Input Complementarity and Spatial Organization of Firms*

Edwin Jiang†
The University of Sydney

Vladimir Tyazhelnikov‡
The University of Sydney

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Abstract

We introduce a quantifiable model of international production in which complex goods require multiple inputs and any pair of inputs may exhibit production complementarity. When complementary inputs are produced in different countries, firms pay pair-specific unbundling costs, making sourcing decisions interdependent and generating clusters of related inputs across locations. Estimating the model with US input-output and industry-level data, we find that shutting down input complementarity raises imported input use by 9.8 percentage points and welfare by 6.2 percent. Complementarity also changes the welfare content of conventional trade liberalization: a one percent reduction in iceberg trade costs generates a *larger* import response in the calibrated economy than in a no-complementarity benchmark, but a *smaller* welfare gain. We introduce structural and empirical measures of fragmentation that show that import exposure is not a sufficient statistic for welfare when the organization of production matters: its economic content depends on whether imported inputs belong to complementary bundles and whether those bundles are already co-located across countries.

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†edwin.jiang@sydney.edu.au

‡vladimir.tyazhelnikov@sydney.edu.au

1 Introduction

Dramatic advances in communication, computing, and coordination technologies have transformed how multinational corporations organize production across borders. Baldwin (2006) describes this process as "the second unbundling": the separation of production stages that previously had to be performed in close geographic proximity. These technological changes have made it easier for firms to coordinate complex production processes across countries and have been an important force behind the fragmentation of production in recent decades.[1]

Yet the implications of these changes have received less attention in the quantitative trade literature compared to the consequences of conventional trade liberalization, such as reductions in tariffs or transportation costs. One reason is that the relevant frictions are harder to measure. The barriers we study in this paper, are non-tariff and non-transportation costs of fragmenting production, which we call unbundling costs. Unlike conventional trade costs, which apply to individual inputs when they cross a border, unbundling costs are defined over pairs of inputs: they arise when a firm produces two complementary inputs in different countries. These costs are not directly observed at the border, but they affect firms' sourcing decisions and can therefore be inferred from the organization of international production.

We argue that tariffs and transportation costs are not the only reasons firms co-locate production activities. Similar inputs may benefit from shared managerial expertise, common workers, related production knowledge, or common regulatory and technical standards.[2] Co-location may also reduce compatibility problems at the final assembly stage, especially when laws, standards, and regulations differ across countries.[3]

These various considerations suggest that there is interdependence in input sourcing decisions: the value of producing one input in a given location depends on where other inputs are produced. A common way to model such interdependence is to impose a sequential production structure, so that sourcing choices at adjacent stages are linked through the cost of moving intermediate goods across borders. In this paper, we argue that such an approach is limiting and offer a rich and flexible alternative framework.[4]

[1] Fort (2017) finds that firms' adoption of communication technology leads to greater fragmentation of the production process.

[2] Antràs et al. (2008) study a related channel linking managerial activity and communication technologies.

[3] Dhingra et al. (2023) document the rapid rise of deep trade agreements. In our framework, such agreements can affect unbundling costs directly by making it easier to coordinate related production activities across countries.

[4] Consider the Boeing 787 Dreamliner. A large fraction of the aircraft's value is produced in Japan, including wings and parts of the fuselage, which are then shipped to Everett, Washington, for final assembly. The wings were also designed in Japan. These production and development decisions are unlikely to be independent, even though the tasks are not naturally ordered as adjacent stages of a sequential production

We introduce a model of international production in which a complex good requires many inputs and any pair of inputs can exhibit production complementarity. When a firm produces complementary inputs in different countries, it pays a pair-specific unbundling cost.[5] We allow these costs to be different for every pair of inputs, thereby allowing the strength of complementarity to vary across input pairs. Inputs from different countries differ in costs and are perfect substitutes , and firms have industry-specific input requirements. The general pairwise structure allows firms to form richer structure of production clusters than either benchmark permits.

The mechanism has two immediate implications. First, firms do not simply source each input from the individually cheapest location. They choose a sourcing allocation that balances input-level cost advantages against the cost of splitting complementary input bundles across countries.[6] As a result, unbundling costs lead firms to organize production in clusters of related inputs. Second, reductions in unbundling costs can generate non-monotone changes in sourcing. Lower unbundling costs reduce the incentive to keep complementary inputs together, making individual input cost advantages more important. This can induce both additional offshoring and reshoring, where an input previously sourced abroad moves back home as the firm reorganizes its production cluster.

These implications matter for how we interpret trade liberalization. In many canonical trade models, import shares and trade elasticities play the role of sufficient statistics for the welfare gains from trade. In our environment, import exposure remains an important object, but it is not sufficient. A firm may import more because foreign inputs become cheaper, or because it becomes easier to separate complementary input bundles across countries. These two margins have different welfare implications. A given increase in imported input use may be more or less valuable depending on whether it reflects cheaper foreign sourcing on an existing allocation or a reorganization of production that reduces the cost of splitting complementary inputs. Thus, the model changes the mapping from trade costs to trade volumes, and from trade volumes to welfare.

chain. Sequential models capture an important form of interdependence, but they restrict complementarities to adjacent stages. For complex goods, this can miss most potential links among inputs. For a good with N parts, a sequential model can account for at most $N-1$ links. Thus, even for a good with 10 parts, the sequential structure accounts for only 20 percent of all possible input pairs. For an aircraft with millions of parts, the share is negligible.

[5]Production complementarity is well studied in industrial organization, both theoretically (Milgrom et al. (1990)) and empirically (Biesebroeck (2007), Friedlaender et al. (1983)). Related theoretical models in international trade include Thompson (1985), Markusen (1989), Lopez-de Silanes et al. (1994), Costinot (2009a), Costinot (2009b), and Ding et al. (2019).

[6]The outsourcing of call centers to India illustrates this distinction. Call centers can be detached from many other production and service tasks at relatively low organizational cost. Other activities may also be cheaper abroad but remain costly or infeasible to separate from headquarters or production facilities because of coordination, compatibility, or technological constraints.

To quantify the model, we combine this complementarity mechanism with standard elements of the quantitative trade literature. We follow Antras et al. (2017) in using a heterogeneous-firm environment with monopolistic competition and CES demand, and we use the Ricardian input-cost structure of Eaton and Kortum (2002). We construct complementarity matrices from US data on occupational similarity, R&D flows, and patent citation patterns, combining the labor and technology components using the relative importance of Marshallian coagglomeration forces estimated by Ellison et al. (2010). The quantitative analysis uses US input-output tables for 22 industries, each of which uses the output of all 22 industries as inputs. We estimate the remaining parameters by simulated method of moments, targeting the matrix of domestic input shares for each input used by each sector.

The complex nature of complementarity makes firms' problem non-trivial and leads to a computational challenge: with N inputs and two sourcing locations, brute-force solution requires evaluating 2^N possible allocations for each firm, which is infeasible in estimation and counterfactual exercises even for the $N = 22$ input structure used in the quantitative analysis. We therefore solve firms' allocation problems using the combinatorial discrete-choice algorithm introduced by Jia (2008), and further developed by Arkolakis et al. (2026). This algorithm exploits the structure of the complementarity problem to narrow the set of possible allocations.

Turning to the quantitative analysis, we find that unbundling liberalization has distinctive aggregate effects. Because firms choose discrete sourcing allocations, this organizational margin can be highly nonlinear: small reductions in unbundling costs may leave sourcing patterns nearly unchanged, while larger reductions can move many firms across reallocation thresholds. In our equivalent-liberalization exercise, the reduction in unbundling costs that matches the import response of a one percent reduction in iceberg trade costs raises welfare by 1.47 percent, compared with 0.23 percent for the iceberg-cost reduction.

The firm-level reallocations explain this pattern. A one percent reduction in iceberg trade costs induces one-sided offshoring: foreign inputs become cheaper, and marginal inputs switch from domestic to foreign sourcing. By contrast, lower unbundling costs reorganize input bundles. The trade-equivalent unbundling reform changes 9.46 percent of input–firm sourcing decisions and leads 30.81 percent of firms to change at least one input location. These changes go in both directions. Some inputs are newly offshored once complementary bundles become easier to split; others are reshored when firms no longer need to keep them abroad as part of a broader foreign-sourced cluster. This reorganization drives the difference in welfare gains: reoptimization accounts for only 1.9 percent of the gain from the iceberg-cost reduction, but 43.2 percent of the gain from the trade-equivalent unbundling reform.

Input complementarity also changes the consequences of conventional trade liberaliza-

tion. When foreign inputs become cheaper, firms adjust sourcing decisions; stronger complementarity shifts firms away from mixed sourcing and toward bundled domestic-only or foreign-only allocations. As a result, an iceberg-cost reduction can generate more import growth without generating larger welfare gains, because the induced import expansion occurs in an economy where complementary inputs remain costly to split across countries. For instance, a one percent reduction in iceberg trade costs raises imported input use by 1.58 percentage points in the calibrated model, compared with 0.94 percentage points in the no-complementarity benchmark, yet welfare rises by only 0.23 percent in the calibrated model versus 0.35 percent without complementarity. Eliminating complementarity raises imported input use by 9.8 percentage points and welfare by 6.2 percent, illustrating the quantitative importance of this friction. Complementarity therefore changes the mapping from conventional trade liberalization to imports, and from imports to welfare gains.

These results indicate that sectoral import shares are not sufficient statistics for the trade and welfare consequences of trade liberalization. They measure how much a sector sources from abroad, but not what kinds of inputs are imported, whether those inputs are complementary, or how much scope remains for further reorganization of production. We therefore introduce measures of fragmentation that capture the organizational content of imported input use.

The first two measures are structural. One captures the direct cost-saving margin: the share of marginal cost that firms pay as unbundling costs. The other captures reorganization potential by locating the current sourcing allocation between two benchmarks, one where all complementary inputs are kept together, and one where they can be split across countries at no cost. Together, these measures characterize both what firms are currently paying to maintain production clusters and how much they stand to gain from cheaper fragmentation.

Both structural measures require solving the model, so we construct less data demanding empirical counterparts using data on input-output expenditure shares, sector-input sourcing shares, and the complementarity matrix. The first empirical measure captures how much complementarity is embedded in a sector's input bundle; the second captures whether complementary inputs are currently sourced from similar locations. While these empirical proxies do not recover all firm-level reallocation margins, they substantially improve the prediction of welfare and sourcing responses relative to imported-input shares alone.

