessment of whether a country's GVC participation lies above or below the average, conditional on other determinants. In the second stage, we employ a Spatial Autoregressive (SAR) specification to examine whether these estimated participation measures exhibit spatial dependence. We find robust evidence of positive spatial dependence, particularly stronger after the 2008 Global Financial Crisis.

Building on section 4, which shows that GVC participation is reinforced by the participation of neighbouring countries, section 5, then quantifies how productivity improvements in one country, through changes in technology could indirectly affect other countries through altering location choices, thereby shaping regional GVC participation and value-added exports of spatially proximate countries. We begin by conducting panel Lagrange Multiplier (LM) diagnostics to determine the appropriate spatial specification. Consistent with our priors, the test statistics favour a SAR specification over alternatives incorporating spatial dependence in the error term. Nonetheless, a combined specification accounting for spatial dependence in both the dependent variable and the error term yields robust results. Moreover note, that both exercises in section 4 and section 5 are robust to standard checks in accordance with the literature.

The remainder of the paper is structured as follows. Section 3 develops the theoretical framework, drawing on Antràs and Gortari (2020), and theoretically characterises the spatial dependence, and associated spillover effects. Section 4 introduces our adaptation of a two-stage structural gravity estimation strategy to identify spatial dependence in GVC participation, and presents the main empirical results alongside robustness checks. Section 5 extends the analysis to explore how value-added exports are shaped by spatial interdependencies, incorporating extensions to the baseline specification, particularly to address potential endogeneity arising from the two-way causal relationship between trade and technology. Proofs of key propositions, details of the first-stage estimation from section 4, and the full discussion of the dataset and variable construction are provided in the appendix.

2 Review of Literature

The key feature of any GVC is that the production process employs intermediate commodities to produce intermediate commodities. Timmer, Los, Stehrer, and De Vries (2013) defines GVC activities as a set of all activities directly or indirectly involved in production of any final commodity, with at least some of the activities being completed at a foreign country. As a result of the advancements in ICT, roughly two-thirds of global trade is attributed to the trade of intermediate commodities (Johnson & Noguera, 2012a), which are commonly linked with GPNs. When determining the optimal allocation of tasks, lead firms face two opposing forces: an incentive to offshore driven by international factor cost differentials, and a countervailing pull towards agglomeration due to scale economies and trade costs. The interaction of these forces gives rise to localised production networks, as shown by Johnson and Noguera (2012b). Their work introduces the concept of "Local Production Networks" and documents that cross-border production chains are increasingly concentrated among geographically proximate countries. This is reflected in declining value-added to export ratios among nearby trading partners and in gross trade flows travelling shorter distances than value-added flows. They provide sectoral examples which include the concentration of auto parts trade within North America, while the regional organisation of electronic component production and assembly within Asia.

Empirical evidence from trade patterns reinforces this argument. Bilateral trade between the United States and Mexico accounts for roughly 14% of total U.S. trade, and a large share of these exchanges involve intermediate goods: about 40% of U.S. exports to Mexico and 75% of Mexico's exports to the United States, reflecting deeply integrated regional supply chains (see Table 1)[6]. Similar regional clustering is evident in East Asia,

[6] Although partly shaped by NAFTA, these flows predominantly involve components for auto-mobile

Table 1: Shares of U.S. Trade in Goods

	U.S. Imports from		U.S. Exports to	
	Mexico	All Countries	Mexico	All Countries
Intermediate input trade	40%	45%	75%	62%
Related-party trade	67%	51%	40%	29%
Majority-owned affiliate trade	21%	16%	22%	21%

Sources: Amiti, Freund, and Bodine-Smith (2017); U.S. Census Bureau, Bureau of Economic Analysis.
Note: Related-party trade is defined as trade within firms with at least 10 percent ownership in the trading partner.

where Vietnam's integration into global value chains is largely regional: nearly 80% of its imported intermediate inputs originate from neighbouring economies, primarily China, South Korea, Japan, and Taiwan. Specifically, China and Korea accounted for 95% of the imported inputs related to manufacturing of communication devices and nearly 44% of key integrated circuits and associated products were imported from China, Japan and Taiwan. While 61% of the knitted fabrics and woven textiles were supplied from China (Jones, 2021). A comparable pattern exists in Central Europe, where Germany's neighbouring economies, Poland, Hungary, Slovakia, and the Czech Republic heavily rely on intermediate inputs produced in Germany (Baldwin & Lopez-Gonzalez, 2013b).

This paper addresses two broad strands of scholarship: (1) determinants of GVC participation (2) the trade channels of productivity spillover on real income. Hereafter, the discussion that follows outlines each strand.

Multiple studies have taken place to empirically understand the determinants which affect the likelihood of participation of firms and countries into the production network. The works of Fernandes, Kee, and Winkler (2022) help summarise the key findings in this body of literature. Fernandes et al. (2022) embedded the determinants in a unified framework, studying their relative contribution in determining GVC participation. Other studies include the works of Baldwin and Taglioni (2014); Brooks and Ferrarini (2014); Cheng, Rehman, Seneviratne, and Zhang (2015); Ignatenko, Raei, and Mircheva (2019); Kowalski, Gonzalez, Ragoussis, and Ugarte (2015). They find that the traditional factors[7] that help explain bilateral trade in final commodities (or, Ricardian Trade) are also central in determining the participation of a country or, a firm. They further conclude that these factors have a greater impact on affecting GVC trade compared to traditional trade.

Recent studies such as Antràs and Gortari (2020); Johnson and Moxnes (2019); Tyazhel-

and computer production. See Amiti et al. (2017).

[7] Which include the first and second nature determinants; see, Krugman (1993).

nikov (2022) model multi-country, multi-stage production networks and show that, when the geography of trade costs and firms' optimisation are considered, location choices are path-dependent. As a result, some potentially efficient locations may remain excluded from the global production network. Yet, these studies do not explicitly examine whether a country's participation in a GPN is reinforced by the integration of its spatially proximate neighbours. Building on Antràs and Gortari (2020) for analytical tractability, we highlight this mechanism. However, as discussed in the earlier sections, majority of the studies rely on measures of bilateral distance to infer spatial dependence. For instance, Fernandes et al. (2022) use proximity to major GVC hubs (which includes, Germany, China and the United States) as a determinant of GVC participation. While this measure has merits, it has limitations in capturing the spatial dependence.

We now proceed with the discussion on the impact of cross-country productivity spillovers on real income. In this regard, one of the fundamental insights from the scholarship on international trade is that, productivity changes in one country would spillover international borders to affect the real incomes of other countries through channels of international trade. A substantial body of literature including Coe and Helpman (1995); Coe, Helpman, and Hoffmaister (2009); Fracasso and Marzetti (2015); Grossman and Helpman (1991)examines the spillover effect on total factor productivity through avenues of cross-country technology and knowledge diffusion facilitated through international trade. An alternate enquiry into the subject could be traced back to the works of Hicks (1953). Hicks (1953) was of the opinion that an increase in productivity on the import-competing sector, would hurt the terms of trade for its trading partners' and vice-versa. Even through intra-industry trade models (Krugman, 1980),Venables (1985, 1987) argue that an increase in productivity along sectors would have ambiguous impact on their trading partners real-income. The idea runs parallel to Hicks (1953), as productivity growth is always export biased in theoretical formulations of intra-industry trade since each country specialises in a specific set of commodities.

The empirical work on this topic can be broadly summarised by the findings of Eaton and Kortum (2002); Hsieh and Ossa (2016). The seminal study by Eaton and Kortum (2002) uses their framework to estimate the effect of a productivity shock in the USA and Germany on 19 OECD countries, focusing mainly on the terms-of-trade effect. Similarly, Hsieh and Ossa (2016) examine how productivity growth in China impacts the real income of the 14 largest economies, building on the earlier insights of Venables (1985, 1987). Existing research like these do not consider the spillover effects that may result from deeper CCA, especially through the way firms choose locations within a GPN. It also largely ignores the importance of the spatial organisation of countries. Moreover, it does not explore whether these productivity spillovers vary with distance, a key factor that could influence the extent and reach of such effects.

Building on the theoretical framework of Antràs and Gortari (2020), our study explores the missing channel and arrives at the necessary and sufficient condition, which re-iterates the importance of proximity (defined broadly), also highlighting the possible link between productivity spillovers and distance.

However note, in a different context, the opinion that flows of commodities, capital, or labour between any two regions are intrinsically coupled across space[8] is deeply rooted in the economics literature, and is particularly central in the study of international trade. This particular dependence may at times stem from the fact that our phenomenon of interest does not confine itself within economic boundaries; or, at other times, it arises from shared underlying factors, while at several instances, spatial dependence is a consequence of spatial spillovers. Anderson and van Wincoop (2003) argue through its formulation of multilateral resistance terms that bilateral trade flows do not only depend on the bilateral trade barriers but also on trade barriers imposed across all trading partners. This highlights the complex interaction among all trading nations. Similarly, the arguments put forth by Behrens et al. (2012); LeSage and Pace (2008), in continuation of the arguments put forward by Anderson and van Wincoop (2003), highlight the presence of spatial dependence in trade flows.

3 Theoretical Framework

In this section, we adapt the probabilistic multi-stage production framework of Antràs and Gortari (2020); Eaton and Kortum (2002) to characterise how geography of trade frictions shape GPN and cross-border spillovers.

3.1 Environment

Consider a globalised world economy consisting of J countries, indexed as $j \in \Omega$, consumers partake in the final commodity produced, by sequentially combining N distinct intermediate commodities, indexed by $n \in \mathbb{N}$. Every region j, is endowed with $\bar{L}_j$ units of primary factor, labour. The labour supply is assumed to be perfectly inelastic and is only mobile between sectors within a given country. Therefore, each country j is assumed to have varying domestic wage rate w_j. Critical to our formulation, the spatial organisation of the countries, is captured by the bilateral iceberg trade costs, $\tau_{ij} \geq 1$, associated with commodities exported by country i and imported by country j. Note, equality holds (i.e., $\tau_{ij} = 1$) in an economy without trade costs. Firms at each production stage $n \in \mathbb{N}$, employ a composite factor consisting of (i) domestic labour L, (ii) ancillary inputs M_n, along with (iii) the intermediate good from stage $n-1$. Firms, $\forall n > 1$ operating from country $l_n \in \Omega$, use the output of stage $n-1$, $y^{n-1}_{l_{n-1}}$, as an input and add value by transforming it

[8] Flows between any two regions are shaped, directly or indirectly, by their neighbouring spatial units.

with the composite factor, thereby advancing the commodity, $y^n_{l_n}$, along the chain. The technology of production could be described using the cost function

$$B^n_{l_n} = b_n \left[\frac{(w_{l_n})^\gamma \, (\tilde{P}^n_{l_n})^{(1-\gamma)}}{a^n_{l_n}} \right]^{\alpha_n} \left(P^{n-1}_{l_{n-1}l_n} \right)^{1-\alpha_n} y^n_{l_n} \tag{1a}$$

Where,

$$P^{n-1}_{l_{n-1}l_n} = p^{n-1}_{l_{n-1}} \tau_{l_{n-1}l_n} \tag{1b}$$

$$\tilde{P}^n_{l_n} = \left[\int_0^1 \left(\tilde{p}_j(i;n) \, \tau_{jl_n} \right)^{1-\xi} di \right]^{\frac{1}{1-\xi}} \tag{1c}$$

$$\tilde{p}_j(i;n) = \frac{w_j}{\tilde{a}^n_j(i)}. \tag{1d}$$

Wherein, the factors of production are augmented by country and stage specific technological factor, $a^n_{l_n}$. Parameter $(1 - \alpha_n) \in [0, 1]$ denotes the cost share of the intermediate commodity from stage $n - 1$. Although α_n varies across production stages, it remains constant across countries. At stage $n = 1$, we set $\alpha_n\big|_{n=1} = 1$, implying that production relies entirely on the composite factor. With $\gamma \in [0, 1]$, $\gamma\alpha_n$ and $(1 - \gamma)\alpha_n$ denotes the domestic labour and ancillary input share at stage n. Moreover, ancillary input can be considered to be produced combining a mass of material inputs, with ξ being the constant elasticity of substitution between the material inputs. And, each input i is produced locally in country j with domestic labour only, with productivity determined by the stage- and country-specific technology parameter $\tilde{a}^n_j(i)$.

Considering marginal cost pricing, the price paid by stage-$(n+1)$ firms in the absence of trade costs ($\tau_{l_n l_{n+1}} = 1$) is

$$p^n_{l_n} = b_n \left[\frac{(w_{l_n})^\gamma \, (\tilde{P}^n_{l_n})^{(1-\gamma)}}{a^n_{l_n}} \right]^{\alpha_n} \left(P^{n-1}_{l_{n-1}l_n} \right)^{1-\alpha_n} \tag{2}$$

Here, b_n is a scaling constant. The discussion above elucidates three primary reasons why production costs $B^n_{l_n}$ are location-specific. Firstly, focusing on the country specific factors, countries differ in domestic wage rates and also differ in the efficiency in production of both intermediate commodity n or the material input for stage n, $m_n(i)$. Secondly, the landed cost (the price of the intermediate or material input multiplied by the ice-berg trade cost term, which is the final price incident on the importing firm) of intermediate commodities varies depending on the distance between the current node and its predecessor, as represented τ_{ij}. Finally, each firm operating at stage n in a particular location has a specific least cost producer for all its intermediate inputs. Therefore, the objective of the lead firm is to solve for the optimal location $l^*_n \in \boldsymbol{\ell}^*$ for each task $n \in \mathbb{N}$

$$\boldsymbol{\ell}_j^* = \arg \min_{\boldsymbol{\ell}^* \in \Omega^N} P_{\boldsymbol{\ell}j}^Y = \arg \min_{\boldsymbol{\ell} \in \Omega^N} \left\{ \prod_{n=1}^{N} {b_n}^{\beta_n} \times \prod_{n=1}^{N} \left[\frac{(w_{l_n})^{\gamma} (\tilde{P}_{l_n}^n)^{1-\gamma}}{a_{l_n}^n} \right]^{\alpha_n \beta_n} \times \prod_{n=1}^{N-1} {\tau_{l_{n-1} l_n}}^{\beta_n} \times \tau_{l_N j} \right\} \tag{3}$$

Note, that when $\tau_{ij} = \tau \ \forall (i,j) \in \Omega^2$, implying that the trade costs are uniform across all trading partners, the last two terms of the objective function in equation (3) become constant. Consequently, the choice of the optimal location l_n^* for all $n \in \mathbb{N}$ is not influenced by the trade costs. In such a scenario, each node's location would be determined by the place offering a cost advantage for completing the stage.

Now akin to Antràs and Gortari (2020); Eaton and Kortum (2002), we employ a probabilistic specification for the technological parameter, $a_{l_n}^n$. The parameter $a_{l_n}^n = \frac{1}{z_{l_n}^n}$ for each country is assumed to be stochastic and drawn independently (i.e., productivity draws across stages are independent), from a type II (or Fréchet) extreme-value probability distribution satisfying the following cumulative distribution function

$$\mathbb{P}[(z_j^n)^{\alpha_n \beta_n} \geq z] = \exp\left[-z^{\theta} \ \Theta_j^{\alpha_n \beta_n}\right] \qquad \forall j \in \Omega \ \ n \in \mathbb{N} \tag{4}$$

Here, $\mathbb{P}(\cdot)$ is the probability measure. Θ_j is a country specific factor, determining the location of the distribution. Countries with higher value of Θ_j have a greater probability of hosting highly productive firms. θ is the shape parameter and is assumed constant across all countries and governs the variation within the distribution. Since the production function also requires a continuum of ancillary material inputs, we assume that the productivity draws for this entire continuum are also governed by the same Fréchet distribution, thereby extending the probabilistic specification uniformly across both stage outputs and material inputs.

We further assume that only consumers in country F consume a continuum of final-good varieties $h \in [0,1]$, with preferences represented by a CES utility function:

$$U\left(\{Y(h)\}_{h=0}^{1}\right) = \left(\int_0^1 Y(h)^{\frac{\sigma-1}{\sigma}} \, dh \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1, \tag{5}$$

where σ denotes the elasticity of substitution across varieties. Each final-good variety is produced through an N-stage production network, as described by the cost structure in equations (1a)–(1d).

In this paper, we solve for the decentralised equilibrium using an environment akin to Antràs and Gortari (2020); Johnson and Moxnes (2019); Tyazhelnikov (2022) adapting on Eaton and Kortum (2002): where firms at every stage minimise the cost of production for their own produce. Since stage-n firms take intermediate and ancillary input prices, technology, and domestic wage rates as given, their only remaining decision variable in minimising production costs is the choice of location i.e., the set of countries from which to source intermediate and ancillary material inputs. However, Antràs and Gortari (2020) shows that under the maintained assumption of CRS production function, the solution under the centralised and the decentralised cases turns out to be identical.

Following Antràs and Gortari (2020), the sourcing decision at each stage of production is independent of the choices made at the previous stage. Consequently, the probability that a GVC passes through a particular sequence of locations $\{l_1,\ l_2, \ldots,\ l_N\} = \boldsymbol{\ell} \in \Omega^N$ is given by equation (6).

$$
\begin{aligned}
\mathbb{P}\left(\bigcap_{n=1}^{N} l_n\right) &= \mathbb{P}\left(l_N^F = l_N | l_{N-1}^{l_N} = l_{N-1}\right) \times \prod_{n=2}^{N-1} \mathbb{P}\left(l_n^{l_{n+1}} = l_n | l_{n-1}^{l_n} = l_{n-1}\right) \times \mathbb{P}(l_1^{l_2} = l_1) \\
\pi_{\boldsymbol{\ell}F}^N &= \mathbb{P}\left(l_N^F = l_N\right) \times \prod_{n=1}^{N-1} \mathbb{P}\left(l_n^{l_{n+1}} = l_n\right) \\
&= \frac{\prod_{n=1}^{N-1} \left\{\Theta_{l_n}^{\alpha_n \beta_n} \left\{\left(w_{l_n}{}^{\gamma} \tilde{P}_{l_n}^{n\,1-\gamma}\right)^{\alpha_n} \tau_{l_n l_{n+1}}\right\}^{-\beta_n \theta} \times \Theta_{l_N}^{\alpha_N} \left\{\left(w_{l_N}{}^{\gamma} \tilde{P}_{l_N}^{N\,1-\gamma}\right)^{\alpha_N} \tau_{l_N F}\right\}^{-\theta}\right\}}{\sum_{\boldsymbol{\ell} \in \Omega^N} \left[\prod_{n=1}^{N-1} \left\{\Theta_{l_n}^{\alpha_n \beta_n} \left\{\left(w_{l_n}{}^{\gamma} \tilde{P}_{l_n}^{n\,1-\gamma}\right)^{\alpha} \tau_{l_n l_{n+1}}\right\}^{-\beta_n \theta}\right\} \times \Theta_{l_N}^{\alpha_N} \left\{\left(w_{l_N}{}^{\gamma} \tilde{P}_{l_N}^{N\,1-\gamma}\right)^{\alpha} \tau_{l_N F}\right\}^{-\theta}\right]}
\end{aligned} \tag{6}
$$

Equation (6) therefore characterises the probability that a specific production network $\ell \in \Omega^N$ is the cost-minimising path for producing a final good consumed in country F. Note, that for a unit measure of final goods, $\pi_{\ell F}$ may also be interpreted as the share of GVCs ending in F that follow path ℓ. Moreover, because the distribution of final-good prices paid by consumers in F is independent of the underlying production path, $\pi_{\ell F}$ equally represents the share of F's expenditure on final goods that are produced via path ℓ.

3.2 Spatial Dependence

Now consider E_F to represent the aggregate expenditure made by consumers of final commodities in country F. Following from our previous discussion, we can confirm that $\pi_{\ell F}^N E_F$ represents the expenditure incurred by consumers in country F on final commodities that flow through the production network $\ell \in \Omega^N$. Therefore, for any particular production network $\ell \in \Omega^N$ the value added by any country j denoted by μ_j can be mathematically represented by,

$$\mathrm{VA}_j = \sum_{n:\ l_n=j} \left\{\gamma\alpha_n\beta_n\pi^N_{\ell F}E_F\right\} + \sum_{l_n\in\ell} \tilde{\pi}^n_{jl_n}\left(1-\gamma\right)\alpha_n\beta_n\pi^N_{\ell F}E_F \tag{7}$$

Where $\gamma\alpha_n\beta_n$ denotes the cost share of labour, directly involved in the production of intermediate inputs, as reflected in the first term of equation (7). The summation preceding this term accounts for the possibility that a single country may participate in the production of multiple intermediate commodities. Additionally, each country j may also contribute material inputs to firms engaged in the production of intermediate commodities within the production network, as reflected in the second term of equation (7). At each stage n of the production network, every participating firm allocates a share of $(1-\gamma)\alpha_n\beta_n$ to material inputs, with a fraction $\tilde{\pi}^n_{jl_n}$ of the total expenditure on material inputs spent on varieties provided by country j. Summing over all stages, we obtain the total value added through material input by firms in country j within the given production network.

Similarly, to determine the total gross value added by any country j, and with $\mathbb{P}(l_n = j; F)$ representing the probability of country j to be least cost provider of intermediate commodities operating at stage-n: this expression thus also represents the share of spending by country F on final goods produced through a production network in which country j is the least-cost provider for stage n of an intermediate commodity. Therefore, the gross value added exports associated with GVCs can be expressed as,

$$\begin{aligned}\mathrm{GVA}_j &= \sum_{\mathbb{N}} \left\{\gamma\alpha_n\beta_n \sum_{\ell\in\Omega^N_{\{l_n=j\}}} \pi^N_{\ell F}E_F\right\} + \sum_{\ell\in\Omega^N} \left\{\sum_{l_n\in\ell} \tilde{\pi}^n_{il_n}\left(1-\gamma\right)\alpha_n\beta_n\pi^N_{\ell F}E_F\right\} \\ &= w_j\bar{L}_j\end{aligned} \tag{8}$$

Consider $\gamma = 1$ for simplicity. Now, through a sequence of straightforward, though not entirely trivial, algebraic manipulations of the conditional probability structure and equilibrium conditions introduced earlier, we arrive at the spatial-gravity expression for value-added exports across production stages. The expression, given in equation (9), relates value-added originating in country j at stage n to its eventual absorption in the final destination $\bar{j}$:

$$VA_j^n = \alpha_n \beta_n E_F \overbrace{\left\{ \frac{Y_j^n / Y^n}{\Pi_j^n} \sum_{l_{n+1}} \frac{\left(\tau_{jl_{n+1}}^n\right)^{-\beta_n \theta}}{t_j^n} \left[\frac{Y_{l_{n+1}}^n / Y^n}{\phi_{l_{n+1}}^{n-1} \Pi_{l_{n+1}}^n} \right] \right\}}^{\text{Origin Term}}$$

$$\times \overbrace{\left\{ \sum_{\ell(n+1,N-1)} \left[\prod_{m=n+2}^{N-2} \left(\frac{Y_j^m / Y^m}{\phi_j^{m-1} \Pi_j^m} \right) \right] \left[\left(\tau_{jl_{n+1}}^n\right)^{-\beta_n \theta} \prod_{m=n+1}^{N-2} \left(\tau^m\right)^{-\beta_m \theta} \left(\tau_{l_{N-1}\bar{j}}^{N-1}\right)^{-\beta_{N-1} \theta} \right] \right\}}^{\text{Country-Pair}}$$

$$\times \underbrace{\left\{ \left[\frac{Y_{\bar{j}}^N / Y^N}{\phi_{\bar{j}}^{N-1} \Pi_{\bar{j}}^N} \right] \frac{\left(\tau_{\bar{j}F}^N\right)^{-\beta_N \theta}}{\phi_F^N} \sum_{l_{N-1}} \left[\frac{Y_{l_{N-1}}^{N-1} / Y^{N-1}}{\phi_{l_{N-1}}^{N-2} \Pi_{l_{N-1}}^{N-1}} \right] \frac{\left(\tau_{l_{N-1}\bar{j}}^{N-1}\right)^{-\beta_{N-1} \theta}}{t_{\bar{j}}^N} \right\}}_{\text{Destination Term}} \quad (9)$$

Here, Y_j^n and Y^n denote, respectively, the output of country j and total world output at stage n; The terms ϕ_j^n and Π_j^n can be interpreted as the inward and outward multilateral resistance indices, measuring respectively, a country's ease of accessing inputs and its competitiveness in downstream markets. The normalisation factors $t_j^n = \sum_{l_{n+1}} \left(\tau_{jl_{n+1}}^n\right)^{-\beta_n \theta}$ and $t_{\bar{j}}^N = \sum_{l_{N-1}} \left(\tau_{l_{N-1}\bar{j}}^{N-1}\right)^{-\beta_{N-1} \theta}$ scale bilateral trade frictions. The separability of the above equation, is ensured under the simplifying assumption that trade costs among all other country pairs not involving j or $\bar{j}$ are identical. The expression thus encapsulates the probabilistic transmission of value-added through sequential production stages, linking economic size, trade frictions, and multilateral resistance into a unified spatial-gravity framework.

Proposition 3.1. *In the gravity formulation given by equation (9), the value-added exports from country j to the final destination $\bar{j}$ depend not only on their bilateral trade frictions but also on the participation of spatially proximate countries that connect j to $\bar{j}$ through intermediate production stages. The flow of value-added is therefore shaped by how effectively neighbouring economies downstream of j integrate into the production network, since their involvement determines the probability that value originating in j is transmitted forward and ultimately absorbed in $\bar{j}$.*

3.3 Spatial Spillovers

The probability that stage n is hosted in country $\hat{j}$, with the final consumption happening at country F is the sum of the path probabilities $\pi_{\boldsymbol{\ell F}}^N \ \forall \boldsymbol{\ell} \in \Omega^N$,

$$\begin{aligned}\mathbb{P}\big(l_n = \hat{j}; F\big) &= \sum_{\substack{\boldsymbol{\ell}\in\Omega^N \\ l_n=\hat{j}}} \pi^N_{\boldsymbol{\ell}F} \\ &= \frac{1}{\phi^N_F} \sum_{\substack{\boldsymbol{\ell}\in\Omega^N \\ l_n=\hat{j}}} \left[\prod_{m=1}^{N-1} \left(\Theta_{l_m}\right)^{\alpha_m\beta_m} \Big\{ b_m \tau_{l_m l_{m+1}} \big(w^{\gamma}_{l_m}\, \tilde{P}^{m\,1-\gamma}_{l_m}\big)^{\alpha_m} \Big\}^{-\beta_m\theta} \right. \\ &\qquad \left. \times\ \left(\Theta_{l_N}\right)^{\alpha_N\beta_N} \Big\{ b_N \tau_{l_N F} \big(w^{\gamma}_{l_N}\, \tilde{P}^{N\,1-\gamma}_{l_N}\big)^{\alpha_N} \Big\}^{-\theta} \right].\end{aligned} \tag{10}$$

Where,

$$\phi^N_F = \sum_{\boldsymbol{\ell}\in\Omega^N} \underbrace{\left[\prod_{n=1}^{N-1} \left\{ \Theta^{\alpha_n\beta_n}_{l_n} \ \left\{ \left({w_{l_n}}^{\gamma} \tilde{P}^{n\,1-\gamma}_{l_n} \right)^{\alpha} \tau_{l_n l_{n+1}} \right\}^{-\beta_n\theta} \right\} \times \Theta^{\alpha_N}_{l_N} \ \left\{ \left({w_{l_N}}^{\gamma} \tilde{P}^{N 1-\gamma}_{l_N} \right)^{\alpha} \tau_{l_N F} \right\}^{-\theta} \right]}_{A_{\ell F}\ \text{(suppose)}}$$

Here, $A_{\ell F}$ is inversely related to the expected price of the final good produced along production path ℓ and consumed at F, and can therefore be interpreted as a measure of the attractiveness of path ℓ. For ease of notation, consider,

$$P\left(l_n = \hat{j}; F\right) = \frac{\sum_{\substack{\ell\in\Omega^N \\ l_n=\hat{j}}} A_{\ell F}}{\sum_{\ell\in\Omega^N} A_{\ell F}} \tag{11}$$

Consider an alternate region $\tilde{j} \in \Omega$, where, $\Omega^N_{\{j\}} \subseteq \Omega^N$ denotes the set of all production paths ℓ such that $\tilde{j} \in \ell$. Note, $\Omega^N_{\{j\}} \cup \Omega^N_{\{-j\}} = \Omega^N$. Suppose country $\tilde{j}$ has experienced an increase in productivity parameter $\Theta_{\tilde{j}}$, where $\hat{j} \neq \tilde{j}$, and therefore,

$$\frac{d\ A_{\ell F}}{d\ \Theta_{\tilde{j}}}\bigg|_{\ell\in\Omega^N_{\{j\}}} = \underbrace{\left[\overbrace{\sum_{k;l_k=\tilde{j}} \left(\frac{\alpha_k\beta_k}{\Theta_{\tilde{j}}} \right)}^{\text{Explicit Channel}} + \overbrace{\sum_{\mathbb{N}} \left(\frac{-\alpha_n\beta_n\theta\,(1-\gamma)}{\widetilde{P}^n_{l_n}} \times \frac{d\ \widetilde{P}^n_{l_n}}{d\ \Theta_{\tilde{j}}} \right)}^{\text{Implicit Channel}} \right]}_{=S^{\tilde{j}}_{\ell}\ \text{(suppose)}} A_{\ell F} = S^{\tilde{j}}_{\ell} \times A_{\ell F} \tag{12}$$

From the above equation, we understand that an increase in the productivity parameter $\Theta_{\tilde{j}}$ gives rise to two distinct effects, which we refer to as the explicit and implicit channels. The explicit channel captures the direct impact of the productivity increase when country $\tilde{j} \in$

Ω is directly involved in the production network i.e., $\tilde{j} \in \ell$. In this case, the improvement in $\Theta_{\tilde{j}}$ increases $A_{\ell F}$ by lowering the marginal cost of production at the stage(s) operated in $\tilde{j}$. As country $\tilde{j}$ could be involved directly in multiple stages of production, the explicit effect is obtained by summing over all stages in which $\tilde{j}$ hosts these stages of production. Alternatively, the implicit channel reflects the indirect effects whereby higher productivity in $\tilde{j}$ reduces the price index (since, $\frac{d\tilde{P}^n_{l_n}}{d\Theta_{\tilde{j}}} < 0$) of stage-specific ancillary inputs, affecting $A_{\ell F}$ even for paths $\ell \in \Omega^N_{\{-\tilde{j}\}}$, where the explicit effect vanishes. However, we can conclude, that

$$A'_{\ell F} = \frac{d\ A_{\ell F}}{d\ \Theta_{\tilde{j}}}\Big|_{\ell \in \Omega^N} > 0$$