These empirical measures support a simple taxonomy of organizational regimes and show that these regimes matter for the effects of trade liberalization. Sectors with little embedded complementarity behave much like a conventional trade environment, where import shares straightforwardly reflect foreign input use. Sectors with high complementarity but fragmented current sourcing have latent organizational complexity: they retain substantial

unrealized unbundling gains, so lower unbundling costs trigger considerable reorganization. Sectors where complementary inputs are already co-located are more bundled, so import exposure is more informative about how trade-cost reductions spread through connected input clusters. Across these regimes, the same import share does not carry the same meaning: a higher import share predicts a stronger response to trade liberalization in some regimes and a weaker one in others.

Our paper fits into a large strand of literature on organizational structure and global value chains including Feenstra and Hanson (1996), Grossman and Rossi-Hansberg (2008), Grossman and Rossi-Hansberg (2012), Fally and Hillberry (2015), Johnson and Moxnes (2019), and Harms et al. (2012) (for an excellent review of this literature see Chor (2019)).

Our paper contributes to an actively developing area of the global value chains literature on the complex interdependence of allocation decisions that includes Antràs and De Gortari (2020), Tintelnot (2017), Antras et al. (2017), Oberfield et al. (2020), and Tyazhelnikov (2022). In particular, our framework nests Tyazhelnikov (2022) for the two-country case and allows for richer patterns of proximity-concentration trade-off. Moreover, our model moves beyond the dichotomy of simultaneous and sequential production structures raised by Baldwin and Venables (2013) and offers a unifying framework that nests both structures.

Our complementarity mechanism is closely related to the combinatorial location and sourcing trade-offs studied by Tintelnot (2017) and Antras et al. (2017), and our quantitative implementation builds on a similar discrete-choice algorithm of Arkolakis et al. (2026). In Tintelnot (2017), firms choose whether to open a plant in each country, and the payoff from opening one plant depends on the presence of plants in all other locations. In Antras et al. (2017), firms choose whether to source each input from each country, with the return to sourcing from one country depending on the set of countries from which the firm sources inputs. A recent literature extends this complementarity approach to dynamic settings. Alfaro-Urena et al. (2023) studies firms' dynamic export-market choices in the presence of cross-country complementarities, while Liu (2024) uses a related algorithm to study firms' dynamic decisions to co-locate production and innovation activities. In contrast to this literature, we work in a two-country setting and study the binary decision of whether to produce each input domestically or offshore it. The key distinction is that complementarities in our model operate across input pairs rather than across countries or markets.

Similar to Head and Mayer (2019), we consider two types of trade costs. In Head and Mayer (2019), however, a firm incurs additional costs only when headquarters and production activities are performed in different countries; it can be regarded as a particular case of our assumption that any pair of tasks produced in different countries generates a cost penalty.

Our paper also contributes to the literature on measuring the intensity of offshoring

(for another excellent review of the literature, see Antràs (2020)). While the main focus of this literature is to address the problem of double counting (for example, Johnson and Noguera (2012)), in our approach, we abstract from this issue and focus on accounting for the similarity/dissimilarity of offshoring activities and its implications for trade outcomes. To properly account for potential complementarities, as in De Gortari (2019), we have to rely on a more structural approach than most literature in this area.

Finally, our paper serves as a bridge between two key bodies of literature: International Trade and Economic Geography. Traditionally, trade economists have focused on understanding how trade costs influence the global fragmentation of multinational production. Conversely, scholars of Economic Geography (Ellison et al. (2010), Greenstone et al. (2010), Kerr and Kominers (2015) among others) have examined the factors driving spatial agglomeration within individual countries. We integrate these two perspectives and propose that there is a close connection between international production fragmentation and spatial agglomeration.

The remainder of the paper is organized as follows. Section 2 develops the theoretical framework, characterizes the firm's pairwise sourcing problem, and shows how the model nests simultaneous and sequential production as limiting cases. Section 3 describes the data, constructs the labor and technology complementarity measures, presents reduced-form evidence on input co-location, and explains the calibration of the quantitative model. Section 4 presents the counterfactual results: aggregate effects of unbundling and trade-cost liberalization, trade-equivalent and welfare-equivalent reforms, sourcing reallocation and welfare decomposition, and structural and empirical measures of fragmentation. Section 5 concludes.

2 Theoretical Framework

We construct a two-country, many-sector framework in which firms produce complex goods using multiple intermediate inputs. The demand side and market structure are standard: consumers have CES preferences over differentiated varieties, sectors are monopolistically competitive, and input costs follow a Ricardian structure. The key departure from standard quantitative trade models is on the production side. A firm does not choose the sourcing location of each input independently. Instead, its cost of sourcing one input from a given country depends on where other, complementary inputs are produced. When complementary inputs are split across countries, the firm pays an unbundling cost. These pairwise costs make the firm's sourcing problem non-trivial and lead to clustering of related inputs across locations.

Countries are denoted by i and j in superscripts, while industries are denoted by the

subscripts m, n, and k. There are $N+1$ sectors in each country, with one sector perfectly competitive and the remaining N sectors characterized by monopolistic competition.

The assumptions on demand and market structure are chosen to make the framework comparable with the quantitative trade literature and the main mechanism operates through the firm's input-location allocation problem.

2.1 Preferences

Consider a representative consumer, whose preferences are quasilinear with respect to an external homogeneous sector 0 and a Cobb-Douglas aggregator over the consumption of heterogeneous goods from N other sectors.

$$U = \frac{1}{\zeta}\left(\prod_{n=1}^{N} U_n^{\alpha_n}\right)^{\zeta} + q_0, 0 < \zeta < \frac{\sigma-1}{\sigma},$$

where ζ is the elasticity of substitution between the aggregator of heterogeneous varieties and a homogeneous good, α_n is the weight of consumption of goods from sector n and U_n is the CES-aggregator:

$$U_n = \left(\int_{\omega\in\Omega} q_n(\omega)^{\frac{\sigma-1}{\sigma}}\, d\omega\right)^{\frac{\sigma}{\sigma-1}}, 1 < \sigma,$$

where σ is the elasticity of substitution between varieties from the same industry. The demand function for good ω from industry n is then

$$q_n(\omega) = \alpha_n P_n^{\frac{\zeta-\sigma}{1-\zeta}} p_n(\omega)^{-\sigma},$$

where P_n is a CES price index for industry n: $P_n = \left[\int_{\omega\in\Omega} p_n(\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}}$

2.2 Production Technology

Every firm produces a final good, which requires combining intermediate inputs; inputs from different sectors are perfect complements and have to be used in a fixed proportion.[7] For all firms in sector n of country i, input requirements are characterized by an input requirement vector of length N, $\Theta_n^i = (\theta_{1n}^i, ..., \theta_{Nn}^i)$, where $\theta_{mn}^i \in (0,1)$ is sector n's requirement (in terms of quantity) for sector m input, and $\sum_{m=1}^{N} \theta_{mn}^i = 1$ for $\forall\ n$.

[7]Leontief production function is both intuitive and tractable in our setting of production co-location and fragmentation. The model can be extended for the case of other production functions with an added external loop accounting for firms' changes of their input mix, which can be interpreted as technological adjustments.

Firm z in sector n solves a problem of allocating each of its input plants in one of two countries $i = 1$ and $i = 2$: the same inputs sourced from different countries are perfect substitutes.[8] In this paper, we abstract from a discussion of property rights and assume that a firm takes its organizational structure as given, regardless of whether an input is produced by the firm itself or sourced from a subsidiary.

For firm z in sector n, the production cost of one unit of intermediate input from sector m and country i is given as $a^i_{mn,z}$. The firm's cost of using this input, after accounting for the firm's input requirements, is hence $c^i_{mn,z} \equiv \theta^i_{mn} a^i_{mn,z}$.

The firm's production decisions are collected in a decision vector of length N, $S_{n,z} = (s_{1n,z}, ..., s_{Nn,z})$, where $s_{mn,z}$ is an indicator that equals 1 if an intermediate input from sector m is sourced from country 1, and 0 if the input is instead sourced from country 2. If at least one of the inputs is sourced from a different location from the rest, unbundling costs arise and are added to the total costs of the final good. Assuming that the final good is assembled in country 1, the marginal costs that firm z in sector n incurs for the production of its final good are then the sum of input costs from each country, trade costs, and unbundling costs:

$$MC_{n,z} = \sum_{m=1}^{N} [s_{mn,z} c^1_{mn,z} + (1 - s_{mn,z}) \tau^{21} c^2_{mn,z}] + \varphi \sum_{m=1}^{N} \sum_{k=1}^{N} |s_{mn,z} - s_{kn,z}| \, \mathbf{C}_{mk}. \qquad (1)$$

where τ are conventional iceberg trade costs,[9] $\mathbf{C}_{mk}$ is the (m, k) element of the complementarity matrix and reflects the costs associated with the production of inputs m and k in different countries,[10,11] and φ is a cost multiplier that regulates the scale of unbundling costs.[12]

[8] While we generally abstract from the quality of inputs dimension, we can reinterpret individual inputs cost draws as quality-adjusted input prices.

[9] The model can be extended straightforwardly to allow for specific trade costs and endogenous assembly location. We impose iceberg trade costs and domestic assembly in the baseline specification to simplify notation and to match the calibration setup in Section 3.

[10] Note that we focus on the case of two countries for tractability and because of data limitations. Our framework can be easily extended to the case of $K > 2$ countries; in this case, the location of each task can be coded by $\tilde{K} = \lceil \log_2 K \rceil$ dummy variables. For example, for the case of $K = 4$ countries, marginal costs can be written down as: $MC = \sum_{m=1}^{N} [s^1_m s^2_m c^1_m + (1 - s^1_m) s^2_m c^2_m + s^1_m (1 - s^2_m) c^3_m + (1 - s^1_m)(1 - s^2_m) c^4_m + T(s^1_m, s^2_m, c^1_m, c^2_m, c^3_m, c^4_m)] + \varphi \sum_{m=1}^{N} \sum_{k=1}^{N} \left(\left|s^1_m - s^1_k\right|\right) \left(\left|s^2_m - s^2_k\right|\right) \mathbf{C}\,(m, k)$, where $T\,(.)$ captures arbitrarily rich trade costs across country pairs. All of the propositions from Section A.1 are valid and the solution algorithm from Section 3.4 applies.

[11] Alternatively we could have represented complementarity in the cost function through a reduction in costs if inputs m and k are produced in the same country. Both notations correspond to the same values of costs and hence identical optimal allocations.