Alternatively,

$$\frac{d\ \mathbb{P}(l_n = \hat{j}; F)}{d\ \Theta_{\hat{j}}} = \frac{1 - \mathbb{P}(\hat{j})}{\phi^N_F} \overbrace{\sum_{\ell \in \Omega^N_{\{l_n = \hat{j}\}}} \left[\sum_{k; l_k = \tilde{j}} \left(\frac{\alpha_k \beta_k}{\Theta_{\tilde{j}}} \right) + \sum_{\mathbb{N}} \left(\frac{-\alpha_n \beta_n \theta\, (1-\gamma)}{\widetilde{P}^n_{l_n}} \times \frac{d\ \widetilde{P}^n_{l_n}}{d\ \Theta_{\tilde{j}}} \right) \right]}^{\text{Scale Effect}} - \frac{\mathbb{P}(\hat{j})}{\phi^N_F} \underbrace{\sum_{\ell \in \Omega^N - \Omega^N_{\{l_n = \hat{j}\}}} \left(A_{\ell F} S^{\tilde{j}}_{\ell} \right)}_{\text{Substitution Effect}} \tag{13}$$

Equation (13) decomposes how the sourcing probability changes when productivity in country $\tilde{j}$ improves. Differentiating this probability with respect to the productivity parameter of another country $\tilde{j}$, $\Theta_{\tilde{j}}$, captures how a productivity improvement in $\tilde{j}$ shifts the allocation of global value chain stages across countries, and identifies two distinct channel of cross border transmission: The scale effect captures the fact that higher productivity in country $\tilde{j}$ reduces costs along all production paths through either the explicit or the implicit channel or both, depending on whether the production path includes $\tilde{j}$, thereby raising the likelihood that stage n is completed in $\hat{j}$. On the contrary, the substitution effect reflects the fact that the same productivity shock also makes competing paths (excluding $\hat{j}$) more attractive, reducing $\hat{j}$'s probability of participating in stage n. The overall effect is therefore ambiguous and depends on the balance between scale and substitution. Now, with $1_{\{l_n = \hat{j}\}}$ defined as an indicator variable that only takes the value one if $\ell \in \Omega^N_{\{l_n = \hat{j}\}}$, equation (13) can be further expressed as,

$$\frac{d\ \mathbb{P}(l_n = \hat{j}; F)}{d\ \Theta_{\hat{j}}} = \text{Cov}\left[S_\ell^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right] \tag{14}$$

Equation (14) indicates that a systematically higher $S_\ell^{\tilde{j}}$ across production paths $\ell \in \Omega^N_{\{l_n=\hat{j}\}}$ raises the likelihood of $\hat{j}$'s participation as the productivity parameter $\Theta_{\tilde{j}}$ increases.

Lemma 3.1. *With $\Theta_{\tilde{j}}$ representing the productivity parameter associated with technology in $\tilde{j}$, and $S_\ell^{\tilde{j}}$ denoting the consequent spillover potential (proportionate change in $A_{\ell F}$) along production path $\ell \in \Omega^N$, suppose that for all $\ell \in \Omega^N_{\{l_n=\hat{j}\}}$, the values of $S_\ell^{\tilde{j}}$ are weakly greater than for paths $\ell \notin \Omega^N_{\{l_n=\hat{j}\}}$. Then, an increase in $\Theta_{\tilde{j}}$ strictly increases the likelihood of $\hat{j}$'s participation at stage-n of the production network.*

Since $S_\ell^{\tilde{j}}$ can be decomposed into explicit and implicit components, $S_\ell^{\tilde{j}} = S_{\ell,\text{exp}}^{\tilde{j}} + S_{\ell,\text{imp}}^{\tilde{j}}$, it follows that $\text{Cov}\left[S_\ell^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right] = \text{Cov}\left[S_{\ell,\text{exp}}^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right] + \text{Cov}\left[S_{\ell,\text{imp}}^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right]$. For simplicity, we assume $\text{Cov}\left[S_{\ell,\text{imp}}^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right] = 0$, where $1_{\{l_k=j\}}$ denotes an indicator variable equal to one if, along production path ℓ, $l_n = j$ for all n. Therefore,

$$\text{Cov}\left[S_{\ell;\ \text{exp}}^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right] > 0 \quad \text{iff} \quad \mathbb{P}\left(l_{n-1} = \tilde{j} \middle| l_n = \hat{j}\right) > \frac{\alpha_n\beta_n + \alpha_{n-1}\beta_{n-1}}{\alpha_{n-1}\beta_{n-1}} \mathbb{P}\left(l_{n-1} = \tilde{j}\right)$$

with $\alpha_n\beta_n \in [0,1] \quad \forall n \in \mathbb{N}$, this implies that,

$$\mathbb{P}\left(l_{n-1} = \tilde{j} \middle| l_n = \hat{j}\right) > \mathbb{P}\left(l_{n-1} = \tilde{j}\right)$$

is a necessary condition to achieve $\text{Cov}\left[S_{\ell;\ \text{exp}}^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right] > 0$. Therefore, in order for $S_\ell^{\tilde{j}}$ to be systematically larger for production paths $\ell \in \Omega^N_{l_n=\hat{j}}$, it is necessary that the occurrence of stage-n at $\hat{j}$ increases the likelihood of firm participation in $\tilde{j}$ at stage $n-1$.

Corollary 3.1. *An increase in $\Theta_{\tilde{j}}$ strictly increases the likelihood of $\hat{j}$'s participation at stage-n of the production network only if $\mathbb{P}\left(l_{n-1} = \tilde{j} \mid l_n = \hat{j}\right) > \mathbb{P}\left(l_{n-1} = \tilde{j}\right)$*

3.3.1 A Simplified Illustration:

We begin by considering a simplified case in which $\text{Cov}\left[S_{\ell;\ \text{imp}}^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right] = 0$[9]. Further, to build intuition, we consider a simple case with only two stages of production, i.e., $N = 2$. However, the results derived in this section hold true for $\forall N \in \mathbb{R}_+$. Now as the objective in this section is to isolate the effects of trade costs, we assume that countries and firms are otherwise identical in all other respects. Hence, we could factor the homogeneity into

[9] An equivalent restriction to the imposed covariance restriction is to set $\gamma = 1$.

a single positive constant, $A > 0$. However, accommodating the geography of trade costs, while maintaining the simplifying assumption that all countries are equidistant from the final destination of consumption, we conclude

$$\begin{aligned} \frac{\tau_{\tilde{j}\hat{j}}^{-\beta_1\theta}}{\sum_k \tau_{\tilde{j}k}^{-\beta_1\theta}} &> \frac{\sum_i \tau_{i\hat{j}}^{-\beta_1\theta}}{\sum_i \sum_k \tau_{ik}^{-\beta_1\theta}} \\ \Rightarrow \tau_{\tilde{j}\hat{j}} &< \left(\frac{\sum_k \tau_{\tilde{j}k}^{-\beta_1\theta} \times \sum_i \tau_{i\hat{j}}^{-\beta_1\theta}}{\sum_i \sum_k \tau_{ik}^{-\beta_1\theta}} \right)^{-\frac{1}{\beta_1\theta}} \end{aligned} \tag{15}$$

This inequality in equation (15) captures the economic intuition that $\tilde{j}$ is more likely to be the upstream supplier of $\hat{j}$ at a given stage whenever their bilateral trade cost is sufficiently low relative to the network-wide benchmark of alternative trade costs. Alternatively, consider the expression in (16),

$$\frac{\tau_{\tilde{j}\hat{j}}^{-\beta_1\theta}}{\sum_i \tau_{i\hat{j}}^{-\beta_1\theta}} > \frac{\sum_k \tau_{\tilde{j}k}^{-\beta_1\theta}}{\sum_i \sum_k \tau_{ik}^{-\beta_1\theta}} \tag{16}$$

The L.H.S can be interpreted as the proximity (inverse distance) between $\tilde{j} - \hat{j}$, relative to the proximity between all other countries and $\hat{j}$. While the expression on the R.H.S could be interpreted as the overall 'spatial' centrality of country $\tilde{j}$[10]. Specifically the inequality, suggests that the relative spatial proximity between $\tilde{j}$ and $\hat{j}$ must exceed the partners' global spatial centrality. The parameter $\beta_n\theta > 0$ governs the sensitivity of the probability of a production path to differences in trade costs. A higher importance of stage 1 or a lower variance in the distribution of productivity parameters increases the elasticity of a country's attractiveness to trade costs.

Proposition 3.2. *The likelihood of $\tilde{j}$'s participation at stage $n-1$ is higher given that country $\hat{j}$ is operating at stage $n-1$ if the share of proximity that $\hat{j}$ accounts for in the neighbourhood of $\tilde{j}$ exceeds the overall centrality of $\hat{j}$ in the global system, or, equivalently, if the share of proximity that $\tilde{j}$ accounts for in the neighbourhood of $\hat{j}$ exceeds the overall centrality of $\tilde{j}$. In other words, the dyadic link $(\tilde{j}, \hat{j})$ is stronger than would be implied by the aggregate spatial prominence of either location taken in isolation.*

Corollary 3.2. *The likelihood that $\tilde{j}$ serves as the upstream supplier to $\hat{j}$ at stage n increases, and the condition stated in Corollary 3.1 is satisfied, whenever their bilateral trade cost $\tau_{\tilde{j}\hat{j}}$ is sufficiently low relative to alternative trade costs in the network. More generally, $\tau_{\tilde{j}\hat{j}}$ must be close to the minimum among $\tilde{j}$'s cheapest suppliers, $\hat{j}$'s cheapest ex-*

[10] We interpret in terms of spatial centrality, however the inequality could accommodate a more broader definition of network centrality, including geo-political ties.

port links, or the global minimum across all bilateral trade links. Across all configurations, lower relative trade costs increase the probability of $\tilde{j}$'s participation.

Case of Non-Homogeneity: Further, if we allow other factors such as state of technology parameter Θ_j and domestic wage rates w_j to vary across countries. Such that,

$$\begin{aligned} A(i,k) &= \{\Theta_i\,(w_i)^{-\alpha_1}\}^{\beta_1\theta}\{\Theta_k\,(w_k)^{-\alpha_2}\,\tau^{-1}\}^{\theta}\tau_{ik}{}^{-\beta_1\theta}; \qquad \beta_N\Big|_{N=2} = 1 \\ &= A_i \times A_k \times \tau_{ik}{}^{-\beta_1\theta} \times \tau^{-\theta} \end{aligned}$$

Therefore,

$$\begin{aligned} & \mathbb{P}(l_1 = \tilde{j} \mid l_2 = \hat{j}) > \mathbb{P}(l_1 = \tilde{j}) \\ \Rightarrow \quad & s_{\tilde{j}} > \sum_i \sum_k \omega(i,k)\frac{s_i r_k}{v_{ik}} \quad \text{where} \quad \omega(i,k) = \frac{A_i A_k v_{ik}}{\sum_i \sum_k A_i A_k v_{ik}}, \quad \sum_{i,k}\omega(i,k) = 1 \\ \Rightarrow \quad & \tau_{\tilde{j}\hat{j}} < \left[\sum_{i,k}\omega(i,k)\left(\frac{\tau_{i\hat{j}} \times \tau_{\tilde{j}k}}{\tau_{ik}}\right)^{-\beta_1\theta}\right]^{-\frac{1}{\beta_1\theta}} \end{aligned} \tag{17}$$

The above inequality derived through (17), is the non-homogenous analogue of the condition derived in equation (15) under Proposition 3.2. Note, when we assume trade costs to trivial, i.e., $\tau_{ik} = 1$ or if $\tau_{ik} = \tau$, a constant, $\forall (i,k) \in \Omega^2$ equality holds, and in such a case we can conclude that the inclusion of $\tilde{j}$ at stage $n-1$ is independent of the location choice of stage n firm, and hence, the production network is not path dependent[11]. In such a case, and under the assumption that $\text{Cov}\left[S^{\tilde{j}}_{\ell;\ \text{imp}}, 1_{\{l_n=\hat{j}\}}\right] = 0$, if trade costs are trivial or identical, there would be no spatial spillovers. The intuition behind such a result is based on the fact that an increase in productivity for country $\tilde{j}$ cannot alter the production network, as the choice of a particular node as the least cost production location is independent of the production path, and is completely dependent on a countries' own CCA. And since we do not allow for any other form of productivity spillovers, that alters a countries' own CCA, the spillover effect is absent.

Lemma 3.2. *The conditional and unconditional probabilities coincide, i.e.,* $\{l_{n-1} = \tilde{j}\} \perp \{l_n = \hat{j}\}$, *when trade costs are homogeneous across all country pairs.*

It follows from Lemma 3.2, that non-homogenous trade costs are a necessary condition for having significant spillover effects in GVC participation through the mechanism we

[11] For any events A and B, $\mathbb{P}(A \mid B) - \mathbb{P}(A) = 0$ if and only if $A \perp B$.

discuss in this paper. Therefore, the necessary and sufficient condition for a positive spillover can be stated as,

$$\tau_{\tilde{j}\hat{j}}^{\ -\beta_1\theta} > \frac{\alpha_1\beta_1 + \alpha_2\beta_2}{\alpha_1\beta_1}\left[\sum_{i,k}\omega(i,k)\left(\frac{\tau_{i\hat{j}} \times \tau_{\tilde{j}k}}{\tau_{ik}}\right)^{-\beta_1\theta}\right]$$

If $\tau_{ij} = \tau \geq 1 \quad \forall (i,j) \in \Omega^2$, the above inequality does not hold true as was suggested by **??**.

4 Distance and Spatial Dependence

This section empirically examines our findings from Proposition 3.1, where we suggest that a country's integration into a GPN is shaped not only by its own characteristics but also by the degree of economic integration among its spatially proximate economies. Specifically, we test the hypothesis that offshoring activities generate spatial spillovers, such that greater integration in neighbouring economies reinforces a country's own participation in GVCs.

4.1 Estimation Strategy

Following the best practices in gravity literature (Fally, 2015; Yotov et al., 2016) we employ a two-stage estimation procedure to uncover the spatial dependence in likelihood of GVC participation:

First Stage:

$$T_{ijt} = \exp[\alpha_0 + \pi_{it} + \chi_{jt} + DIST^{w}_{ij}\alpha_d + CTG_{ij}\alpha_c + CL_{ij}\alpha_l + BORDER_{ijt}] \times \epsilon_{ijt} \quad (18)$$

$$T_{ijt} = \exp[\alpha_0 + \pi_{it} + \chi_{jt} + \mu_{ij} + RTA_{ijt} + \alpha_\tau \tau_{ijt} + BORDER_{ijt}] \times \epsilon_{ijt} \quad (19)$$

Second Stage:

$$\tilde{\pi}_{it} = \beta_0 + [W \times \tilde{\pi}_{it}] \ \lambda + X\beta + \eta_i + \varepsilon_{it} \quad (20)$$

Here, T_{ijt} is a bilateral measure of value added export associated with GVC trade by any country i, that is embodied in the final commodity production by country j[12]. α_m's,

[12] For a more complete definition of the variables and dataset used for the empirical analysis, please

β_n $\forall m, n$ and the fixed effects (π_{it}, χ_{jt}, μ_{ij}, η_i) in equations (18), (19) and (20) are the parameters to be estimated.

The specifications in equations (18) and (19) correspond to the TWFE and 3WFE models, respectively. Following Baier and Bergstrand (2007), we include directional country-pair fixed effects (μ_{ij}) to obtain unbiased estimates of trade policy variables, controlling for time invariant bilateral trade costs and country pair specific heterogeneity. Accordingly, variables such as bilateral distance ($DIST^w_{ij}$), common border (CTG_{ij}), and common language (CL_{ij}) are omitted due to collinearity with μ_{ij}. Time-varying trade costs are captured using bilateral tariffs (τ_{ijt}) and a regional trade agreement indicator (RTA_{ijt}). Consistent with Bergstrand, Larch, and Yotov (2015), we include time-varying border dummies ($BORDER_{ijt}$) to account for the global decline in international relative to domestic trade costs. We also correct for the Incidental Parameter Problem (IPP) following Weidner and Zylkin (2021). The time varying trade costs are controlled using a measure of bilateral tariff and an indicator variable of RTAs. Following the recommendations in Bergstrand et al. (2015), we introduce time varying border dummy variables ($BORDER_{ijt}$) which account for the common effects of globalisation which includes the effect of average decline in international trade cost relative to the domestic trade cost. We also address the bias arising from the Incidental Parameter Problem (IPP), as recommended by Weidner and Zylkin (2021).