[12] We write the complementarity term as a double sum to match the notation and implementation used throughout the paper. If the complementarity matrix is symmetric and has zeros on the diagonal, this expression is equivalent to $2\varphi \sum_{m<k} |s_{mn,z} - s_{kn,z}| \, \mathbf{C}_{mk}$. An alternative formulation using the unordered-

The complementarity cost matrix, $\mathbf{C}$, summarizes multiple factors that could affect firm's optimal production allocation. It can be thought of as unbundling costs that result from breaking up the production chain. These costs can represent additional coordination efforts, or an increased likelihood of incompatible inputs from using outsourced components. The matrix is of size N by N,

$$\mathbf{C} = \begin{pmatrix} 0 & \mathbf{C}_{12} & \cdots & \mathbf{C}_{1m} \\ \mathbf{C}_{21} & 0 & \cdots & \mathbf{C}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C}_{m1} & \mathbf{C}_{m2} & \cdots & 0 \end{pmatrix},$$

where the element $\mathbf{C}_{mk}$ represents the complementarity cost on component k that arises from outsourcing component m. All diagonal elements are equal to 0, meaning that any given input does not exhibit cost complementarity with itself. The firm's decision vector determines which elements of this matrix are active in the firm's cost function.

Consider the following simple example: firm z from country 1 in sector n uses inputs from 6 sectors. Its decision vector $S_{n,z}$ is then a vector of 6 indicators: for instance, $S_{n,z} = (1, 0, 1, 1, 0, 1)$, which suggests parts 1, 3, 4, and 6 are produced in country 1, and parts 2 and 5 in country 2. In this case, the active elements of matrix $\mathbf{C}$ will correspond to the input pairs produced in different countries. The firm's complementarity costs incurred through the production process are then equal to the sum of the active elements of the complementarity matrix.

$$\varphi \begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \end{pmatrix} \mathbf{C} = \varphi \begin{pmatrix} 0 & \mathbf{C}_{12} & 0 & 0 & \mathbf{C}_{15} & 0 \\ \mathbf{C}_{21} & 0 & \mathbf{C}_{23} & \mathbf{C}_{24} & 0 & \mathbf{C}_{26} \\ 0 & \mathbf{C}_{32} & 0 & 0 & \mathbf{C}_{35} & 0 \\ 0 & \mathbf{C}_{42} & 0 & 0 & \mathbf{C}_{45} & 0 \\ \mathbf{C}_{51} & 0 & \mathbf{C}_{53} & \mathbf{C}_{54} & 0 & \mathbf{C}_{56} \\ 0 & \mathbf{C}_{62} & 0 & 0 & \mathbf{C}_{65} & 0 \end{pmatrix}$$

Interestingly, in both cases, when a firm chooses to produce all inputs domestically or internationally, all elements of $\mathbf{C}$ will be inactive because all inputs are produced in the same country, and the firm will not incur any unbundling costs.

In this formulation, we have two types of trade costs, iceberg trade costs τ, which we interpret as tariff barriers and the costs of shipping intermediate inputs, and unbundling costs $\mathbf{C}$, which we interpret as organizational and non-tariff frictions associated with fragmenting production. For clarity, we ignore the shipment costs of the final good, as including them will create a channel of horizontal FDI, which is well studied in the trade literature (see for example, Tintelnot (2017) and Ramondo and Rodríguez-Clare (2013)). This simplification

pair sum over $m < k$ would therefore deliver the same optimal allocations after a corresponding normalization of φ.

allows us to not distinguish between domestic and foreign firms and consumers.

Note that we incorporate unbundling costs as part of the marginal cost determination. While some unbundling costs, such as ongoing coordination efforts and risks of incompatible inputs, may be considered as variable costs, other costs associated with offshoring, such as the process of searching for, communicating, and connecting with foreign suppliers, can be considered as one-off, fixed costs.

In this model, we disregard fixed costs for clarity: however, our model can be extended to account for fixed costs of operation. So long as individual firm size remains constant, the optimization problem of a firm remains identical except that a firm is minimizing its average, not marginal costs. When a firm's size changes, it affects the weight of fixed costs in firm's average costs and the model has to be solved again until it converges to a fixed point. This extended model can be solved by an algorithm from Arkolakis et al. (2026) but rather than considering heterogeneous productivity, we would solve the model for each possible value of firm's sales.

2.3 Firms' Sourcing Problem

Each firm's objective is to choose a production decision vector, $S_{n,z}$, that minimizes its costs as outlined by Equation 1. The last term of Equation 1 connects unbundling costs to the firm's cost-minimization problem; this term makes the firm's production-location decisions interdependent: the firm does not simply choose the cheapest location for each input, but instead takes into account the production locations of all other inputs. Because each input-location decision affects the cost of splitting every other complementary input pair, the firm's problem generally has no closed-form solution. In Section 3.4, we discuss a discrete-choice algorithm that, for given production cost vectors, trade costs, and complementarity matrix, computes an optimal allocation without calculating costs associated with all 2^N sourcing vectors.

To make the role of pairwise complementarity clear, we first consider two limiting cases. In the first limiting case, every element of the complementarity matrix equals 0 ($\mathbf{C}_{mk} = 0$ for $\forall m, k \in \{1, ..., N\}$). In this case, the complementarity channel is shut down, the firm's decisions become independent, and the model exhibits the behavior of simultaneous production models such as in Feenstra and Hanson (1996).

A second limiting case is when only adjacent off-diagonal elements of $\mathbf{C}$ are non-zero, and all other elements are equal to zero. In this case, firms' decisions are also interrelated, but only through the production locations of adjacent inputs.[13] Dropping the iceberg trade

[13] As the order of inputs in $\mathbf{C}$ is arbitrary, any matrix that has non-zero elements only on adjacent off-diagonals after reordering the inputs also satisfies this property.

cost component for simplicity, Equation 1 can then be written as

$$MC_{n,z} = \sum_{m=1}^{N} \left[s_{mn,z} c^1_{mn,z} + (1 - s_{mn,z}) c^2_{mn,z} \right] + \tilde{\varphi} \sum_{m=2}^{N} \left| s_{mn,z} - s_{(m-1)n,z} \right| \mathbf{C}_{m,m-1},$$

where $\tilde{\varphi} = 2\varphi$ under the symmetric double-sum normalization in Equation 1.

This is the cost function of a sequential production model as in Tyazhelnikov (2022). Tyazhelnikov (2022) shows that the sequential production model generates a proximity-concentration trade-off that he calls clustering. The unbundling-cost formulation therefore nests both simultaneous and sequential production models in the two-country case, generates more general patterns of clustering, and can be interpreted as a more general way to model firms' organizational structure. We provide a further discussion of properties of the model in Appendix Section A.1.

2.4 Market Structure and Equilibrium

There are $N + 1$ sectors in each of the two countries. The N sectors, indexed as $n, m \in \{1, ..., N\}$, are characterized by monopolistic competition on the final goods market, while the other sector is perfectly competitive with country-specific productivity γ_i.

There is free entry in each monopolistically competitive sector, and there are industry-specific sunk costs η_n. We assume that there are no fixed costs of production or exporting, thus shutting down the firm selection mechanism from Melitz (2003). Due to the free-entry assumption, equilibrium expected profits in each industry are equal to the sunk cost in that industry, which determines the mass of firms in each sector and country, denoted by Z_n.

Inputs are produced from labor in a perfectly competitive environment and then are costlessly assembled in the final good (costly assembly can be easily introduced as one of the inputs). Workers are perfectly mobile across all sectors within a country. The homogeneous sector pins down the wage in country i at γ_i.[14] We normalize the wage at home to 1, so $\gamma_1 = 1$ and $\gamma \equiv \gamma_2$ can be interpreted as a relative wage. Finally, we assume that there are industry-specific productivity shifters, μ^i_n, which capture sector-country productivity differences and enter input production costs.

The model takes the set of demand $(\sigma, \zeta, \boldsymbol{\alpha})$ and supply $(\varphi, \mathbf{C}, \tau, \boldsymbol{\eta}, \gamma, \boldsymbol{\mu})$ parameters as exogenous.

Facing the set of intermediate input costs $\mathbf{c}(\varphi, \mathbf{C}, \tau, \boldsymbol{\eta}, \gamma, \boldsymbol{\mu})$, each firm z in industry n,

[14] Tyazhelnikov (2022) shows that in a setting without a homogeneous good sector, for given labor endowments in both countries, there exists a unique equilibrium with endogenous wages that clears the labor market. This analysis can be applied in this paper to cases with an industry-specific or perfectly mobile labor force.

chooses its optimal production allocation

$$S^*_{n,z} = \arg\min_{S \in \{0,1\}^N} MC_{n,z}(S, \mathbf{c}),$$

with associated marginal cost $MC^*_{n,z} \equiv MC_{n,z}(S^*_{n,z}, \mathbf{c})$.

Given consumer demand and its marginal cost, firm z sets the price of its output to

$$p_{n,z} = \frac{\sigma}{\sigma - 1} MC^*_{n,z}.$$

The price index for sector n is

$$P_n = \left(\sum_{z \in Z_n} p_{n,z}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

Let E denote total expenditure on differentiated goods and let $E_n = \alpha_n E$ denote expenditure on sector n. The quantity sold by firm z is then

$$q_{n,z} = \frac{E_n}{P_n} \left(\frac{p_{n,z}}{P_n} \right)^{-\sigma},$$

and firm revenue is $r_{n,z} = p_{n,z} q_{n,z}$. The output weight of firm z in sector n is:

$$w_{n,z} = \frac{q_{n,z}}{\sum_{z \in Z_n} q_{n,z}}.$$

These weights are used below to aggregate firm-level input costs into sector-level sourcing shares.

Domestic share of input m used in sector n in country 1, measured net of iceberg trade costs, is then

$$\pi^1_{mn} = \frac{\sum_{z \in Z^1_n} w_{n,z} s_{mn,z} c^1_{mn,z}}{\sum_{z \in Z^1_n} w_{n,z} \left[s_{mn,z} c^1_{mn,z} + (1 - s_{mn,z}) c^2_{mn,z} \right]} \tag{2}$$

Equation 2 is the model counterpart of the domestic input shares used as a target moment in the calibration.

3 Quantification

In this section we present the data used, how we construct the complementarity cost matrix, and the calibration process to fit the model to data.

3.1 Data

For industry-level input requirements, Θ_n, and expenditure share on each sector, α_n, we use the input-output account data from the Bureau of Economic Analysis (BEA) between 2003 and 2020. The annual release of input supply and use tables covers 71 3-digit 2012 North American Industry Classification (NAICS) industry categories in the United States. We limit our analysis to 22 of the 71 industries based on the availability of data on industry complementarities, with most of them in the manufacturing sector. The BEA also provides import matrices of inputs at the same level, which allow us to calculate the home share of intermediate inputs for each industry, i.e. the proportion of each required input that is sourced from the home country, π^1_{mn}.[15]

To establish complementarity relations, we use the Occupational Employment and Wage Statistics (OEWS) data from the Bureau of Labor Statistics (BLS) over the same period to estimate labor complementarity across industries. The OEWS data is derived from survey responses from nonfarm establishments in the US. The survey responses are compiled to produce semiannual employment and wage estimates for around 800 occupations at various levels of industry classifications. We use the relationship between occupations and 3-digit NAICS industries to construct part of the complementarity relations.