We incorporate exporter-time (π_{it}) and importer-time (χ_{jt}) fixed effects to control for time-varying country-specific factors. The estimated exporter effects capture determinants of a country's attractiveness as a supplier, while importer effects absorb factors influencing the desirability of a destination for final production, including domestic capacity, market size, and nearby market potential. These fixed effects also account for the network dependencies highlighted in the theoretical framework. Finally, as Silva and Tenreyro (2006) demonstrate, OLS estimation of the structural gravity model is biased and inconsistent; therefore, we employ the Poisson Pseudo-Maximum Likelihood (PPML) estimator, which offers consistent and efficient estimates for equations (18) and (19).

We estimate NT exporter-time fixed effects ($\hat{\pi}_{it}$) for N countries over T periods, following Correia, Guimarães, and Zylkin (2020). To avoid multicollinearity, we impose the restriction that the weighted sum of fixed effects, where weights are the conditional means or predicted values of the outcome variable, equals zero. This allows separate estimation of the fixed effects and the intercept term ($\hat{\alpha}_o$), which captures the scale of the dependent variable. Following Fally (2015), the estimated exporter-time effects have a structural interpretation as multilateral resistance (MR) terms within the Anderson and van Wincoop (2003) gravity framework. We treat these effects as consistent measures of a country's export attractiveness. Since fixed effects are identifiable only up to a normalisation, we

see appendix B.

set the exporter fixed effects for the United States to zero in each period ($\hat{\pi}_{US,t} = 0,\ \forall t$), providing a consistent benchmark for interpretation without affecting the estimated coefficients.

$$\tilde{\pi}_{it} = \hat{\pi}_{it} - \hat{\pi}_{US,t} \tag{21}$$

We now estimate the parameters in the SAR specification represented through equation (20) using maximum likelihood estimation following the discussion in Anselin, Gallo, and Jayet (2008); Debarsy and Ertur (2010); Elhorst (2010); Lee and Yu (2010). We assume that W the weight matrix is constant over time and that we have a balanced panel dataset. W of order $N \times N$, is a row-normalised, inverse distance matrix which establishes the neighbourhood of countries, where, N denotes the number of countries in the sample. While X denotes the control added to specification. η_i controls for all country specific time invariant factors that affect the attractiveness to make value addition in GVC activities.

The spatial weight matrix establishes systematic relationships across spatial units and facilitates the transmission of spatial dependence. Our choice of inverse-distance weights is theoretically grounded and exogenous to the analysis. For N spatial units the weight matrix can be computed as:

$$W = \begin{pmatrix} 0 & w_{12} & \cdots & w_{1N} \\ w_{21} & 0 & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & 0 \end{pmatrix}$$

W is a non-negative matrix, with all diagonal elements (w_{ii}) assumed equal to zero[13]. In our empirical analysis, we define w_{ij} as a measure of the relative proximity (or, nearness) of country j to country i, compared to all other countries' proximity to country i and is represented by

$$w_{ij} = \begin{cases} \frac{d_{ij}^{-1}}{\sum\limits_{j \in J_i} d_{ij}^{-1}}, & \text{if } j \in J_i \\ 0, & \text{otherwise.} \end{cases}$$

A higher value of w_{ij} indicates a greater influence of spatial unit j on i. Similarly, $w_{ij}\big|_{i \neq j} = 0$ implies that country j is not a part of the neighbourhood for country i. The column element of a weight matrix shows the impact of a particular unit on all other units, while

[13] As no spatial unit can be considered as the neighbour of itself.

the row denotes the effects on one unit by all neighbouring units. It is common practice to row-normalise W, therefore each element $w_{ij} \in [0, 1]$ and $\sum_j w_{ij} = 1$[14]. Therefore, the operation $W \times Y$ averages the neighbourhood values. Row normalising also equalises the impact on every geographical unit.

As Fernandes et al. (2022) note, most within-country determinants of GVC participation are time-invariant or slow to evolve and are thus absorbed by country fixed effects (η_i)[15]. Real GDP is retained as a control to capture meaningful changes in resources and technological capacity. Accordingly, in the second-stage estimation, the coefficient on $\log(RGDP^e_{it})$ identifies how within-country improvements in production capacity enhance a country's attractiveness for GVC participation. We also explore the role and spatial spillovers of other country-specific factors such as institutional quality, resource endowments, and infrastructure. The second-stage results are corrected for biases arising from the IPP, following Lee and Yu (2010). Discussion of the first-stage estimates appears in appendix C.1.

4.2 Results: Spatial Dependence

The estimation strategy approach adopted in this section aligns closely with the widely used gravity model framework. In this context, the exporter-time fixed effects can be perceived (or, serve) as a dynamic measure of the exporting country's attractiveness for participation in the production network, specifically by contributing value-added to the final commodity. This measure is derived after accounting for country-pair effects, importer-time fixed effects, the common effects of globalization, and trade policy variables, as discussed in section 4.1. The inclusion of this rich set of fixed effects ensures that we control for a broad range of factors that could influence the exporting country's participation in the production network[16]. In this section we focus on the results from the TWFE specification, presented in Table 2.

We find that the SAR coefficients λ are statistically significant, positive and large in magnitude for both the range of years indicating strong spatial dependence. In essence, an average increase of 1 unit in the attractiveness of the neighbouring spatial units increase the attractiveness of the country by ~ 0.37 units pre financial crisis and by ~ 0.88 units

[14] The non-negativity of W and the fact that each row sums to one imply that W is a row-stochastic matrix.

[15] Including geographic, institutional, and cultural factors that change little over time but influence participation in GVC activities.

[16] The exporter time and importer time fixed effects control for the feature of the relationship we study, where the flow of value added between two countries is enhanced or diminished by the trade costs of the exporting or importing country with other trading partners. Similarly, the country pair FE in the 3WFE specification controls for all possible country pair-specific factors that could have determined the relationship.

Table 2: Spatial Dependence: Stage 2 (TWFE)

	Dependent Variable: $\tilde{\pi}_{it}$				
	Country FE			TWFE	
Variables	2002–2008	2012–2018	2000–2019	2002–2008	2012–2018
	(1)	(2)	(3)	(4)	(5)
λ	0.368***	0.879***	0.600***	0.439***	0.431***
	(0.062)	(0.019)	(0.038)	(0.120)	(0.124)
$\log(RGDP^{e}_{it})$	0.604***	0.630***	0.309***	0.733***	1.433***
	(0.051)	(0.083)	(0.026)	(0.045)	(0.064)
Observations	532	532	1520	532	532
Country FE	✓	✓	✓	✓	✓
Time FE				✓	✓
Direct Effect	0.607***	0.691***	0.314***	0.738***	1.443***
	(0.049)	(0.097)	(0.025)	(0.044)	(0.063)
Indirect Effect	0.350***	4.417***	0.458***	0.569*	1.075*
	(0.102)	(0.982)	(0.086)	(0.332)	(0.655)
Total Effect	0.957***	5.108***	0.773***	1.307***	2.518***
	(0.127)	(1.051)	(0.100)	(0.344)	(0.673)

Standard Errors in Parentheses
Estimates corrected for the bias specified in Lee and Yu (2010)
*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

post the financial crisis. This suggests that a country's GVC participation is positively influenced by that of its neighbouring countries, reflecting the interconnected nature of global trade networks. Alternatively, if on average, the neighbouring countries are more deeply integrated into the GPN, the likelihood of countries in their neighbourhood to become a part of such a production network also increases. The spatial dependence is significantly higher post-financial crisis. The increase in spatial dependence in the post-crisis period can be attributed to the trade disruptions and geopolitical tensions that followed, which not only strengthened regional trade linkages but also compelled countries to reassess their positions within GVCs. This period appears to mark a shift towards greater reliance on regional suppliers to meet production needs, accompanied by a relative decline in engagement with more distant partners. Firms increasingly reorganised production around regional clusters, thereby reinforcing interdependence among geographically proximate economies. At the same time, the growing influence of dominant hub countries, most notably China in Asia, Germany in Europe, and the US-Mexico bloc in North America, further synchronised the trade patterns of smaller economies with those of their regional anchors. Moreover, the technological advances and the growing role of emerging markets as major destination for final commodities, often expanded South-South linkages. In summary, our result implies that by the 2010s, countries' GVC participation was increasingly shaped not just by their own bilateral choices, but also by the integration trajectories of their neighbours, giving rise to stronger spatial interdependence in trade flows.

As the coefficient of the regression parameters are only indicative of the underlying effects we compute the direct and the indirect effects. Direct effects are greater than the regression coefficients for real GDP indicating a positive feedback effect. Alternatively, we find this standard across all regressions that the indirect effects of domestic production capacity proxied by real GDP in an economy are positive and statistically significant. Specifically, a 1% increase in $RGDP_{it}^{e}$ raises $\tilde{\pi}_{it}$ by approximately 0.60% units during 2002–2008, 0.63% during 2012–2018, and 0.31% units over the full sample period of 2000–2019. In our estimates, the larger indirect effects relative to the direct effects indicate that productivity shocks diffuse more powerfully across borders, so that a 1% rise in real GDP produces a greater cumulative impact on neighbours than on the home country itself. Moreover, the significant feedback effect underscores how policy or productivity interventions in one location resonate back through the network, reinforcing local outcomes via multi-step spatial feedback loops. These results suggest that improvements in economic conditions, both domestically and regionally, play an important role in enhancing $\tilde{\pi}_{it}$ supplementing the findings from Behrens et al. (2012); LeSage and Pace (2009).

Given that the estimated SAR coefficient exhibits notable variation across different sample periods, we introduce time fixed effects to account for common shocks and other time-varying factors that may have influenced all countries simultaneously. The corresponding results, reported in Columns (5) and (6) of Table 2, remain qualitatively consistent with the baseline specification. As expected, the estimated SAR parameter (λ) is quantitatively stable, lying in the range of 0.43–0.44 after controlling for time effects. Moreover, both the direct and indirect spillover effects remain positive in magnitude and statistically significant, underscoring the robustness of the spatial dependence observed in trade flows.

To explore the role of different structural characteristics in shaping participation in global production networks, we turn to the alternative specifications presented in Table 3. Each column introduces a different explanatory variable, such as productive capabilities to institutions, while conserving the same fixed effects structure and spatial econometric approach.

Across all specifications, the spatial autoregressive parameter (λ) remains positive, highly significant, and economically meaningful. This consistency reinforces our conclusion that

Table 3: Spatial Dependence: Stage 2 (TWFE) – Alternate Specification

	Dependent Variable: $\tilde{\pi}_{it}$						
	PCI	Natural Resources	Human Capital	Institutions	Transportation	ICT	$RGDP^o_{it}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
λ	0.641***	0.857***	0.819***	0.854***	0.848***	0.671***	0.590***
	(0.037)	(0.022)	(0.026)	(0.022)	(0.022)	(0.037)	(0.038)
$\log(X_{it})$	1.044***	0.039	0.212***	0.783***	0.152***	0.189***	0.319***
	(0.083)	(0.076)	(0.057)	(0.080)	(0.044)	(0.020)	(0.025)
Observations	1520	1520	1520	1520	1520	1520	1520
Country FE	✓	✓	✓	✓	✓	✓	✓
Direct Effect	1.067***	0.042	0.225***	0.845***	0.163***	0.194***	0.325***
	(0.090)	(0.081)	(0.064)	(0.092)	(0.050)	(0.019)	(0.026)
Indirect Effect	1.842***	0.226	0.945***	4.485***	0.832***	0.381***	0.455***
	(0.331)	(0.459)	(0.326)	(0.915)	(0.298)	(0.079)	(0.076)
Total Effect	2.909***	0.267	1.170***	5.330***	0.995***	0.575***	0.780***
	(0.383)	(0.539)	(0.381)	(0.974)	(0.342)	(0.091)	(0.089)

Standard Errors in Parentheses
Estimates corrected for the bias specified in (Lee & Yu, 2010)
*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

spatial dependence is an intrinsic feature of global value chain participation. Regardless of the specific channel considered, the results indicate that a country's attractiveness to engage in production-sharing arrangements is positively and significantly influenced by the attractiveness of its neighbouring economies.

The inclusion of distinct country-level variables serves to highlight additional channels through which economic fundamentals might shape GVC engagement. We conclude that stronger production capacity which is augmented through proper institutional characteristics, abundant resources (human capital and natural resources) and improved infrastructure and ICT capabilities improve a countries' participation in GVC. However, the coefficient on natural resources is statistically insignificant. This is consistent with the expectation that resource endowments are largely time-invariant. As a result, they do not exhibit sufficient within-country variation to yield identifiable effects in this specification. The direct and indirect effects associated with each explanatory variable, similar to the baseline esitmates underscore the broader spatial dynamics at play.

4.3 Robustness Checks

One inevitable question that could arise from our econometric strategy, is our choice of spatial neighbours. A question that has been excessively discussed in the spatial econometric literature. And therefore, in addition to the other robustness checks, we check whether our results are robust to the various definitions of neighbourhood.