Furthermore, we use the technology flows matrix by Scherer (1982) and the National Bureau of Economic Research (NBER) Patent Database to estimate technological complementarity using the methodology proposed by Ellison et al. (2010). Scherer's technology matrix is calculated based on how much research and development (R&D) expenditure flows from one industry to another. The NBER Patent Database records the patent citation patterns between 1975 and 1999, namely how many patents generated in one industry are cited by another. Since both sets of data are classified in 1987 Standard Industrial Classification (SIC), we use the concordance files in the NBER and U.S. Census Bureau's Center for Economic Studies (NBER-CES) Manufacturing Industry Database to bring these datasets to 3-digit 2012 NAICS level.[16]

3.2 Constructing the Matrix of Complementarity

Following Ellison et al. (2010), we consider the three Marshallian factors behind geographical industrial agglomeration to construct an empirical counterpart of the matrix of complementarity $\mathbf{C}$: input-output linkages, shared labor market pooling, and technological spillovers.

[15]The BEA data have several observations with negative import values corresponding to domestic input shares larger than one. We set these shares to one.

[16]We would like to acknowledge Richard Hornbeck who kindly provided relevant data.

Of these three factors, input-output linkage is captured in the input-output relations that we calibrate in the estimation process, and is thus excluded from this section.

We refer to the labor complementarity matrix as $\mathbf{C}^L$, and the technology complementarity matrix as $\mathbf{C}^T$: each of these matrices shares the same size of N by N as $\mathbf{C}$.

First, we construct a measure of labor force similarity for each pair of industries. Let $Lshare_{on}$ be the share of occupation o employment among industry n's total employment, element $\mathbf{C}^L_{nm}$ in the labor complementarity cost matrix is then

$$\mathbf{C}^L_{nm} = \sum_{o \in O} min\{Lshare_{on}, Lshare_{om}\} \quad \in [0, 1],$$

where O is the collection of all occupations in the dataset. For this study we use occupations at the 5-digit level. For any pair of industries nm and each occupation o, we can calculate $min\{Lshare_{on}, Lshare_{om}\}$ which shows how much of the occupation o employment in one industry can be readily used by the other. For instance, if $Lshare_{on} < Lshare_{om}$, the extent of labor force similarity in terms of occupation o is determined by the smaller proportion $Lshare_{on}$. Two industries with similar occupation composition will end up with higher complementarity: in other words, locating these two industries in the same location gives rise to more potential of cost saving.[17] With 18 annual releases of the OEWS data, we calculate the labor complementarity cost matrix for each year and take the mean as the benchmark matrix in order to filter out any idiosyncratic noise.[18]

For technological spillovers, we construct a technology complementarity matrix based on the methodology of Ellison et al. (2010). The similarity of industries can be reflected by how much of one industry's R&D expenditures and patent citation originates from or is directed to another industry. For each pair of industries nm, we calculate

$$Tech_{nm} = max\{TechIn_{n \to m}, TechIn_{n \leftarrow m}, TechOut_{n \to m}, TechOut_{n \leftarrow m}\},$$

where $TechIn_{n \to m}$ is the share of R&D expenditure by industry n among all R&D expenditure spent on m, and $TechOut_{n \to m}$ is the share of R&D expenditure on m among all R&D expenditure spent by n. These four terms in the maximization operator represent the technology flow between the two industries, and the largest among them reflects their degree of

[17] This index can be interpreted as the share of workers a supplier can keep when switching from producing input n to input m. Higher values of this index suggest that workers can be costlessly switched between different production tasks or multitask.

[18] The estimated labor complementarity cost matrix is robust to different levels of occupation aggregation: a matrix constructed based on 3-digit occupations has a correlation coefficient of 0.970 with the estimated matrix based on 5-digit level occupations.

similarity. Similarly, we calculate

$$Cit_{nm} = max\{CitIn_{n\to m}, CitIn_{n\leftarrow m}, CitOut_{n\to m}, CitOut_{n\leftarrow m}\},$$

where $CitIn_{n\to m}$ and $CitOut_{n\to m}$ are citation counterparts defined in the same way as $TechIn_{n\to m}$ and $TechOut_{n\to m}$ above.

In principle, Cit_{nm} and $Tech_{nm}$ could be treated as separate sources of unbundling frictions. We combine them into a single measure of technological complementarity to keep the number of structural parameters small and preserve tractability. To do so, we use the relative magnitudes of the estimated coefficients in Ellison et al. (2010), where Marshallian factors are used to explain pairwise industry coagglomeration in the United States. This gives the following technology-complementarity matrix:[19]

$$\mathbf{C}^T_{nm} = \frac{0.180}{0.180 + 0.081} Tech_{nm} + \frac{0.081}{0.180 + 0.081} Cit_{nm}.$$

Combining labor and technology complementarity, the total complementarity cost matrix is

$$\varphi\mathbf{C} = \varphi^L\mathbf{C}^L + \varphi^T\mathbf{C}^T,$$

where φ^L and φ^T are the complementarity cost multipliers for labor and technology complementarity cost matrices, respectively. To simplify the notation, we consider the complementarity cost multiplier introduced in Section 2.2 as the collection of these two parameters, $\varphi \equiv (\varphi^L, \varphi^T)$.

There are various reasons why industries experiencing high patent flows and sharing similar occupational profiles may demonstrate production complementarities. Extensive economic geography literature[20] highlights these factors, illustrating how they contribute to the spatial clustering of related industries and delving into their underlying mechanisms. In our study, we draw upon this rich body of literature, operating under the assumption that if these forces drive agglomeration within regions and states, they are likely to be relevant across international borders as well. However, we refrain from making assumptions about the magnitude of these effects and opt to calibrate it in the model.

In Appendix Tables 12 and 13 we present the two complementarity cost matrices. Among manufacturing industries (NAICS 31-33), the largest labor complementarity is 0.7493 be-

[19] As we show in Section 3.3 empirically and in 3.5 with calibration, technological complementarity is quantitatively unimportant and most of the complementarity results are driven by labor complementarity.

[20] For example Ellison et al. (2010), Greenstone et al. (2010), Kerr and Kominers (2015); Carlino and Kerr (2015) and Combes and Gobillon (2015) provide comprehensive reviews of the related studies.

tween 332 (Fabricated Metal Product Manufacturing) and 333 (Machinery Manufacturing), while the largest technology complementarity is 0.3874 between 313-314 (Textile Mills and Textile Product Mills) and 315-316 (Apparel Manufacturing and Leather and Allied Product Manufacturing). The lowest labor complementarity is 0.2554 between 311-312 (Food Manufacturing and Beverage and Tobacco Product Manufacturing) and 334 (Computer and Electronic Product Manufacturing), while the lowest technology complementarity is 0.0001 between 315-316 (Apparel Manufacturing and Leather) and 324 (Petroleum and Coal Products Manufacturing). The correlation between two complementarity cost matrices is 0.2777, reflecting the fact that they are somewhat related but ultimately capturing different relations between industry pairs.

3.3 Reduced-Form Evidence

This section provides reduced-form evidence on the relationship between input complementarity and observed sourcing patterns. We begin with descriptive evidence on the sourcing-share matrix used in the calibration. This establishes how far classical input- and sector-level sourcing forces go in explaining domestic input shares, and how much variation remains to be explained. We then turn to the model's pairwise implication: inputs that are more complementary should be less likely to be separated across domestic and foreign sourcing margins. For this purpose, co-location is the natural empirical outcome. It directly measures whether two inputs are sourced from similar locations and is therefore the closest reduced-form counterpart of the model's pairwise unbundling term. In the quantitative exercise below, we discipline the model using the underlying sector-input sourcing shares that generate these co-location patterns.

The two key empirical objects are domestic sourcing shares and measures of input-pair closeness. Let π_{mn} denote the domestic share of input m used by sector n. Table 1 reports summary statistics for the 2019 sourcing shares and for the pair-level objects used in the co-location regressions. Domestic sourcing is high on average, with a mean of 0.809, but there is substantial variation across input–using-sector cells. The corresponding imported-input share has a mean of 0.191, a standard deviation of 0.184, and a 90th percentile of 0.437. Thus, the data contain sizeable differences in sourcing intensity across inputs and using sectors. The pairwise co-location measure also varies substantially, with a mean of 0.801 and a standard deviation of 0.171.

We next ask how much of the variation in domestic sourcing shares is accounted for by classical input- and sector-level forces. Input fixed effects capture input-specific sourcing propensities, while using-sector fixed effects capture sector-level import intensity. Table 2

Table 1: Summary Statistics for Sourcing and Complementarity Moments

Variable	N	Mean	SD	Min	P10	P25	P50	P75	P90	Max
Domestic sourcing share, π_{mn}	405	0.809	0.184	0.000	0.563	0.712	0.855	0.953	1.000	1.000
Imported input share, $1 - \pi_{mn}$	405	0.191	0.184	0.000	0.000	0.047	0.145	0.288	0.437	1.000
Pairwise co-location, $1 - \lvert\pi_{mn} - \pi_{kn}\rvert$	3559	0.801	0.171	0.000	0.569	0.716	0.844	0.930	0.976	1.000
Labor complementarity, C^L_{mk}	3559	0.401	0.143	0.086	0.219	0.292	0.404	0.492	0.603	0.749
Technology complementarity, C^T_{mk}	3559	0.010	0.013	0.000	0.000	0.002	0.007	0.013	0.022	0.162

Notes: Domestic sourcing shares are measured at the input–using-sector level for active input-use cells in 2019. The sample contains 405 active cells with positive observed input use and valid domestic sourcing shares. The balanced 22-by-22 matrix contains 462 off-diagonal cells, but cells with zero input use are excluded because domestic sourcing shares are not economically meaningful for inputs not used by a sector. Imported input shares are one minus the domestic sourcing share. Domestic shares are cleaned by setting nonfinite and negative values to missing and bounding values above one at one. Pairwise co-location is defined as $1 - |\pi_{mn} - \pi_{kn}|$ for unordered input pairs $m < k$ used by the same sector n. The pairwise sample contains 3,559 input-pair–using-sector observations. The same input-pair complementarity measure may appear for multiple using sectors; the co-location outcome varies by using sector through π_{mn} and π_{kn}.

Table 2: Fixed Effects and Domestic Sourcing Shares

Fixed effects included	R^2
Input FE	0.523
Using-sector FE	0.031
Input FE + using-sector FE	0.552

Notes: The dependent variable is the domestic sourcing share $\pi_{mn,2019}$ for active input–using-sector cells. The sample contains 405 observations. Regressions are unweighted.

shows that input fixed effects explain 0.52 of the variation in π_{mn}, using-sector fixed effects explain much less on their own, and including both sets of fixed effects marginally raises the R^2 to 0.55. Thus, the standard input-level sourcing channel is quantitatively important, but still leaves a lot of unexplained residual variation.

The model's mechanism is not a prediction about isolated input–sector cells alone. It is a prediction about the joint sourcing of pairs of inputs: complementary inputs should be less likely to be split across domestic and foreign sourcing margins. We therefore turn from the level of π_{mn} to pairwise co-location.

For each unordered input pair $m < k$ used by sector n, we define the empirical co-location index

$$\text{Coloc}_{mkn} = 1 - |\pi_{mn} - \pi_{kn}|,$$

where π_{mn} is the domestic share of input m used by sector n. This index is high when two inputs have similar domestic sourcing shares and low when one input is mostly domestic

while the other is mostly imported. The model predicts that input pairs with higher complementarity should be more likely to be co-located. We examine this prediction using labor complementarity and technology complementarity. Both regressors are standardized within each regression sample, so the coefficients measure the association between co-location and a one-standard-deviation increase in the corresponding complementarity measure.

The baseline exercise uses the same sourcing data as the calibration: 2019 domestic input shares. We estimate

$$\text{Coloc}_{mkn,2019} = \beta_L C^L_{mk} + \beta_T C^T_{mk} + \Gamma_{mkn} + \varepsilon_{mkn},$$

where C^L_{mk} and C^T_{mk} denote labor and technology complementarity between inputs m and k, and Γ_{mkn} denotes the fixed effects included in each specification. The fixed-effect specifications become progressively richer across columns, absorbing general using-sector sourcing patterns, input-side sourcing patterns, and input-by-using-sector variation.

Table 3 reports the results. Labor complementarity is positive and statistically significant in every specification. The coefficient is 0.0185 without fixed effects and remains significant after adding using-sector fixed effects. Once input-side fixed effects are included, the coefficient increases to about 0.040. In the most saturated baseline specification with mn and kn fixed effects, the coefficient is 0.0427 and is significant. Thus, even after controlling for the domestic sourcing tendency of each input within each using sector, input pairs with higher labor complementarity have more similar domestic sourcing shares.

Technology complementarity does not display the same robust pattern in the baseline cross-section. Its coefficient is small in all specifications and is never statistically significant. Conditional on labor complementarity and the fixed effects, the technology measure does not explain additional baseline co-location variation. This does not imply that technology complementarity is irrelevant in the structural model, but it suggests that the reduced-form co-location pattern is primarily captured by the labor complementarity measure in this validation exercise.

Appendix Table 14 repeats the exercise in a richer panel setting using domestic sourcing shares over 2002–2020 and lagged complementarity measures. The panel structure allows for richer fixed effects, including year fixed effects, using-sector-year fixed effects, input-year fixed effects, input-pair fixed effects, and input-by-using-sector-year fixed effects. The results mainly mirror the baseline table: labor complementarity remains positively associated with co-location across the preferred specifications. The coefficient remains positive and significant with input-side and time-varying fixed effects, and it continues to be positive in specifications that include input-pair fixed effects and therefore identify the relationship from within-pair

Table 3: Baseline Co-Location Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor complementarity	0.0185***	0.0173***	0.0397***	0.0397***	0.0418***	0.0403***	0.0427***	0.0374***
	(0.0030)	(0.0029)	(0.0058)	(0.0057)	(0.0052)	(0.0053)	(0.0046)	(0.0060)
Technology complementarity	0.0013	0.0020	0.0012	0.0013	0.0003	0.0016	0.0008	-0.0002
	(0.0030)	(0.0029)	(0.0032)	(0.0031)	(0.0028)	(0.0030)	(0.0026)	(0.0034)
Using-sector FE, n	N	Y	N	Y	N	N	N	Y
Input m FE	N	N	Y	Y	N	Y	N	Y
Input k FE	N	N	Y	Y	Y	N	N	Y
Input–using FE, mn	N	N	N	N	Y	N	Y	N
Input–using FE, kn	N	N	N	N	N	Y	Y	N
Restricted sample	N	N	N	N	N	N	N	Y
R^2	0.012	0.058	0.276	0.312	0.493	0.471	0.648	0.318
Observations	3559	3559	3559	3559	3559	3559	3559	3176

Notes: Dependent variable: empirical co-location, $1 - |\pi_{mn,2019} - \pi_{kn,2019}|$, for unordered input pairs $m < k$ used by sector n. The regressors are average labor complementarity and technology complementarity between inputs m and k. Both regressors are standardized within each regression sample. The restricted sample in column (8) excludes pairs in which either input is the using sector. Standard errors are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

time variation. Technology complementarity is weaker and less stable: it is insignificant in the baseline cross-section, changes sign across less saturated panel specifications, and is absorbed by input-pair fixed effects as a time invariant regressor.

Overall, the reduced-form evidence supports the model's central mechanism. Input fixed effects capture an important part of domestic sourcing, consistent with the standard explanation based on input-level foreign cost differences, but substantial sourcing variation remains after controlling for input and using-sector propensities. The co-location regressions then show that this remaining structure is related to measured input closeness: labor complementarity has the predicted sign and remains statistically significant across a wide range of fixed effects. The result is strongest in specifications that preserve meaningful pairwise variation while controlling for general input and using-sector sourcing patterns.

3.4 Solving Firms' Allocation Problems

We solve each firm's optimal sourcing allocation in order to characterize the extent of international production fragmentation. As described in Section 2.2, a firm that uses N inputs chooses the sourcing location of each input. With two possible locations, an allocation can be represented by a binary vector $S \in \{0,1\}^N$, where s_m=1 indicates that input m is produced in country 1 and $s_m = 0$ indicates that it is produced in country 2. Because the cost of sourcing any input depends on the locations chosen for other inputs through pairwise

complementarity costs, the firm's problem is a discrete combinatorial optimization problem rather than a collection of independent input-level sourcing decisions.

A brute-force solution would require evaluating all 2^N possible allocations for each firm. This is computationally costly even for the relatively aggregated input structure used in the quantitative analysis. With $N = 22$, the number of possible allocations exceeds four million for a single firm. Since the allocation problem must be solved repeatedly across firms, simulation draws, estimation iterations, and counterfactual exercises, the brute force approach is not feasible.

We solve the firm-level allocation problem using the algorithm first proposed by Jia (2008) and further developed and generalized by Arkolakis et al. (2026). The algorithm is designed for discrete allocation problems with complementarities and avoids going through all possible allocations by brute force. The intuition is that the structure of the cost function can be used to restrict the set of potential allocations. In our application, the relevant complementarity terms are nonnegative, so the cost function satisfies the single crossing assumption required for the algorithm.

3.5 Calibration

We quantify the model from the perspective of the United States. Throughout the quantitative analysis, the United States is country 1 and the rest of the world is country 2.[21] We set the demand parameters to $\sigma = 4$ and $\zeta = 0.5$, and take the final-good expenditure shares $\boldsymbol{\alpha}$ from the input-output use tables. To generate firm-level heterogeneity in input costs, we follow the stochastic formulation in Eaton and Kortum (2002) and assume that input cost draws $a^i_{mn,z}$, $i = 1, 2$, are independently drawn from a Fréchet distribution with common shape parameter $\kappa = 4.12$, as estimated by Simonovska and Waugh (2014).[22] For a firm z in sector n, the unit cost of input m sourced from country i is

$$c^i_{mn,z} = \theta^i_{mn}\mu^i_m a^i_{mn,z},$$

where θ^i_{mn} is the quantity requirement for input m in sector n, and μ^i_m is a country- and sector-specific cost shifter. We normalize $\mu^1_m = 1$ for all m, so the estimated foreign shifter μ^2_m measures the relative cost of sourcing input m from the rest of the world. We also shut down entry and variety channels: for any parameter values, the sunk costs η_i are chosen

[21] The procedure can be extended to target moments for both countries simultaneously. In the present application, we focus on matching US input-sourcing patterns.

[22] Because the firm's sourcing problem has no closed-form solution for any of the common parametric distributions, the Fréchet assumption is not used to obtain an analytical gravity equation. We use it because it is standard in quantitative trade models and allows for comparison with the existing literature.

so that $Z_m^1 = Z_m^2 = 100$ in each sector. Hence, differences across quantitative exercises are driven by sourcing decisions and costs rather than by changes in the number of firms.

The main empirical target is the $N \times N$ matrix of US domestic input shares, denoted by $\pi = \{\pi_{mn}\}$. We construct π_{mn} from the import matrices in the input-output accounts, where each entry measures the domestic share of input m used by sector n in the United States.

The calibration targets these domestic input shares rather than the co-location index used in the reduced-form evidence. The reason is that the two exercises play different roles. The reduced-form exercise asks whether the qualitative mechanism is visible in the data, so it relates complementarity to observed co-location. The calibration asks the model to reproduce the underlying sourcing allocation, so it targets the sector-input domestic shares from which co-location patterns are constructed. Matching the co-location index directly would compress the sourcing data into a nonlinear summary and would ask the model to fit the diagnostic statistic rather than the underlying allocation. We therefore discipline the model using input-level sourcing shares and use co-location-based measures for reduced form diagnostics.

For any candidate parameter vector, the model implies a simulated counterpart $\hat{\pi}_{mn}(\cdot)$ constructed using Equation (2). This simulated share is computed by solving the sourcing problem for all firms in sector n and then aggregating the share of factor payments made to domestic suppliers of input m.

The parameters estimated by simulated method of moments are the complementarity-cost multiplier(s) $\boldsymbol{\varphi}$, the iceberg trade cost τ, and the vector of relative foreign cost shifters $\boldsymbol{\mu}^2$. Let $\Psi = (\boldsymbol{\varphi}, \tau, \boldsymbol{\mu}^2)$ denote this parameter vector. We then choose Ψ to minimize the unweighted distance between observed and simulated domestic input shares:

$$\hat{\Psi} = \arg\min_{\Psi} \sum_{n=1}^{N} \sum_{m=1}^{N} \left[\hat{\pi}_{mn} \left(\Psi; \hat{\Theta}(\Psi) \right) - \pi_{mn} \right]^2 .$$

Here, $\hat{\Theta}(\Psi)$ denotes the quantity input requirements used to simulate the model for a candidate value of Ψ, as described below.