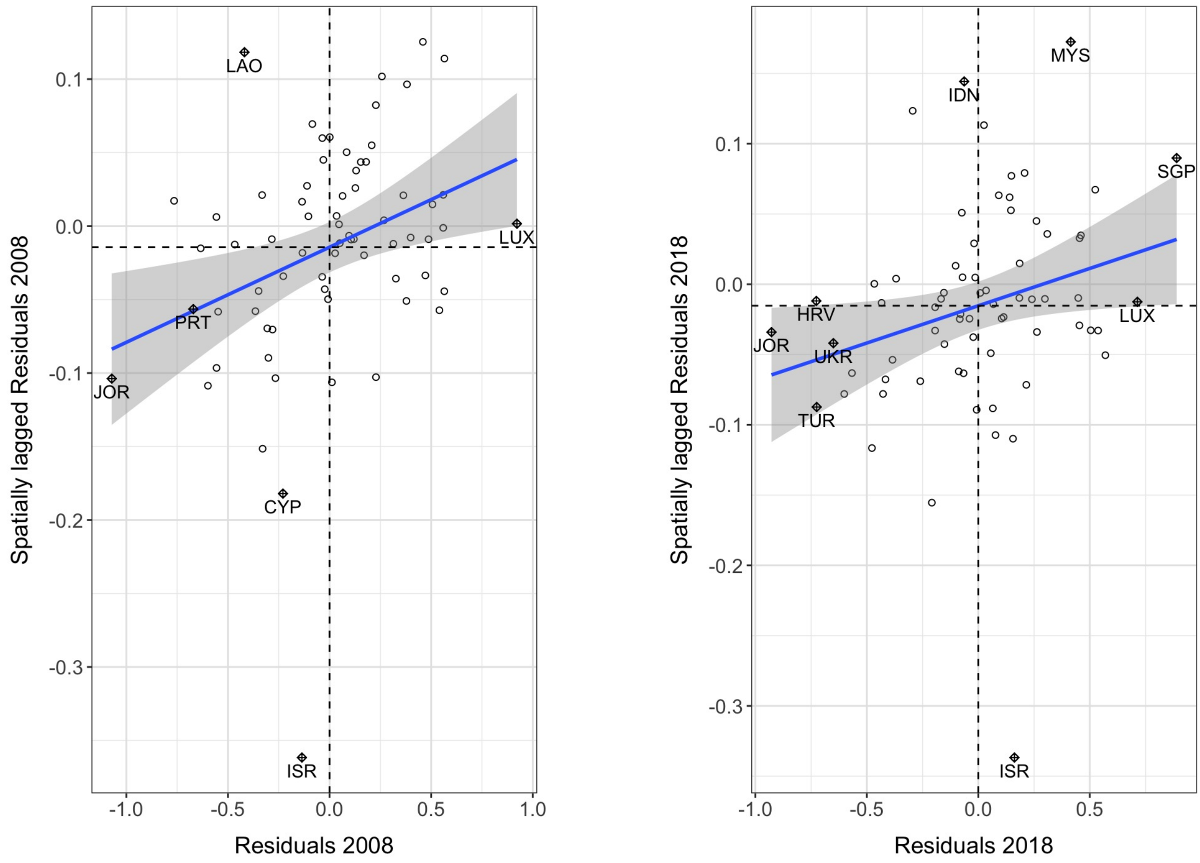
We conduct several robustness checks to validate the spatial dependence in GVC participation. First, employing a three-way fixed effects specification confirms the baseline two-way fixed effects findings: the spatial autoregressive coefficient (λ) remains positive and highly significant across multiple sample periods (2002–2008, 2012–2018, and 2000–2019), underscoring persistent spatial spillovers. Both direct and indirect effects of the real GDP are consistently positive and significant, highlighting the importance of domestic economic conditions and regional spillovers. Second, redefining spatial proximity using the distance between capital cities rather than population-weighted geographical distance yields similar positive and significant spatial dependence results, robust under both TWFE and 3WFE frameworks. Third, varying the neighbourhood definition through geographic distance cut-offs around the average bilateral distance ($\sim$ 6800 km) and using the contiguity criterion for being classified as neighbours confirms that the spatial autoregressive coefficient remains significant and positive, though somewhat attenuated with more restrictive neighbourhoods. These findings reveal that spatial spillovers in forward GVC participation operate at multiple spatial scales: immediate neighbours and broader regional groupings both contribute substantially. Overall, the robustness checks reinforce the conclusion that spatial economic interdependence captured through diverse spatial weighting schemes and fixed effects controls is a key driver of cross-country GVC integration dynamics.

5 Geo-Spatial Proximity and Cross Border Effects of Technological Change

The baseline specification to estimate the impact of a technological change, on the value added associated with GVC of other spatially proximate countries is given through the equation (22). We spare a detailed discussion for the estimation procedure in this section, as the estimation strategy directly follows from the MLE discussed in Anselin et al. (2008).

$$VA_{it} = \alpha_0 + (W \times VA_{it})\ \lambda + \gamma TFP_{it} + X\beta + \mu_i + \delta_t + \varepsilon_{it} \tag{22}$$

In the above specification, i denotes spatial units and t time, while ε_{it} denotes the idiosyncratic error term. $VA_{it} = \sum_j T_{ijt}$ represents the total domestic value added in exports through GVC activities by economy i at time t. Thus, the spatial lag term $W \times VA_{it}$ captures the spatially weighted average of value added associated with GVC trade. A key explanatory variable in the model is TFP_{it}, representing the level of technology. Additional regressors denoted by the vector X account for a country's capital services, capital-to-labour ratio, average applied tariffs, and overall productive capacity, as captured by the Productive Capacities Index. As highlighted by Fernandes et al. (2022), many determinants of value-added trade, only evolve gradually with time, to control for



(a) 2008 (b) 2018

Figure 1: Spatial Auto-Correlation in Estimated Error Term

Note: After controlling for all the exogenous variables in the baseline estimate, we find that the residuals are spatially auto-correlated, indicating that the model might not be capturing important spatial patterns and could potentially lead to unreliable inferences. The Moran's I statistic is positive and statistically significant at the 1% level.
Source: Author's calculation.

these variables, we include country FE. Finally, these results are also corrected for the biases stemming from IPP following Lee and Yu (2010)

5.1 Results: Technology Spillover

This section provides empirical evidence for the presence of a location effect in productivity spillovers through the channel of International trade and Global Production Network. Spatial econometric analysis is typically divided into two stages, first stage requires us to check for the presence of spatial dependence in our model.

We begin by estimating the LM-Lag and LM-Error statistics, followed by their robust counterparts, which are the panel extensions of the diagnostic tests in Anselin, Bera, Florax, and Yoon (1996). The robust versions are considered only if the null of no spatial dependence is rejected in both the LM-Lag and LM-Error tests. Table 4 reports the baseline results. Column (1) presents the panel fixed effects estimates (without the SAR term), while column (2) reports the baseline specification along with the LM test results based on the same econometric model and spatial weight matrix. Both LM-Lag and LM-Error tests are significant at the 1% level, indicating spatial dependence. The LM-Lag statistic is larger in magnitude than the LM-Error statistic. Turning to the robust tests, the robust LM-Lag test rejects the null at the 5% level, whereas the robust LM-Error test does not. Thus, spatial dependence is present in the dependent variable, justifying the use of the SAR specification in subsequent estimations.

We now proceed to the estimates from the SAR specification. However, before discussing the estimates from our baseline specification, we first present the results from the PLM estimates. The standard errors reported in column (1) are clustered at the country (spatial unit) level. However, we find that technological change proxied by the measure of TFP is positive and statistically significant at 1% level of significance. Rejecting the null hypothesis of no impact on total value added export associated with GVC for a country. We can further infer from the estimate that a 1% increase in TFP leads to a 0.6% increase in the dependent variable. We now consider the specification in column (2) of Table 4, with columns (3), (4) and (5) indicating the direct, indirect and total effects of a unit change in the explanatory variables on the dependent variables across all related spatial units respectively. As shown in Table 4, the spatial autoregressive coefficient λ is statistically significant and positive, indicating clear spatial dependence in value-added exports associated with GVC among geographically proximate countries. This suggests that the effect of a productivity boost is not strictly confined within national borders. In other words, the total value added in a country's GVC-related exports is influenced by the value added in the GVC trade of its neighbouring regions. Specifically, a 1% increase in the spatially weighted average of value-added GVC exports leads to an approximate 0.33% increase in the country's own value-added GVC trade.

We find that improvements in technology, proxied by TFP, have a positive and statistically significant effect on the total value added exported through GVCs, with an elasticity of approximately 0.6, consistent with the results from the TWFE PLM estimation.

However, these estimators provide only an idea of the interactions among countries and productivity; and therefore we compute and provide the sign and magnitude of the direct and indirect impacts to provide accurate measures of *spillover effects*. These measures are provided for the baseline specification. The direct impact estimates are similar to the corresponding regression coefficients (in absolute terms) shown in column (1) but the former are slightly higher. From the direct effects we conclude that a 1% increase in the TFP measure increases value added associated with GVC after incorporating the feedback effects by 0.599%. The sign and coefficient of indirect effects are of prime importance to

Table 4: Spatial Productivity Spillover on Value Added in Production Associated with GPN (Baseline Estimate)

	Dependent Variable: $\log(VA_{it})$				
	PLM	BE	Direct	Indirect	Total
Variables	(1)	(2)	(3)	(4)	(5)
λ		0.331***			
		(0.074)			
$\log(TFP_{it})$	0.600***	0.597***	0.599***	0.293***	0.892***
	(0.160)	(0.040)	(0.040)	(0.107)	(0.126)
LM Tests					
LM_ℓ		13.434***			
LM_e		8.493***			
RLM_ℓ		5.335**			
RLM_e		0.394			
Observations	1380	1380			
Country Fixed Effects	✓	✓			
Time FE	✓	✓			
Additional Regressors	✓	✓			

Standard errors in parentheses corrected for bias specified in Lee and Yu (2010)
For column (1), we report clustered robust standard errors.
*** p<0.01, ** p<0.05, * p<0.1

our study as they explain the spillover effects particularly of the technological and productivity improvements[17] The coefficients turn out to be statistically significant and positive, supporting our hypothesis of positive spatial spillovers of technology. Our estimates suggest that, on average, a 1% increase in the TFP measure in a given country leads to an approximate $\sim 0.3\%$ increase in forward GVC value added in its neighbouring countries. This spillover effect primarily occurs through the initial rise in the value added generated by the country experiencing the productivity improvement. The resulting increase in GVC-related exports fosters greater participation in GVC among neighbouring countries, thereby enhancing their own value added through increased involvement in cross-border production activities. Finally, total effects denotes the aggregate effect of an increase in the explanatory variable of a spatial unit on all spatial units including itself. We find that a 1% increase in technology indicated by the TFP measure accentuates value added in

[17] These coefficients can be explained as the average effect of a change in the dependent variable in its neighbourhood due to the change in the explanatory variable in a country.

Table 5: Spatial Extensions

	Dependent Variable: log(VA_{it})				
SLX	$RGDP^o_{it}$	K^s_{it}	$Avg\ \tau_{it}$	C_{it}	TFP_{it}
Variables	(1)	(2)	(3)	(4)	(5)
λ	0.350***	0.344***	0.330***	0.291***	0.276***
	(0.077)	(0.075)	(0.074)	(0.081)	(0.082)
log(TFP_{it})	0.598***	0.596***	0.596***	1.312***	0.593***
	(0.040)	(0.040)	(0.040)	(0.061)	(0.040)
log(SLX)	-0.065	-0.059	-0.022	0.513***	0.526*
	(0.115)	(0.103)	(0.129)	(0.138)	(0.285)
Observations	1380	1380	1380	1380	1380
Country Fixed Effects	✓	✓	✓	✓	✓
Time Fixed Effects	✓	✓	✓	✓	✓
Additional Regressors	✓	✓	✓	✓	✓

Bias corrected SE in parentheses following Lee and Yu (2010)
*** p<0.01, ** p<0.05, * p<0.1

GVC trade for the own and other spatially proximate countries by $\sim 0.9\%$. The estimates for the control variables follow our theoretical prior.

5.2 Extensions

It can be argued that the effect of a country's domestic production capacity on the GVC participation measure through the domestic value added export associated with GVC is ambiguous. Since, larger domestic capacity can be associated with attracting greater GVC activities onshore, and simultaneously have a ripple effect on the value added in exports of the neighbouring countries, it may on the other hand induce competition in the region for hosting intermediate stages or reduce dependence on intermediate imports. To test these impacts we introduce into the baseline model spatial lag of some regressors. These results are presented in Table 5 with their impacts evaluated and presented in Table 6. The first set of results, presented in columns (1) and (2), incorporate the spatial lags of real GDP and capital services, which serve as proxies for domestic productive capacity. Column (3) extends the specification by including the spatial lag of the average tariff rate, while column (4) adds the spatial lag of real household and government consumption expenditure. Finally, column (5) introduces the spatial lag of total factor productivity ($TFP_{i,t}$).

We find that across all model specifications, the SAR coefficient and the coefficient for TFP remains positive and statistically significant, aligning closely with our baseline estimates and reaffirming the presence of spatial spillovers in GVC participation. Other control variables also show consistent effects when compared with the baseline estimates.

Now focusing on our key variable of interest, the domestic production capacity, proxied by domestic capital expenditure and real GDP we observe a negative but statistically insignificant direct effect on the GVC participation of neighbouring countries. This suggests that when a country enhances its own production capacity, it may reduce the need for external inputs from nearby economies. However, this increase in domestic capacity still promotes the country's own participation in GVCs, which in turn positively influences the participation of spatially proximate countries through indirect spatial effects as we see from the baseline estimates and from the coefficient of similar variables from the extended specification. We also find that a larger domestic market in neighbouring countries, captured through higher household and government consumption in these countries, is associated with greater GVC participation in nearby countries. This relationship is positive and statistically significant. One plausible explanation to these evidences is that a larger domestic market tends to demand more imports of both final and intermediate goods to meet local consumption needs. As noted by Antràs and Gortari (2020), neighbouring countries are often well-positioned to carry out the downstream stages of production in such cases.

Additionally, we find that higher tariffs on imports imposed by neighbouring countries tend to reduce GVC participation in the region. This result reflects the disruptive nature of trade barriers, which can weaken the interconnectedness of production networks. High tariffs may also encourage firms to substitute imports with local production, even the multinational firms may find it more efficient to serve the market through local production, thereby reducing the scope for neighbouring countries to participate in the value chain. Consistent with the analysis, we report the estimated direct and indirect effects in Table 6, which quantitatively support the narrative outlined above. Critically in column (6), the coefficient on the spatial lag of TFP is also positive and marginally significant, suggesting that a country's economic performance is influenced not only by its own productivity but also by the productivity levels of its geographically proximate neighbours. This supports the presence of spatial spillovers, where improvements in TFP among nearby countries can enhance a country's own likelihood of participating in economic activities such as GVCs. This mechanism captures second-order, indirect pathways through which productivity gains diffuse across borders, reinforcing the notion that comparative advantage is not only a function of internal factors but also shaped by regional dynamics.

Table 6: Impacts from Table 5

	$RGDP^o_{it}$			K^s_{it}			$Avg\ \tau_{it}$			C_{it}			TFP_{it}		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
log(TFP_{it})	0.600***	0.320***	0.920***	0.599***	0.31***	0.909***	0.599***	0.291***	0.890***	1.316***	0.534**	1.850***	0.595***	0.225***	0.820***
	(0.038)	(0.121)	(0.134)	(0.043)	(0.100)	(0.119)	(0.039)	(0.103)	(0.119)	(0.059)	(0.234)	(0.254)	(0.037)	(0.092)	(0.103)
log(SLX)	-0.066	-0.035	-0.101	-0.060	-0.031	-0.091	-0.022	-0.011	-0.032	0.515***	0.209**	0.724***	0.528**	0.120	0.727*
	(0.110)	(0.067)	(0.174)	(0.117)	(0.065)	(0.180)	(0.138)	(0.074)	(0.210)	(0.140)	(0.106)	(0.214)	(0.271)	(0.150)	(0.401)

SE in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3 Results: Instrumental Variables for TFP

A growing literature emphasises the spatial interdependence of productivity, as technological progress in one region can diffuse to others through geographically bounded channels such as trade, FDI, and knowledge transfer (Ertur & Koch, 2007; Keller, 2002). Studies including Coe and Helpman (1995); Coe et al. (2009); Fracasso and Marzetti (2015); Grossman and Helpman (1991) show that international trade facilitates cross-border technology diffusion, with innovation responding to incentives shaped by cumulative R&D and learning. However, these productivity gains are not instantaneous; they emerge gradually as firms adapt to new technologies and competitive pressures. Evidence from Ciarli, Coad, and Moneta (2023); Constantinescu, Mattoo, and Ruta (2019) indicates that GVC participation enhances labour productivity with a lag, while firm-level analyses such as Berman and Rebeyrol (2010) reveal a unidirectional contemporaneous link from productivity to export growth, alongside a delayed reverse effect.

International trade facilitates technology diffusion by exposing countries to foreign R&D embodied in imports, which complements domestic innovation and enhances TFP. To address potential endogeneity from such interactions and global shocks, the specification employs country fixed effects (μ_i) to control for time-invariant heterogeneity, and time fixed effects (δ_t) to absorb common macroeconomic and technological trends.