The identifying variation comes from differences in sourcing patterns across input pairs and using sectors. The sector-specific shifters μ_m^2 capture persistent input-specific differences in the relative cost of producing input m abroad rather than in the United States. These shifters are disciplined by systematic differences in domestic sourcing across inputs: inputs that are frequently sourced from abroad, conditional on the sectors that use them, imply lower relative foreign costs, while inputs that remain primarily domestic imply higher relative

foreign costs. The iceberg trade cost τ captures conventional costs associated with foreign sourcing. It is disciplined by the overall level of foreign sourcing after accounting for input-specific relative costs; holding $\boldsymbol{\mu}^2$ fixed, a higher τ reduces the attractiveness of sourcing inputs from abroad and raises simulated domestic input shares.

The complementarity multiplier $\boldsymbol{\varphi}$ is disciplined by the pairwise structure of the sourcing-share matrix. Absent complementarity costs, the model can explain domestic sourcing through input-specific foreign cost advantages and the common iceberg trade costs. Complementarity costs are needed when technologically or occupationally similar inputs are sourced together more often than would be predicted by these individual foreign-cost advantages and the common iceberg trade costs alone. Thus, although the estimation targets input-level domestic sourcing shares, $\boldsymbol{\varphi}$ is identified from the extent to which the pattern of those shares implies excess co-location of complementary inputs.

A measurement issue arises because the model requires input requirements in quantity units, while the input-output tables report expenditure shares. Since inputs enter production as perfect complements, expenditure shares cannot be used directly as quantity requirements. For each candidate parameter vector Ψ, we therefore construct a quantity-requirement matrix $\hat{\Theta}(\Psi)$ such that the model-implied input expenditure shares are consistent with the observed input-output expenditure shares. This step should be interpreted as a measurement conversion from observed expenditure shares into model quantity requirements.

The quantification can be viewed as two nested fixed points. The inner fixed point maps observed input-output expenditure shares into quantity requirements $\hat{\Theta}(\Psi)$ for a given candidate parameter vector. The outer simulated-method-of-moments loop searches over $(\boldsymbol{\varphi}, \tau, \boldsymbol{\mu}^2)$, recomputes firms' optimal sourcing allocations, constructs the simulated domestic input shares $\hat{\pi}_{mn}$, and minimizes the objective in equation (3.5). The allocation decisions are therefore not held fixed during the estimation of τ, $\boldsymbol{\mu}^2$, or $\boldsymbol{\varphi}$; they are recomputed for each candidate parameter vector. In smaller versions of the problem where brute force is feasible, we validate the algorithm against brute-force solutions and verify that it recovers the same allocations.

3.6 Calibration Fit

We evaluate the fit of the calibrated model by comparing the benchmark specification with restricted alternatives by shutting down production complementarity. The purpose of this exercise is not to establish complementarity as the only possible source of fit. Rather, it asks whether the complementarity terms help the model reproduce observed sourcing patterns, and how much fit deteriorates when these terms are removed while other margins are allowed

Table 4: Fit Diagnostics Relative to the Benchmark Full Model

Specification	Objective	RMSE	MAE	R^2
Benchmark full model	13.686	0.1682	0.1195	0.7595
Restricted model	24.407	0.2246	0.1464	0.5711
Restricted model, τ only re-estimated	26.723	0.2350	0.1592	0.5304
Full-model parameters with $\phi_L = \phi_T = 0$	51.215	0.3253	0.2370	0.1000

Notes: The benchmark is the estimated full model with production complementarity. Restricted specifications set $\phi_L = \phi_T = 0$. The objective is the sum of squared errors in matching observed home-sourcing shares. In the restricted model, all non-complementarity parameters are re-estimated. In the τ-only specification, all full-model parameters except the iceberg trade cost are held fixed. The final row evaluates the full-model estimates after setting both complementarity coefficients to zero, with no re-estimation.

to adjust.

The benchmark is the estimated full model with production complementarity. As shown in Table 4, the benchmark attains an objective value of 13.686, with an RMSE of 0.1682, an MAE of 0.1195, and an R^2 of 0.7595 in matching observed home-sourcing shares. The restricted model sets $\phi_L = \phi_T = 0$ but re-estimates the remaining non-complementarity margins. Its objective rises to 24.407, while the R^2 falls to 0.5711. Thus, removing complementarity substantially worsens the model's ability to match the sourcing matrix even after the restricted model is allowed to adjust.

The next shows that this deterioration is not driven by a particular treatment of the input-requirement matrix or the common trade-cost parameter. When all full-model parameters except the iceberg trade cost are held fixed and only τ is re-estimated, the fit deteriorates further: the objective rises to 26.723 and the R^2 falls to 0.5304. These results indicate that adjustment in the non-complementarity margins can mitigate the loss of the complementarity channel but only partially.

The most direct diagnostic is the final row of Table 4. Here we take the estimated full-model structure and simply set $\phi_L = \phi_T = 0$, without re-estimating any other parameter. The objective increases to 51.215 and the R^2 falls to 0.1000. This significant decrease shows that complementarity plays a central role within the calibrated full-model allocation. The complementarity terms are not cosmetic additions to the cost function; they organize sourcing decisions in a way that is important for reproducing observed home-sourcing patterns.

4 Results

This section quantifies the role of input complementarity in shaping international production. The central message is that unbundling costs are not simply another additive trade friction. They directly restrict the international fragmentation of production and change the consequences of conventional iceberg-cost liberalization by altering the set of sourcing reallocations available to firms. In the model, a firm does not only decide how much to source from abroad. It decides which inputs can be separated across locations without destroying the value of producing complementary tasks together. This organizational margin changes the mapping from trade costs to trade volumes, and from trade volumes to welfare.

This distinction matters because a large part of applied trade analysis relies on measures of import exposure and trade elasticities. In canonical models, those objects often summarize the welfare consequences of trade liberalization. Here, imported input use remains important, but it is not a sufficient statistic. Two reforms can generate similar increases in imported inputs while producing different welfare gains, because they change different margins of the firm's sourcing problem. A reduction in iceberg trade costs makes foreign inputs cheaper. A reduction in unbundling costs changes how firms can organize complementary input bundles across countries. The results below quantify both effects and show how they interact.

The section proceeds in five steps. Section 4.1 establishes the aggregate importance of complementarity and shows that conventional trade liberalization has different trade-volume and welfare effects when unbundling frictions are present. Section 4.2 compares conventional and unbundling liberalization in equivalent units and uses a policy frontier to summarize their joint effects on welfare and imported input use. Section 4.3 studies the sourcing reallocations behind these aggregate effects and decomposes welfare gains into fixed-allocation and reoptimization components. Section 4.4 introduces structural and empirical fragmentation measures that summarize the direct cost-saving and reallocation channels behind sectoral gains. Section 4.5 then uses these empirical measures to characterize fragmentation regimes. Appendix C reports supplementary numerical tables, robustness checks, and additional diagnostics.

4.1 Aggregate Effects of Trade Liberalization

Table 5 reports benchmark counterfactuals. The first row shuts down input complementarity by setting the complementarity matrix to zero while leaving all other calibrated objects unchanged. Relative to the calibrated economy, eliminating complementarity increases imported input use by 9.8 percentage points, or 52.5 percent, and raises welfare by 6.24 percent. The aggregate price index falls by 5.87 percent and the trade-cost share rises by 2.16 percent-

age points as firms expand foreign sourcing. Thus, complementarity costs are quantitatively meaningful: they substantially restrict foreign sourcing and raise the aggregate price index.

The next two rows compare the response to a one percent reduction in iceberg trade costs in the calibrated model and in the no-complementarity benchmark. A one percent reduction in iceberg trade costs raises imported input use by 1.58 percentage points in the calibrated model, compared with 0.94 percentage points in the benchmark without complementarity. The welfare gains move in the opposite direction: welfare rises by 0.23 percent in the calibrated model and by 0.35 percent in the no-complementarity benchmark. This comparison shows that input complementarity does not simply dampen the trade response to conventional liberalization; instead, it changes the welfare content of the induced trade expansion. In the calibrated model, lower iceberg costs induce a larger increase in imported input use, but this additional trade takes place in an economy where firms still face unbundling frictions.

The final row considers a direct reduction in unbundling costs. A ten percent reduction in the calibrated complementarity matrix raises imported input use by 0.10 percentage points and welfare by 0.12 percent. The aggregate price index falls by 0.12 percent. The complementarity-cost share rises by 0.10 percentage points and the trade-cost share rises by 0.02 percentage points, reflecting the fact that firms use the lower unbundling costs to reorganize sourcing toward configurations with more separated complementary inputs. The small import response should not be interpreted as evidence that complementarity costs are quantitatively unimportant. The model's response to unbundling costs is nonlinear because firms choose discrete sourcing configurations. At the calibrated value of φ, only 19.1 percent of firms source inputs from both locations. Most firms are instead in bundled sourcing regimes, either domestic-only or foreign-only. A small reduction in unbundling costs therefore lowers costs directly but moves relatively few firms across the threshold into mixed sourcing. Larger reductions in unbundling costs activate this extensive margin: as λ falls below its calibrated value, the share of mixed-sourcing firms rises sharply, as shown in Figure 1, which explains the non-linear effects of unbundling liberalization.[23]

Figure 2 shows how the response to conventional trade liberalization varies with the strength of complementarity. Holding all other calibrated objects fixed, we scale the complementarity matrix according to

$$C(\lambda) = \lambda \hat{C},$$

where $\lambda = 0$ corresponds to the no-complementarity benchmark and $\lambda = 1$ corresponds to the calibrated economy. For each value of λ, we compute the response to a one percent reduction in iceberg trade costs.

[23] In Section 4.2, we extend this discussion and compare the two liberalizations in equivalent units.