Based on the preceding discussion, we find strong evidence of unidirectional causality whereby TFP significantly enhances domestic value added in exports. Although reverse causality cannot be fully excluded, any such effect is likely limited and temporally lagged. To address potential endogeneity of TFP and measurement error (Hausman, 2001), we employ instrumental variable (IV) estimation using a two-stage least squares (2SLS) framework. This approach is particularly suitable in spatial dependence models where one or more endogenous regressors arise from simultaneous interactions (Fingleton & Le Gallo, 2008), and where maximum likelihood or Bayesian estimators are often infeasible (Elhorst, 2010). The chosen IVs satisfy standard relevance and exclusion restrictions: they are jointly significant in explaining the endogenous variable and uncorrelated with the second-stage residuals, influencing domestic value added in exports only through TFP. Instrument selection is guided by both theoretical considerations and empirical evidence, with standard statistical tests employed to verify instrument strength and validity.

For our purpose to instrument the spatially lagged dependent variable $W \times VA$ Kelejian, Prucha, and Yuzefovich (2004) suggested $[X^e, WX^e, \cdots, W^n X^e]$ where X^e is the set of exogenous regressors, and n is any predetermined constant[18]. The Internal Rate of Return (IRR) serves as a theoretically grounded and empirically valid instrument for identifying the causal effect of TFP on domestic value added in GVC exports. It satisfies both the relevance and exclusion conditions required for a valid instrument. To elaborate, IRR captures the real marginal product of capital, reflecting the efficiency of capital use across countries and over time, while remaining exogenous to short-run trade shocks. Since economies with higher TFP typically exhibit more efficient capital utilisation and thus higher IRR, the instrument naturally embodies cross-country differences in productivity. Moreover, higher returns on investment stimulate R&D activity and attract foreign capital, both of which foster innovation and technology transfer. The strength and validity of this relationship are confirmed by our first-stage results. Regarding the exclusion restriction, we assume that, conditional on controls, the IRR influences domestic value-added exports only through its effect on TFP. The inclusion of capital services, capital intensity, structural capabilities (PCI), trade policy, and country and year fixed effects accounts for alternative channels, making the remaining variation in IRR plausibly exogenous and consistent with the exclusion restriction. Note the validity of our IV is discussed in appendix C.2.

In Table 7, we present results from the SAR 2SLS estimation. Columns (1) to (3) show estimates where TFP is treated as exogenous. While our main specification relies on a spatial model with TWFE, we also include results from the one-way FE estimator and from the more general SAC specification. Across all three specifications, we find clear evidence of positive spatial dependence in value-added exports, and the estimated coefficients for the explanatory variables remain stable and in line with the baseline estimates from Table 4. The spatial autoregressive coefficient (λ) is slightly larger than in our baseline panel results but remains in a similar range. Importantly, the coefficient on TFP remains consistently in the range of 0.595 - 0.620 across all specifications. In columns (4) and (5), we account for the possible endogeneity of TFP by using instrumental variables. However, similar to our panel IV results, the changes in the estimated coefficients are small when comparing between the respective pairs of estimates, suggesting that our main findings are robust to potential endogeneity concerns.

[18] Usually $n = 1$ or 2.

Table 7: Spatial IV

	Dependent variable: $\log(VA_{it})$				
	(1)	(2)	(3)	(4)	(5)
λ (Spatial Lag)	0.707***	0.514***	0.531***	0.708***	0.472***
	(0.021)	(0.183)	(0.181)	(0.021)	(0.182)
log(TFP)	0.620***	0.595***	0.598***	0.620***	0.595***
	(0.041)	(0.041)	(0.042)	(0.041)	(0.041)
Observations	1380	1380	1380	1380	1380
Country FE	✓	✓	✓	✓	✓
Time FE		✓	✓		✓
Additional Regressors	✓	✓	✓	✓	✓
Spatial Error			✓		

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Robust SEs in Parentheses

5.4 Robustness Checks

To further validate the robustness of our main findings discussed in subsection 5.1, we explore alternative definitions of spatial neighbourhoods and variations in the spatial weight matrix construction. First, by progressively restricting the neighbourhood (similar to the earlier case) using inverse-distance thresholds and ultimately adopting a contiguity-based approach where only countries sharing a border are considered neighbours, we observe that the spatial lag coefficient (λ) remains positive and statistically significant across all specifications. This confirms the presence of strong spatial dependence and the robustness of spillover effects in value added trade irrespective of how the neighbourhood is defined. Additionally, we examine the impact of varying the distance decay factor ρ in the spatial weights matrix, which controls how spatial influence diminishes with distance. Our results show that increasing ρ from 2 to 3 reduces, but does not eliminate, the magnitude of indirect effects, while the direct effects of total factor productivity (TFP) remain stable and highly significant. This suggests that while the intensity of spatial spillovers is sensitive to how quickly influence fades with distance, the core relationship between TFP and value added holds firmly. Overall, these robustness checks reinforce the credibility of our findings, demonstrating that technological improvements generate both substantial domestic gains and meaningful cross-border spillovers across a variety of spatial interaction frameworks.

6 Conclusion

Through this scholarship we contribute to the existing literature in two crucial ways. First, we contribute to the broader literature on the determinants of GVC participation by adapting recent advances in gravity model estimation within a two-stage framework to uncover spatial interdependence in GVC participation. We find that, in addition to domestic factors that typically influence a country's participation in global trade, particularly in the context of GVCs, the productive capacity of neighbouring countries also plays an important role. The channel we investigate indicates that a country's integration into the GPN creates incentives for the geographic concentration of ancillary production nodes in surrounding regions. This tendency is further reflected in the increasing dependence on neighbouring countries for intermediate inputs, as highlighted through earlier discussion in this paper.

We argue that the common practice in the empirical trade literature of using distance based measures or country-pair fixed effects to capture spatial dependence is inadequate, as these approaches reflect fundamentally different concepts. In our analysis, we make use of exporter-time fixed effects estimated consistently through the PPML estimator in the first stage. These fixed effects provide a measure of whether a country' integration into the GVC is above or below the average. In the second stage, we adopt a SAR specification and find that countries with deeper integration into GVCs tend to enhance the participation of their neighbouring countries. This finding highlights a spatial spillover effect in global production networks. Importantly, our results remain robust across alternative model specifications and various definitions of the neighbourhood set, which is exogenously determined in our analysis. While the econometrics literature often critiques the ad hoc nature of neighbourhood construction in spatial models, our robustness checks using alternative spatial structures help to reinforce the credibility and stability of our findings.

Secondly, we examine how improvements in technology and productivity influence the participation of neighbouring countries in GVC, using a general equilibrium framework. Our analysis identifies a new channel through which technological advancement in one country can spread across borders and contribute to income growth in surrounding nations. We measure the GVC participation through the domestic value added that is generated from engagement in international production and trade. Although existing trade literature recognises that technological progress can benefit trading partners through lower input costs or lower relative costs for imported final commodities, it has often overlooked the role of geographic proximity in shaping the extent of these gains. Our findings highlight that productivity improvements in one country not only enhance its own involvement in GVCs but also strengthen the participation of its neighbours. This occurs through production linkages that transmit benefits both upstream and downstream in the value chain.

Our findings have important policy implications, particularly in the current context of persistent global shocks and a shift away from globalisation marked by tariffs, sanctions, and military conflicts. The results suggest that policies should strengthen regional cooperation: As GVCs tend to cluster geographically, regional blocs can magnify productivity spillovers. This implies that negotiating regional trade agreements, common markets, or infrastructure corridors would reinforce these positive effects. Specifically, deeper RTAs and stronger institutional linkages can facilitate regional growth. For instance, RTAs such as ASEAN and NAFTA should be prioritised, as jointly lowering trade barriers among neighbouring economies enhances their overall GVC participation and amplifies productivity spillovers. Policymakers should also invest in cross-border projects, such as highways and railways to reduce shipping time, and streamlined customs procedures to ease commodity flows, so that productivity gains translate more efficiently into higher GVC participation. Moreover, since GVC participation is spatially dependent, efforts to reduce bilateral trade costs should be complemented by mutual capacity building through joint R&D, workforce training, and infrastructure development within neighbouring economies. Countries could also foster industrial clusters through joint ventures, R&D partnerships, and similar collaborative initiatives.

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A Appendix: Mathematical

A.1 Proof of Lemma 3.1

$$
\begin{aligned}
\frac{d\ \mathbb{P}(l_n=\hat{j};F)}{d\ \Theta_{\hat{j}}} &= \left(\frac{1}{\phi_F^N}\right)^2 \left[\phi_F^N \frac{d\left(\sum_{\ell\in\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F}\right)}{d\ \Theta_{\hat{j}}} - \left(\sum_{\ell\in\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F}\right) \frac{d\ \phi_F^N}{d\ \Theta_{\hat{j}}}\right] \\
&= \left(\frac{1}{\phi_F^N}\right)^2 \left[\phi_F^N \sum_{\ell\in\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F}\ S_\ell^{\tilde{j}} - M \sum_{\ell\in\Omega^N} A_{\ell F} S_\ell^{\tilde{j}}\right] \\
&= \frac{1}{\phi_F^N} \sum_{\ell\in\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F}\ S_\ell^{\tilde{j}} - \frac{\mathbb{P}(l_n=\hat{j};F)}{\phi_F^N} \sum_{\ell\in\Omega^N} A_{\ell F} S_\ell^{\tilde{j}}
\end{aligned} \tag{23}
$$

Since, $\Omega^N_{l_n=\hat{j}} \subseteq \Omega^N$, we can decompose the second term on the R.H.S of equation (23) into,

$$
\sum_{\ell\in\Omega^N} A_{\ell F} S_\ell^{\tilde{j}} = \sum_{\ell\in\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F} S_\ell^{\tilde{j}} + \sum_{\ell\in\Omega^N-\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F} S_\ell^{\tilde{j}} \tag{24}
$$

Therefore, equation (23) can be expressed as

$$
\frac{d\ \mathbb{P}(l_n=\hat{j};F)}{d\ \Theta_{\hat{j}}} = \frac{1-\mathbb{P}(\hat{j})}{\phi_F^N}\left(\sum_{\ell\in\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F} S_\ell^{\tilde{j}}\right) - \frac{\mathbb{P}(\hat{j})}{\phi_F^N}\left(\sum_{\ell\in\Omega^N-\Omega^N_{\{l_n=\hat{j}\}}} A_{\ell F} S_\ell^{\tilde{j}}\right) \tag{25}
$$

$$
\begin{aligned}
\frac{d\ \mathbb{P}(l_n=\hat{j};F)}{d\ \Theta_{\hat{j}}} &= \sum_{\ell\in\Omega^N_{\{l_n=j\}}} \frac{A_{\ell F}}{\phi_F^N}\ S_\ell^{\hat{j}} - \mathbb{P}\left(l_n=\hat{j};F\right) \sum_{\ell\in\Omega^N} \frac{A_{\ell F}}{\phi_F^N}\ S_\ell^{\hat{j}} \\
&= \mathbb{P}\left(l_n=\hat{j};F\right) \sum_{\ell\in\Omega^N_{\{l_n=j\}}} \frac{\pi_\ell^N}{\mathbb{P}\left(l_n=\hat{j};F\right)}\ S_\ell^{\hat{j}} - \mathbb{P}\left(l_n=\hat{j};F\right) \sum_{\ell\in\Omega^N} \pi_\ell^N\ S_\ell^{\hat{j}} \\
&= \mathbb{P}\left(l_n=\hat{j};F\right)\ \left\{\mathbb{E}\left[S_\ell^{\hat{j}}\middle| l_n=j\ \right] - \mathbb{E}\left[S_\ell^{\hat{j}}\ \right]\right\}
\end{aligned} \tag{26}
$$

Therefore, the necessary and sufficient condition for, $\frac{d\ \mathbb{P}\left(l_n=\hat{j};F\right)}{d\ \Theta_{\hat{j}}} > 0$ can be expressed as $\mathbb{E}\left[S_\ell^{\hat{j}}\middle| l_n=j\ \right] > \mathbb{E}\left[S_\ell^{\hat{j}}\ \right]$. Now consider $1_{\{l_n=\hat{j}\}}$ be an indicator variable that only takes the value one if $\ell\in\Omega^N_{\{l_n=\hat{j}\}}$. Then, $\mathbb{P}(l_n=\hat{j};F)=\mathbb{E}\left[1_{\{l_n=\hat{j}\}}\right]$ and,

$$
\begin{aligned}
\mathbb{E}\left[S_\ell^{\tilde{j}} \middle| l_n = \hat{j}\right] &= \sum_{\ell \in \Omega^n_{\{l_n=\hat{j}\}}} \frac{\pi_{\ell F} S_\ell^{\tilde{j}}}{\mathbb{P}\left(l_n = \hat{j}; F\right)} \\
&= \frac{1}{\mathbb{P}\left(l_n = \hat{j}; F\right)} \sum_{\ell \in \Omega^N} \pi_{\ell F} S_\ell^{\tilde{j}} 1_{\{l_n=\hat{j}\}} \\
&= \frac{\mathbb{E}\left[S_\ell^{\tilde{j}}\, 1_{\{l_n=\hat{j}\}}\right]}{\mathbb{P}\left(l_n = \hat{j}; F\right)}
\end{aligned}
$$

As a result, equation (26) can be rewritten as

$$
\begin{aligned}
\frac{d\, \mathbb{P}(l_n = \hat{j}; F)}{d\, \Theta_{\hat{j}}} &= \mathbb{P}\left(l_n = \hat{j}; F\right)\ \mathbb{E}\left[S_\ell^{\hat{j}} \middle| l_n = j\ \right] - \mathbb{P}\left(l_n = \hat{j}; F\right) \mathbb{E}\left[S_\ell^{\hat{j}}\ \right] \\
&= \mathbb{E}\left[S_\ell^{\tilde{j}}\, 1_{\{l_n=\hat{j}\}}\right] - \mathbb{E}\left[1_{\{l_n=\hat{j}\}}\right] \mathbb{E}\left[S_\ell^{\hat{j}}\ \right] \\
&= \mathrm{Cov}\left[S_\ell^{\tilde{j}}, 1_{\{l_n=\hat{j}\}}\right]
\end{aligned} \tag{27}
$$

Both equations (27) and (26) suggests that if $S_\ell^{\tilde{j}}$ is systematically larger for production paths $\ell \in \Omega^N_{\{l_n=\hat{j}\}}$, and increase in the productivity parameter $\Theta_{\tilde{j}}$.

A.2 Proof of Corollary 3.1

Now, suppose, $\mathrm{Cov}\left[S^{\tilde{j}}_{\ell;\ \mathrm{imp}}, 1_{\{l_n=\hat{j}\}}\right] = 0$, and with $1_{\{l_k=j\}}$, as an indicator variable taking the value one if for a production path ℓ, $l_n = j,\ \forall n$

$$
S^{\tilde{j}}_{\ell;\ \mathrm{exp}} = \sum_k \overbrace{\frac{\alpha_k \beta_k}{\Theta_{\tilde{j}}} 1_{\{l_k=\tilde{j}\}}}^{x_n}
$$

Since, $\mathrm{Cov}\left(\sum_{m=1}^N x_m,\ Y\right) = \sum_{m=1}^N \mathrm{Cov}(x_m, Y)$

$$
\begin{aligned}
\mathrm{Cov}\left[S^{\tilde{j}}_{\ell;\ \mathrm{exp}}, 1_{\{l_n=\hat{j}\}}\right] &= \sum_{k \in \mathbb{N}} \mathrm{Cov}\left[\frac{\alpha_k \beta_k}{\Theta_{\tilde{j}}} 1_{\{l_k=\tilde{j}\}}, 1_{\{l_n=\hat{j}\}}\right] \\
&= \sum_{k \in \mathbb{N}} \frac{\alpha_k \beta_k}{\Theta_{\tilde{j}}} \mathrm{Cov}\left[1_{\{l_k=\tilde{j}\}}, 1_{\{l_n=\hat{j}\}}\right]
\end{aligned}
$$

Now as, $\mathbb{P}\left[1_{\{l_m=\tilde{j}\}} \cap 1_{\{l_n=\hat{j}\}}\right] = \mathbb{E}[1_{\{l_m=\tilde{j}\}} 1_{\{l_n=\hat{j}\}}]$

$$\begin{aligned}\text{Cov}\left[S^{\tilde{j}}_{\ell;\ \text{exp}}, 1_{\{l_n=\hat{j}\}}\right] &= \sum_{k\in\mathbb{N}} \frac{\alpha_k\beta_k}{\Theta_{\tilde{j}}} \left\{\mathbb{P}\left(l_n=\hat{j}\right)\mathbb{P}\left(l_k=\tilde{j}|l_n=\hat{j}\right) - \mathbb{P}\left(l_n=\hat{j}\right)\mathbb{P}\left(l_k=\tilde{j}\right)\right\} \\ &= \sum_{k\in\mathbb{N}} \frac{\alpha_k\beta_k}{\Theta_{\tilde{j}}} \mathbb{P}\left(l_n=\hat{j}\right)\left\{\mathbb{P}\left(l_k=\tilde{j}|l_n=\hat{j}\right) - \mathbb{P}\left(l_k=\tilde{j}\right)\right\}\end{aligned}$$

However since the location choice of stage-m firms to source intermediate inputs completed upto stage $m-1$ is independent of the choices that are made by other firms operating at stage $n \in \mathbb{N} - \{m\}$, then $\mathbb{P}(l_k = \tilde{j}|l_n = \hat{j})\Big|_{k\neq\{n-1,\ n\}} = \mathbb{P}(l_k = \tilde{j})$ as $\mathbb{P}(l_n = \tilde{j}|l_n = \hat{j}) = 0$, Therefore,

$$\begin{aligned}\text{Cov}\left[S^{\tilde{j}}_{\ell;\ \text{exp}}, 1_{\{l_n=\hat{j}\}}\right] = \frac{\alpha_{n-1}\beta_{n-1}}{\Theta_{\tilde{j}}}\mathbb{P}\left(l_n=\hat{j}\right)\left\{\mathbb{P}\left(l_{n-1}=\tilde{j}|l_n=\hat{j}\right) - \mathbb{P}\left(l_{n-1}=\tilde{j}\right)\right\} \\ - \frac{\alpha_n\beta_n}{\Theta_{\tilde{j}}}\mathbb{P}(l_n=\tilde{j})\end{aligned}$$

This implies,

$$\text{Cov}\left[S^{\tilde{j}}_{\ell;\ \text{exp}}, 1_{\{l_n=\hat{j}\}}\right] > 0 \quad \text{iff} \quad \mathbb{P}\left(l_{n-1}=\tilde{j}|l_n=\hat{j}\right) > \frac{\alpha_n\beta_n + \alpha_{n-1}\beta_{n-1}}{\alpha_{n-1}\beta_{n-1}}\mathbb{P}\left(l_{n-1}=\tilde{j}\right)$$

with $\alpha_n\beta_n \in [0,1] \quad \forall n \in \mathbb{N}$, this implies that, $\mathbb{P}\left(l_{n-1}=\tilde{j}|l_n=\hat{j}\right) > \mathbb{P}\left(l_{n-1}=\tilde{j}\right)$ is a necessary condition to achieve $\text{Cov}\left[S^{\tilde{j}}_{\ell;\ \text{exp}}, 1_{\{l_n=\hat{j}\}}\right] > 0$. Therefore, in order for $S^{\tilde{j}}_{\ell}$ to be systematically larger for production paths $\ell \in \Omega^N_{l_n=\hat{j}}$, it is necessary that the occurrence of stage-n at $\hat{j}$ increases the likelihood of firm participation in $\tilde{j}$ at stage $n-1$.

Conclusion: Thus it is necessary that the occurrence of stage-n at $\hat{j}$ makes the participation of firms in $\tilde{j}$ at stage $n-1$ more likely to ensure that $S^{\tilde{j}}_{\ell}$ is systematically larger for production paths $\ell \in \Omega^N_{\{l_n=\hat{j}\}}$.

A.3 Proof of Corollary 3.2

Taking logarithm on both sides of equation (15),

$$
\begin{aligned}
&\log(\tau_{\hat{j}\tilde{j}}) < -\frac{1}{\beta_1\theta}\left\{ \log\left[\sum_k \tau_{\tilde{j}k}^{-\beta_1\theta}\right] + \log\left[\sum_i \tau_{i\hat{j}}^{-\beta_1\theta}\right] - \log\left[\sum_i\sum_k \tau_{ik}^{-\beta_1\theta}\right]\right\} \\
\Rightarrow \quad &\log(\tau_{\hat{j}\tilde{j}}) < -\frac{1}{\beta_1\theta}\left\{ \log\left[\sum_k \exp\left(-\beta_1\theta\log(\tau_{\tilde{j}k})\right)\right]\right. \\
&\qquad\qquad + \log\left[\sum_i \exp\left(-\beta_1\theta\log(\tau_{i\hat{j}})\right)\right] \\
&\qquad\qquad \left. - \log\left[\sum_i\sum_k \exp\left(-\beta_1\theta\log(\tau_{ik})\right)\right]\right\}
\end{aligned} \tag{28}
$$

Now, let us define,

$$
\mathrm{LSE}[\{x_i\}_{i=1}^n] = \log\left[\sum_{i=1}^N \exp(x_i)\right]; \qquad \max_i x_i \leq \ \mathrm{LSE}[\{x_i\}_{i=1}^n] \ \leq \ \max_i x_i + \log(n)
$$

Thus,

$$
\begin{aligned}
\max_k \tau_{\tilde{j}k} + \max_i \tau_{i\hat{j}} - \max_{i,k} \tau_{ik} - 2\log(J) &\leq \mathrm{LSE}[\tau_{\tilde{j}k}] + \mathrm{LSE}[\tau_{\tilde{j}k}] - \mathrm{LSE}[\tau_{ik}] \\
&\leq \max_k \tau_{\tilde{j}k} + \max_i \tau_{i,\hat{j}} - \max_{i,k} \tau_{ik} + 2\log(J)
\end{aligned}
$$

Hence, the condition stated in equation (28) is satisfied if

$$
\begin{aligned}
&\log(\tau_{\hat{j}\tilde{j}}) \ \leq \ -\frac{1}{\beta_1\theta}\left\{ \max_k\{-\beta_1\theta\log(\tau_{\tilde{j}k})\} + \max_i\{-\beta_1\theta\log(\tau_{i\hat{j}})\}\right. \\
&\qquad\qquad\qquad\qquad \left. - \max_{i,k}\{-\beta_1\theta\log(\tau_{ik})\} + 2\log(J)\right\} \\
\Rightarrow\ &\log(\tau_{\hat{j}\tilde{j}}) \ \leq \ \left\{ \min_k\{\log(\tau_{\tilde{j}k})\} + \min_i\{\log(\tau_{i\hat{j}})\} - \min_{i,k}\{\log(\tau_{ik})\} - \frac{2}{\beta_1\theta}\log(J)\right\} \\
\Rightarrow\ &\tau_{\hat{j}\tilde{j}} < \frac{\min_k \tau_{\tilde{j}k} \times \min_i \tau_{i\hat{j}}}{\min_{i,k}\tau_{i,k}} \times J^{-\frac{2}{\beta_1\theta}}
\end{aligned} \tag{29}
$$

Therefore, a sufficient condition for the inequality in (16),

$$
\begin{aligned}
\frac{\tau_{\tilde{j}\hat{j}}}{\min_k \tau_{\tilde{j}k}} &\leq \frac{\min_i \tau_{i\hat{j}}}{\min_{i,k} \tau_{i,k}} \times J^{-\frac{2}{\beta_1 \theta}} \\
\Rightarrow \frac{\tau_{\tilde{j}\hat{j}}}{\min_k \tau_{\tilde{j}k}} &\lesssim \frac{\min_i \tau_{i\hat{j}}}{\min_{i,k} \tau_{i,k}} \qquad \text{If } \beta_1\theta \to \infty
\end{aligned}
\tag{30}
$$

This inequality in equation (15) captures the economic intuition that $\tilde{j}$ is more likely to be the upstream supplier of $\hat{j}$ at a given stage whenever their bilateral trade cost is sufficiently low relative to the network-wide benchmark of alternative trade costs. The parameter $\beta_n\theta > 0$ governs the sensitivity of the probability of a production path to differences in trade costs. A higher importance of stage 1 or a lower variance in the distribution of productivity parameters increases the elasticity of a country's attractiveness to trade costs. In the limit as $\beta_1\theta \to \infty$, the sufficient condition for inequality (15) collapses to the minimum-cost selection rule, and the threshold reduces the inequality expressed in equation (30).

Several special cases illustrate the mechanics. If $\min_i \tau_{i\hat{j}} = \min_{i,k} \tau_{ik}$, then $\hat{j}$ is globally competitive and only needs a bilateral cost below $\tilde{j}$'s cheapest alternative; if $\min_k \tau_{\tilde{j}k} = \min_{i,k} \tau_{ik}$, the threshold depends on $\hat{j}$'s cheapest export link; if both minima coincide with the global minimum, only the global frontier link matters; and if neither coincides, $\tilde{j}$ and $\hat{j}$ must jointly achieve a sufficiently low bilateral cost relative to the global benchmark. Across all cases, the Corollary 3.1 formalises the idea that lower relative trade costs increase the likelihood of $\hat{j}$'s participation in the production network, with ϕ determining the degree of concentration on the most competitive links.

B Data and Variable

Table 8: Summary of Variables, Definitions, Units, and Sources

Variable	Definition / Description	Units	Source
(A) GVC and Trade Variables			
$T_{ij,t}$	Value added by country i embodied in the final commodity production by country j, consumed domestically or abroad, irrespective of whether the value added is directly or indirectly (through export and re-export by a third country and re-import by country j) imported by country j	Current US$, millions	Author using OECD (2023)
VA_{it}	$VA_{it} = \sum_j T_{ij,t}$: Value added exported by country i in year t associated with GVC activities.	Current US$, millions	Author using OECD (2023)
Z_{odt}	Gross exports of intermediate commodities	Current US$, millions	Author, using OECD (2023)
VA_{Zodt}	Value-added component of intermediate exports	Current US$, millions	Author, using OECD (2023)
F_{odt}	Gross exports of final commodities	Current US$, millions	Author, using OECD (2023)
VA_{Fodt}	Value-added component of final exports	Current US$, millions	Author, using OECD (2023)

Table 8 – continued from previous page

Variable	**Definition / Description**	**Units**	**Source**
$RTA_{ij,t}$	Indicator variable takes the value 1 if a Regional Trade Agreement exists between i and j in year t.	Binary	WTO RTA Database & NSF-Kellogg Institute Data Base on Economic Integration Agreements
$\tau_{ij,t}$	Weighted average applied tariff rates (tariff rates applied by a customs administration on imported goods)	Percent (%)	UNCTAD's TRAINS database
$Avg\ \tau_{it}$	Mean applied tariff rates by a country i at period t	Percent (%)	Author using UNCTAD's TRAINS database
$BORDER_{ij,t}$	The interaction between a indicator variable for international trade i.e. when $i \neq j$ and time FE	Binary	
(B) Geographical and Historical Variables			
$DIST^{w}_{ij}$	distance between two countries i and j based on bilateral distances between the biggest cities of those two countries, those inter-city distances being weighted by the share of the city in the overall country's population	Kilometres (km)	Mayer and Zignago (2011)
$DIST^{c}_{ij}$	Bilateral distance between the capital cities of country i and j calculated using *great circle formula*	Kilometres (km)	Mayer and Zignago (2011)
CTG_{ij}	Indicator variable takes the value 1 if the two countries i and j are contiguous	Binary	Mayer and Zignago (2011)

Table 8 – continued from previous page

Variable	Definition / Description	Units	Source
CL_{ij}	Indicator variable takes the value 1 if the two countries i and j share common official language	Binary	Mayer and Zignago (2011)
(C) Macroeconomic and Production Variables			
$RGDP^e_{it}$	Real GDP (expenditure side) at constant prices and PPP-adjusted.	in millions 2017 US$	Feenstra, Inklaar, and Timmer (2015)
$RGDP^o_{it}$	Real GDP (output side) at constant prices and PPP-adjusted.	in millions 2017 US$	Feenstra et al. (2015)
TFP_{it}	The cross-country comparable TFP measure	Index (USA = 1)	Caves, Christensen, and Diewert (1982); Diewert and Morrison (1986); Feenstra et al. (2015)
K^s_{it}	Capital services levels at current PPPs	Index (USA = 1)	Feenstra et al. (2015); Jorgenson and Nishimizu (1978)
L_{it}	Total employment including informal and armed forces.	in millions	Feenstra et al. (2015); Inklaar and Timmer (2013)
C_{it}	Real consumption of households and government, at current PPPs	Millions of 2017 US$	Feenstra et al. (2015)
IRR_{it}	Real internal rate of return on capital stock	Percent (%)	Feenstra et al. (2015)

Table 8 – continued from previous page

Variable	Definition / Description	Units	Source
(D) Productive Capacities and Institutional Variables			
PCI_{it}	multidimensional index aimed to measure "the productive resources, entrepreneurial capabilities and production linkages which together determine the capacity of a country to produce goods and services and enable it to grow and develop" summarising across 8 dimensions: Human Capital, Natural Resources, Energy, Transport, ICT, Institutions, Private Sector, and Structural Change. These individual scores were scaled to fall in the range of 1 to 100. Using these scaled scores, a geometric mean for these scaled scores provides us with the PCI.	Index (1–100)	UNCTAD (2023)
Natural Resources	PCA-based composite index derived from FAO, UNEP–IRP, World Bank, and OECD data on agricultural land, extraction flows, forest area, material intensity (ratio of total domestic extraction of raw materials and industry value added), and natural resource rents.	Index (1–100)	UNCTAD (2023)
Human Capital	PCA-based composite index derived from WHO, UNESCO, UNDP, and UN Population Division data on health expenditure, R&D intensity, fertility rates, health-adjusted life expectancy, researcher density, and expected years of schooling.	Index (1–100)	UNCTAD (2023)

Table 8 – continued from previous page

Variable	Definition / Description	Units	Source
Institutions	PCA-based composite index derived from the World Bank's Worldwide Governance Indicators, including measures of control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and voice and accountability.	Index (1–100)	UNCTAD (2023)
Transportation	PCA-based composite index derived from ICAO, International Road Federation, and International Union of Railways data on air freight, passenger traffic, road density, rail network length, and carrier departures per capita.	Index (1–100)	UNCTAD (2023)
ICT	PCA-based composite index derived from ITU and World Bank data on broadband and mobile subscriptions, Internet usage, and digital infrastructure (secure Internet servers).	Index (1-100)	UNCTAD (2023)

To perform the empirical analysis, we use a panel dataset for 76 countries over two sets of time periods 2002- 2008 and 2012 – 2018, to analyse the difference in estimates pre- and post- the global financial crisis. However we estimate the coefficients for the full sample i.e., from year 2000-2019 and treat these estimates as baseline estimates. The selection of the sample has been made based on the availability of reliable data for the measure of technological change and value added associated with GVC activities. The final dataset that we use in our analysis is obtained by combining the Penn World Table (PWT) (Feenstra, 2016), the Productive Capacity Index (UNCTAD, 2023), the GeoDist database (Mayer & Zignago, 2011), TRAINS, EIA databases along with the derived measure for the total value added exported by a country in a specific year, using the ICIO developed by OECD (2023)