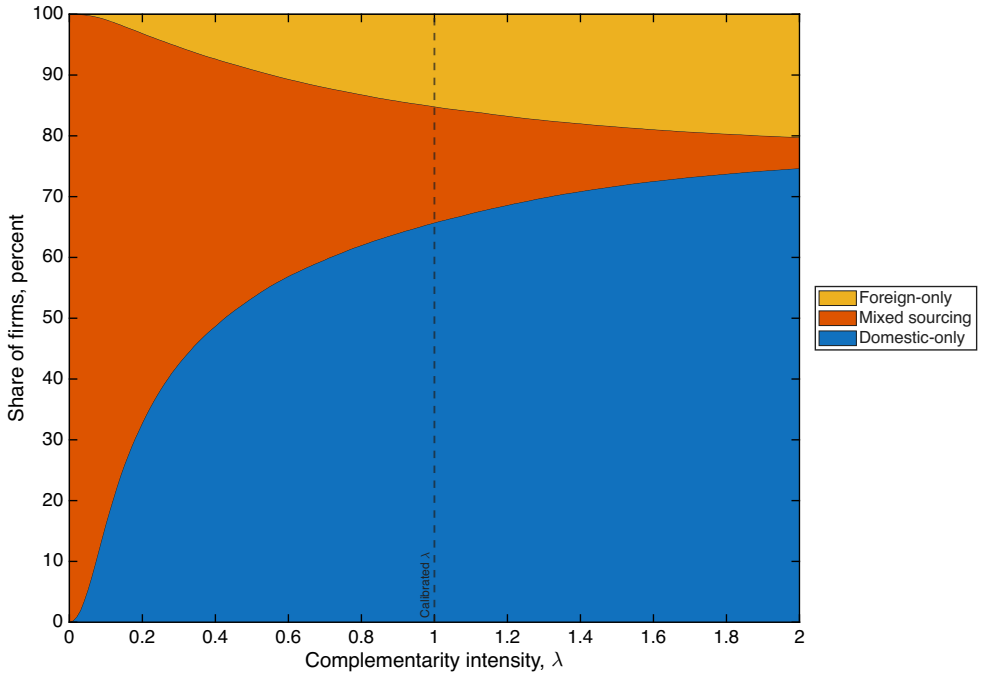
Table 5: Benchmark Counterfactuals

Counterfactual	Imported input use		Welfare and prices		Cost shares	
	Δ pp	Δ %	ΔW %	ΔP %	Δ comp. pp	Δ trade pp
No complementarity, $C = 0$	9.792	52.485	6.240	-5.873	-1.132	2.155
1% lower iceberg trade cost, calibrated model	1.582	8.480	0.234	-0.233	-0.011	0.081
1% lower iceberg trade cost, $C = 0$	0.941	3.307	0.350	-0.349	0.000	-0.159
10% lower unbundling costs, calibrated model	0.100	0.537	0.124	-0.124	0.101	0.018

Notes: The table reports counterfactual changes relative to the relevant baseline economy. The first, second, and fourth rows are relative to the calibrated model. The third row is relative to the no-complementarity benchmark with $C = 0$. Imported input use is measured using the net value of foreign inputs, excluding the iceberg trade costs, relative to total input costs. Δ pp denotes percentage-point changes. Welfare is measured as the inverse of the aggregate price index. The aggregate price index is computed using Cobb–Douglas sectoral expenditure weights. The model is simulated using 5,000 firm draws with a common random seed across counterfactuals.

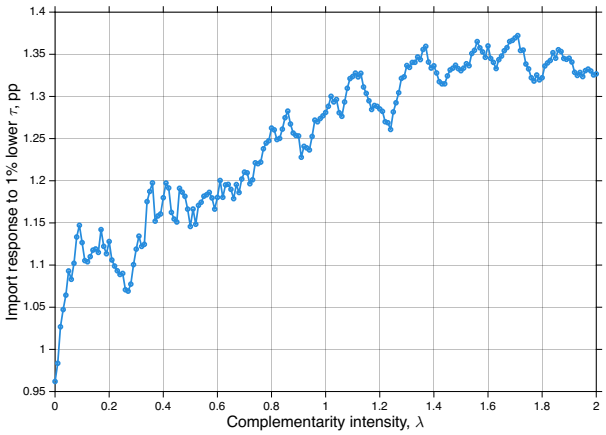
Panel A shows that the import response to lower iceberg trade costs generally rises with complementarity. Complementarity lowers baseline foreign sourcing and creates latent reallocation margins: when foreign inputs become cheaper, some firms discretely reorganize their sourcing decisions. Panel B shows that generally welfare gain from the same reduction in iceberg trade costs falls with complementarity, however for large values of λ, this relationship reverses and becomes weakly positive. This unusual behavior is also explained by Figure 1: moving from low to high λ shifts firms away from mixed sourcing and toward bundled domestic-only or foreign-only allocations. Panel C combines the results from panels A and B and reports the welfare gain per percentage-point increase in imported input use and shows that welfare gains per unit of imports stabilizes for larger values of λ.

Figure 1: Composition of Firm Sourcing Regimes

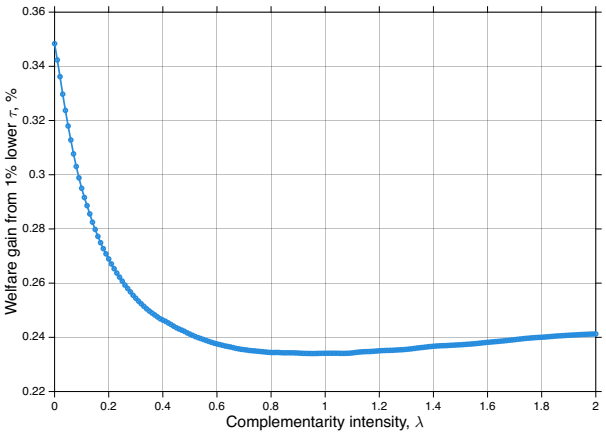


Notes: The figure reports the share of firms in each sourcing regime as the complementarity matrix is scaled according to $C(\lambda) = \lambda \hat{C}$. A domestic-only firm sources all active inputs domestically; a foreign-only firm sources all active inputs from abroad; and a mixed-sourcing firm sources active inputs from both locations. The vertical dashed line marks the calibrated economy, $\lambda = 1$. The model is simulated using 5,000 firm draws with a common random seed across values of λ.

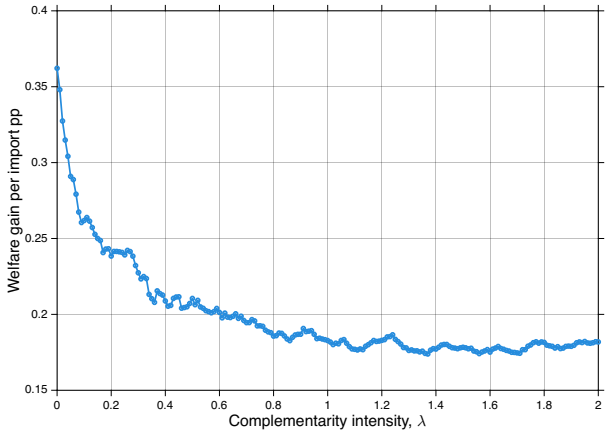
Figure 2: Input Complementarity and the Response to Lower Iceberg Trade Costs



(a) Import response



(b) Welfare response



(c) Welfare per import pp

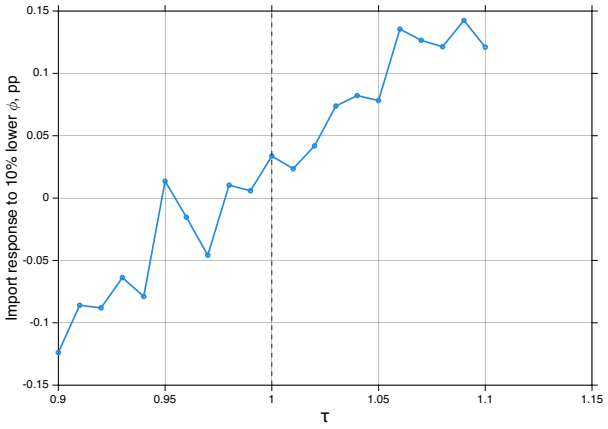
Notes: The figure reports the response to a one percent reduction in iceberg trade costs for different values of λ, where $C(\lambda) = \lambda\hat{C}$. The calibrated economy corresponds to $\lambda = 1$. Panel A reports the percentage-point change in imported input use. Panel B reports the percentage change in welfare, measured as the inverse of the aggregate price index. Panel C reports the welfare gain divided by the percentage-point increase in imported input use. The model is simulated using 5,000 firm draws with a common random seed across counterfactuals.

The effect of unbundling liberalization also depends on the level of iceberg trade costs. Figure 3 varies iceberg trade costs around the calibrated value and, for each value of τ, computes the effect of a ten percent reduction in the complementarity matrix,

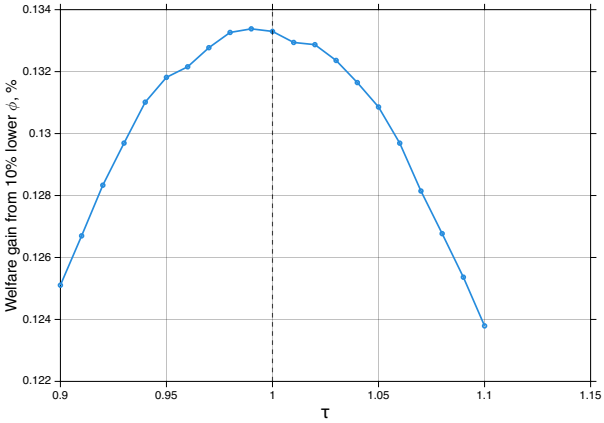
$$C^{cf} = 0.9\hat{C}.$$

Panel A shows that the import response is non-monotone in the level of iceberg trade costs. When trade costs are low, many firms already source inputs from abroad, so lower unbundling costs mainly reorganize sourcing rather than substantially increasing aggregate imported input use. When trade costs are high, foreign sourcing remains unattractive even after unbundling costs fall. Panel B shows that the welfare gain from reducing unbundling costs declines over the range of iceberg trade costs considered. In this calibration, unbundling liberalization is more valuable when foreign inputs are otherwise sufficiently attractive.

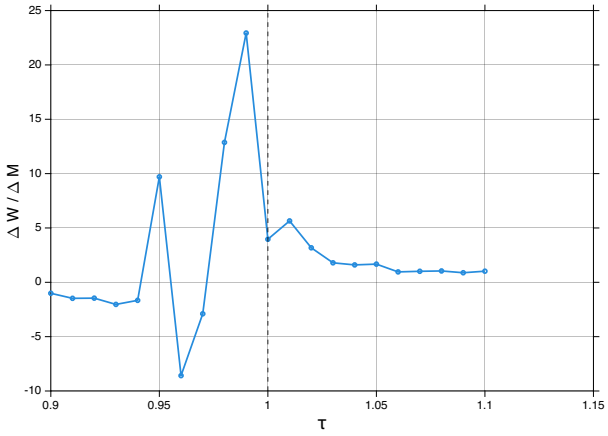
Figure 3: Unbundling Liberalization at Different Levels of Iceberg Trade Costs



(a) Import response



(b) Welfare response



(c) Welfare per import pp

Notes: The figure reports the effect of a ten percent reduction in unbundling costs, $C^{cf} = 0.9\hat{C}$, evaluated at different levels of iceberg trade costs. The horizontal axis reports $\tau/\hat{\tau}$, and the calibrated economy corresponds to $\tau/\hat{\tau} = 1$. Panel A reports the percentage-point change in imported input use. Panel B reports the percentage change in welfare, measured as the inverse of the aggregate price index. Panel C reports the welfare gain divided by the percentage-point increase in imported input use. The model is simulated using 5,000 firm draws with a common random seed across counterfactuals.