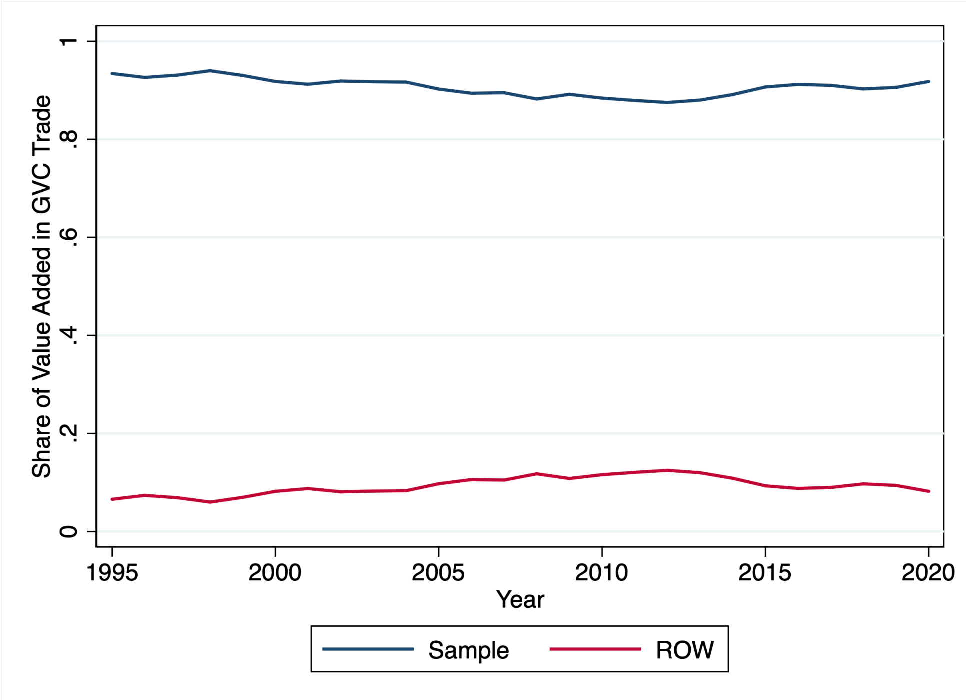

Figure 2: Share of Value Added in GVC Activities

Note: Combined Countries consists of the 76 countries we have considered as our sample. Rest of the World (ROW) clubs the remaining countries together. In between 1995-2020 (2000-2019) the sampled countries accounted for ∼91% (∼90%) of the total GVC activities.
Source: Author's calculation based on OECD (2023)

We employ the ICIO dataset from (OECD, 2023) and implement the decomposition framework proposed by Wang, Wei, Yu, and Zhu (2017); Wang et al. (2022). This dataset, records flows of intermediate and final commodities for 76 countries and a clubbed ROW on an annual basis from 1995 to 2020. The dataset combines information for the most prominent or key economies actively engaged in GVC activities - the 76 countries account for approximately 91% of total value added in GVC (see Figure 2). By incorporating both advanced economies and strategically important emerging markets, the dataset provides a robust and representative picture of the global economic landscape. Hence, the results the following analysis can be generalised to reflect the true state of GVC.

The United Nations Conference on Trade and Development (UNCTAD) devised second edition of the Productive Capacities Index (PCI) on the request of the member states and United Nations Economic and Social Council (UNECOSOC) to aid in policy formulation and fostering development of industrial capacity (UNCTAD, 2023). This multidimensional index was aimed to measure "the productive resources, entrepreneurial capabilities and production linkages which together determine the capacity of a country to produce goods and services and enable it to grow and develop". The index covers 194 countries over the period 2000 to 2022. The PCI is based on 42 indicators categorised into broad 8 categories[19]. Principal component analysis was employed to arrive at scores for the 8 broad categories independently. These individual scores were scaled to fall in the range of 1 to 100. Using these scaled scores, a geometric mean for these scaled scores provides us with the PCI.

As our objective is to analyse the spillover effect associated with technology change though augmenting the participation of spatially proximate countries, unlike Fernandes et al. (2022). Therefore, we use a the composite index of PCI as control for our estimation procedure. The PCI accounts for most of the time varying determinant, such as quality of institutions, Infrastructure and Connectivity, Factor endowment, and many others. A detailed summary of the variables utilised in presented in Table 8.

C Additional Empirical Analysis

C.1 Results: Distance

Table 9 presents the bias-corrected first stage estimates following Weidner and Zylkin (2021). Columns (1) and (2) correspond to the pre-global financial crisis subsample, columns (3) and (4) to the post-crisis subsample, and columns (5) and (6) to the full sample. Columns (1), (3), and (5) show estimates from the TWFE specification in equation (18), while columns (2), (4), and (6) report results from the 3WFE specification in equation (19). Our estimation of the two equation follows Correia et al. (2020), incorporating

[19] The categories being: Human Capital - which captures the education, skill and health embodied in the population and the Research and Development capacity of the country; Natural Resources - accounts for the extractive and agricultural resources; Energy- which measures the availability of sustainable and efficient energy sources, Transportation - measured by the density of road, rail and air connectivity; ICT - and its integration into the society, Institutions - measuring political stability and their efficiency through effectiveness and law enforcement capacity of the government, Private Sector - which measures the ease of doing business and trade; and finally Structural Change which is measured by the sophistication and diversity in exports, intensity of fixed capital and the weight of industry and services on Gross Domestic Product.

Table 9: PPML Estimates (Bias Corrected): Stage 1

	Regressand: $T_{ij,t}$					
	2002 - 2008		2012 - 2018		2000-2019	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$DIST^w_{ij}$	-0.0001424***		-0.0001267***		-0.0001300***	
	(6.4e-06)		(7.3e-06)		(6.7e-06)	
$Contig_{ij}$	0.636***		0.557***		0.589***	
	(0.068)		(0.082)		(0.074)	
CL_{ij}	0.317***		0.316***		0.320***	
	(0.070)		(0.076)		(0.071)	
τ_{ijt}		-0.0006		-0.00021		0.00002
		(0.001)		(0.001)		(0.0003)
RTA_{ijt}		-0.024		0.0085		0.031*
		(0.020)		(0.022)		(0.019)
Observations	40,432	36,328	40,432	35,469	115,520	102,032
Exporter Time FE	✓	✓	✓	✓	✓	✓
Importer Time FE	✓	✓	✓	✓	✓	✓
Country Pair FE		✓		✓		✓
Border	✓	✓	✓	✓	✓	✓

Clustered Robust standard errors in parentheses
*** p≤0.01, ** p≤0.05, * p≤0.1
Note: These estimates are corrected for the bias referred to in Weidner and Zylkin (2021).

the best practices to analyse trade flows.

With the dependent variable measuring the domestic value added by the origin or exporting nation embodied in the final commodity produced by the final destination country, the negative coefficient estimate for geographic distance ($DIST^w_{ij}$) in our gravity specification suggests that geographical distance play a hindrance in shaping GVC linkages. We find that a 1000 km increase in bilateral distance would result in an reduction in value added by approximately 13.43% - 15.3%[20]. For ease of comparison, we also compute the distance elasticity of trade as presented in Table 10.

In contributing to the literature on the distance puzzle, this study finds that the effect of distance on bilateral trade has declined over time, as evidenced by the baseline first-stage estimation results. Prior to the global financial crisis, the estimated trade elasticity

[20] The coefficients on log-transformed regressors represent elasticities. For regressors that are not log-transformed, the corresponding semi-elasticity is given by $100\times(\exp(\beta)-1)\%$, which approximates $100\times\beta$ for values of $\beta \to 0$. Also, equivalent to our computation, a 1 km increase in bilateral distance is associated with a reduction in the value added embodied in bilateral trade of approximately 0.013% to 0.014%. Specifically, if the regressor is scaled by a constant factor, the estimated coefficient is correspondingly multiplied by that same factor.

Table 10: Distance Puzzle

	Regressand: $T_{ij,t}$		
Variables	2002–2008 (1)	2012–2018 (2)	2000–2019 (3)
$\ln(\text{DISTW}_{ij})$	-0.732***	-0.678***	-0.698***
	(0.023)	(0.025)	(0.024)
Observations	40,432	40,432	40,432
Exporter-Time FE	✓	✓	✓
Importer-Time FE	✓	✓	✓
Additional Regressor	✓	✓	✓

Clustered robust standard errors in parentheses
*** p≤0.01, ** p≤0.05, * p≤0.1

Note: These estimates are corrected for the bias referred to in Weidner and Zylkin (2021). The specification was similar to that of the TWFE, with the only difference being, replacing $DIST^{w}_{ij}$ with its logarithmic transformation

with respect to bilateral distance was -0.732, indicating that a 1% increase in distance was associated with a 0.73% decline in bilateral trade. In the subsequent periods, this coefficient decreases to -0.68, suggesting a weakening of the negative impact of distance. This reduction is likely attributable, at least in part, to advancements in ICT that have effectively lowered spatial transaction costs. Although it might be expected that the financial crisis, by encouraging lead firms to re-shore previously offshored production activities under the influence of rising protectionist measures by several governments, would have led to an increase in the trade elasticity, the results indicate otherwise. These findings align with the conclusions of Antràs (2020), who report no significant evidence of widespread reshoring in the post-crisis period.

In Table 11 we exploit a key advantage of employing ICIO databases, namely the fact that these datasets report separately bilateral trade of intermediate commodities Z_{ijt} and that of the finished goods used for direct consumption F_{ijt}. In columns (2), (3), (4), (5) we estimate the specification expressed in equation (18), using the log-transformed values of bilateral distance instead of using them at levels. Columns (2) and (3) restrict the analysis to the flow of intermediate commodities; on the other hand, columns (4) and (5) focus on the flow of final commodities for consumption. Additionally, columns (3) and (5) incorporate value-added flow measures for the analysis.

As we find from Table 11 the elasticity of trade flow to distance is relatively larger for

Table 11: Relative Importance of Distance Across Different Measures of Trade

	Sample: 2000 - 2019				
Dependent Variables	T_{ijt}	Z_{ijt}	VAZ_{ijt}	F_{ijt}	VAF_{ijt}
Variables	(1)	(2)	(3)	(4)	(5)
$\log(DIST_{ij}^{w})$	-0.698***	-0.711***	-0.700***	-0.722***	-0.694***
	(0.024)	(0.020)	(0.019)	(0.020)	(0.019)
Observations	115,520	115,520	115,520	115,520	115,520
Exporter Time FE	✓	✓	✓	✓	✓
Importer Time FE	✓	✓	✓	✓	✓
Additional Regressor	✓	✓	✓	✓	✓

Clustered robust standard errors in parentheses
*** p≤0.01, ** p≤0.05, * p≤0.1

Note: These estimates are corrected for the bias referred to in Weidner and Zylkin (2021). The specification was similar to that of the TWFE, with the only difference being, replacing $DIST_{ij}^{w}$ with its logarithmic transformation

gross trade in final commodities (-0.722) than intermediate inputs (-0.711) similar to what we find in Antràs and Gortari (2020); Buelens and Tirpák (2017). They suggested that the finding reflects a disproportionate impact of trade barriers on downstream production stages relative to upstream ones. Now comparing these results with that of value-added flows, we find that the trade elasticity to distance is significantly smaller for value-added trade (-0.700 for intermediate commodities and -0.694 for final commodities) flows relative to the respective gross measure. This result further supplements the findings from Johnson and Noguera (2012b).

C.2 Validity of IV

We begin with estimating a PLM without the SAR terms to establish the validity of the IV. The IVs from the first stage estimate presented in Table 12 and are reported along with robust standard errors clustered at the country level. They have expected sign and are statistically significant. As TFP are presumed to an indicator for technology, the estimates indicate that higher IRR is associated with an improved state of technology. Table 13 present the results from the second-stage IV within-estimates. The coefficient for TFP is only marginally greater in magnitude for the specification incorporating the IV. Our preferred estimates with TWFE and other included instruments suggest that a 1% increase in TFP increases value added exports associated with GVC by 0.63%, whereas the OLS estimates under the assumption of exogenous regressors, suggests that the outcome variable would increase by 0.60%. The coefficient for other controls are also consistent with the baseline estimate.

Table 12: First Stage PLM

	Dependent variable: $\log(TFP_{it})$	
	(1)	(2)
$\log(IRR_{it})$	0.275***	0.272***
	(0.040)	(0.038)
Observations	1,380	1,380
Country FE	✓	✓
Time FE	✓	
Included Instruments	✓	✓

* p≤ 0.1, ** p≤ 0.05, *** p≤ 0.01.
Robust SEs clustered at the country level.

A general concern with IV estimates is that they could be biased and hence the statistical inference may be invalid if the instruments are weak. We find that the first stage F-statistic are strongly significant. The Kleibergen-Paap F-statistic for the first stage is much larger (48.55 and 52.11 for TWFE and one-way FE respectively) than the critical value of Stock and Yogo (2005) and is also larger than the thumb rule of 10 widely used in empirical research. The Anderson-Rubin Wald test for weak instrument-robust inference for the second stage is in between 2.2 and 2.9 for one-way and TWFE specifications respectively. and is statistically significant only for the TWFE specification. Indicating that in the case of TWFE we reject the null hypothesis, that TFP does not play a role in determining value added export associated with GVC. Further the high and statistically significant Kleibergen-Paap rk LM statistic also rejects the null hypothesis that the estimation is under-identified. Finally in column (5) of Table 13 the IV is directly included in the second stage regression and we cannot reject the null hypothesis that the IV does not have a direct significant impact on the outcome variable satisfying the exclusion restriction.

A comparison between the OLS and IV estimates reveals no significant differences, indicating that potential endogeneity of TFP does not invalidate our inferences. This suggests that, while TFP may be endogenous, the effect is limited, and any resulting bias appears to be negligible. We proceed by estimating the SAR baseline specification, as defined in equation (22), with the corresponding results presented in Table 7.

Table 13: Second Stage PLM

	Dependent variable: $\log(VA_{it})$			
	IV	IV	OLS	OLS
	(1)	(2)	(3)	(4)
$\log(TFP_{it})$ (instrumented)	0.638*	0.595*	0.600***	0.581***
	(0.321)	(0.355)	(0.160)	(0.137)
$\log(IRR_{it})$				0.016
				(0.085)
Observations	1,380	1,380	1,380	1,380
First-stage F-stat (KP Weak Identification)	48.55	52.11		
Under-identification (K-P LM)	6.31**	6.44**		
Anderson-Rubin F-stat	2.91*	2.22		
Country FE	✓	✓	✓	✓
Time FE	✓		✓	✓
Included Instruments	✓	✓	✓	✓

* p≤ 0.1, ** p≤ 0.05, *** p≤ 0.01.

Robust SEs clustered at the country level.

Column (4) included to test exclusion restriction.

When the i.i.d assumption is dropped the Anderson LM and Cragg Donald Wald statistics are invalid. Hence we report the LM and Wald variant of the rk tests derived in Kleibergen and Paap (2006) that follows a chi-squared distribution with degrees of freedom equal to the difference between the number of endogenous regressors and the number of endogenous variables plus one. We also provide the Anderson-Rubin F-stat (T. W. Anderson & Rubin, 1949) weak-instrument robust inference for testing the significance of the endogenous regressors in the structural equation being estimated. The null hypothesis tested is that the coefficients of the endogenous regressors in the structural equation are equal to zero, that the overidentifying restrictions are valid. Both tests are robust to the presence of weak instruments. Note, The Stock–Yogo weak identification test critical values for $K = 1$ and $L = 1$ are: 16.38 (10% maximal IV size), 8.96 (15%), 6.66 (20%), and 5.53 (25%).