Together, Figures 1, 2, and 3 show that conventional and unbundling frictions interact in economically meaningful ways. Conventional trade liberalization remains a reduction in the cost of foreign inputs, but its welfare consequences depend on the organizational frictions that determine whether firms can efficiently split production across countries. Conversely, the value of reducing unbundling costs depends on the conventional trade-cost environment and on how many firms are close to the mixed-sourcing margin. These results establish the central quantitative point for the rest of the section: complementarity changes the mapping from import growth to welfare.

4.2 Equivalent Liberalizations

We next compare conventional trade-cost liberalization and unbundling liberalization in common units. Both reforms can change imported input use, but they act on different margins of the firm's problem: a reduction in iceberg trade costs makes foreign inputs cheaper holding the organizational problem fixed, while a reduction in unbundling costs changes which input bundles can be profitably split across countries. Imported input use is therefore an observable outcome of both reforms, but it need not summarize their welfare consequences.

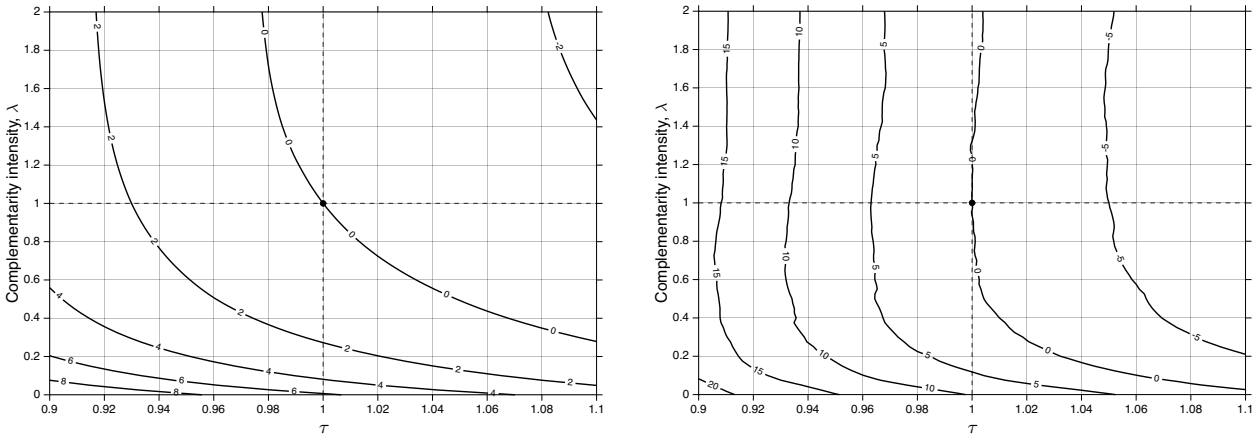
To study the joint policy space spanned by the two frictions, let

$$\tau = \rho\hat{\tau}, \qquad C(\lambda) = \lambda\hat{C},$$

where the calibrated economy is $(\rho, \lambda) = (1, 1)$. Figure 4 plots iso-welfare and iso-import curves in this space. Moving left lowers iceberg trade costs; moving down lowers unbundling costs.

Panel A shows that the two frictions are welfare substitutes: iso-welfare curves slope downward, and their curvature reflects the interaction between the two margins: lower unbundling costs are more valuable when foreign sourcing is already attractive, and the gains from lower iceberg costs depend on how costly it is to split complementary input bundles. Panel B shows that the iso-import curves have a different shape. In most of the relevant region, lower unbundling costs increase imported input use, but at high values of both τ and λ, some iso-import curves become weakly upward-sloping: lower unbundling costs can trigger reorganization that includes reshoring some inputs, so the net import response is non-monotone. The same movement in import use can therefore correspond to very different welfare gains.

Figure 4: Iso-Welfare and Iso-Import Curves



(a) Iso-welfare curves

(b) Iso-import curves

Notes: The figure reports iso-outcome curves over the policy space $(\tau/\hat{\tau}, \lambda)$, where $\tau = \rho\hat{\tau}$ and $C(\lambda) = \lambda\hat{C}$. The calibrated economy is marked by the black dot at $(1, 1)$. The numbers printed on each curve give the value of the corresponding outcome along that iso-outcome curve. Panel A reports welfare relative to the calibrated economy, in percent. Panel B reports imported input use relative to the calibrated economy, in percentage points. Moving left corresponds to lower iceberg trade costs; moving down corresponds to lower unbundling costs. The model is simulated using 5,000 firm draws with a common random seed across counterfactuals.

Table 6 quantifies the two equivalent liberalizations. A one percent reduction in iceberg trade costs raises imported input use by 1.281 percentage points and welfare by 0.234 percent. Matching this import response through unbundling liberalization alone requires a 61.5 percent reduction in unbundling costs, a far larger movement in the policy instrument, yet it delivers a welfare gain of 1.466 percent, more than six times larger. Conversely, matching the welfare gain requires only a 16.5 percent reduction in unbundling costs and raises imported input use by just 0.062 percentage points. The reason is that unbundling liberalization reorganizes the structure of production, inducing both offshoring and reshoring, whereas imported input use captures only the net trade-volume effect of that reorganization.

4.3 Sourcing Reallocation and the Composition of Gains

The equivalent-liberalization exercises show that similar import responses can mask very different welfare effects. To answer why, for each counterfactual, we compare firm–input sourcing decisions to the calibrated baseline and record whether an input switches location. A switch from domestic to foreign sourcing is classified as newly offshored; a switch from foreign to domestic sourcing is classified as reshored. We also decompose welfare gains into a fixed-allocation component, which holds baseline sourcing decisions fixed, and a reoptimization component, which is the additional gain from allowing firms to choose new sourcing

Table 6: Trade-Equivalent and Welfare-Equivalent Unbundling Liberalizations

Counterfactual	λ	ΔM pp	ΔW %	ΔP %	ΔCCS pp
1% lower iceberg trade costs	1.000	1.281	0.234	-0.234	-0.002
Trade-equivalent lower unbundling costs	0.385	1.286	1.466	-1.444	0.539
Welfare-equivalent lower unbundling costs	0.835	0.062	0.234	-0.233	0.146

Notes: The table reports changes relative to the calibrated economy. $C(\lambda) = \lambda\hat{C}$, so the unbundling reduction is $100(1-\lambda)$. ΔM denotes the percentage-point change in imported input use. ΔW denotes the percentage change in welfare, measured as the inverse of the aggregate price index. ΔP denotes the percentage change in the aggregate price index. ΔCCS denotes the percentage-point change in the complementarity cost share. Imported input use is measured using the net value of foreign inputs, excluding iceberg trade costs. The trade-equivalent and welfare-equivalent unbundling reductions are selected from the λ grid to match as closely as possible the import response and welfare gain from a one percent reduction in iceberg trade costs, respectively.

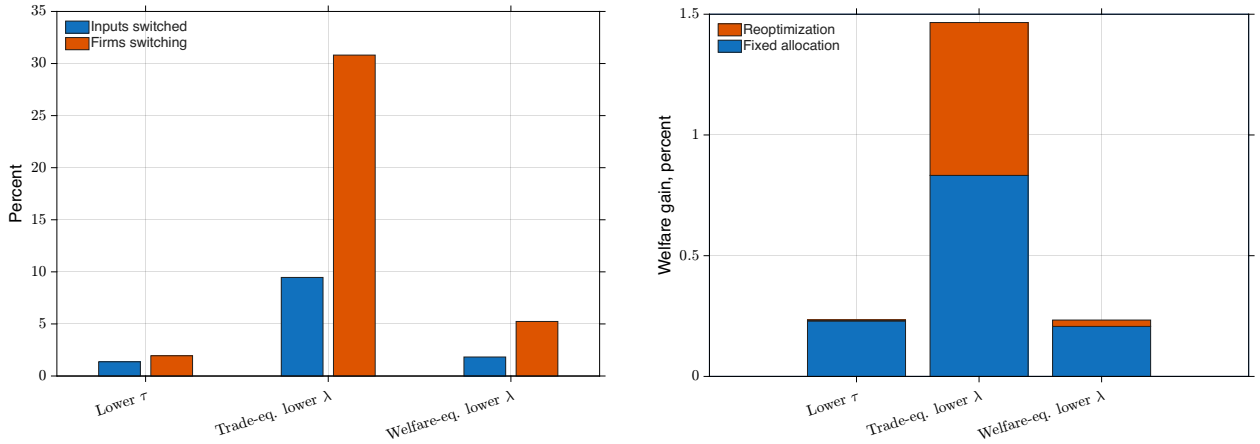
allocations.

Figure 5 illustrates this logic. Panel A shows that iceberg trade liberalization and unbundling liberalization operate through fundamentally different organizational margins. A one percent reduction in iceberg trade costs induces little reallocation: only 1.37 percent of input–firm decisions switch location, and fewer than 2 percent of firms change any sourcing decision. The trade-equivalent unbundling reform generates the same aggregate increase in imported input use, yet it changes 9.46 percent of input–firm sourcing decisions and leads 30.81 percent of firms to switch at least one input. The welfare-equivalent unbundling liberalization mirrors this point: it delivers the same welfare gain as the iceberg-cost reduction with almost no net import expansion, yet still induces more sourcing reorganization than the iceberg-cost reform. Unbundling liberalization is not simply a stronger or weaker version of conventional trade liberalization, it changes the cost of splitting complementary inputs across countries, rather than the cost of foreign inputs themselves.

Panel B shows that this organizational margin has welfare consequences that import volumes do not capture. For the iceberg-cost reduction, almost the entire welfare gain is obtained on the baseline allocation; reoptimization adds very little. For the trade-equivalent unbundling reform, reoptimization accounts for a large share of the gain. This is the direct counterpart of Panel A: lower unbundling costs make new sourcing configurations feasible, so welfare rises not only because the baseline allocation becomes cheaper, but because firms reorganize production.

Table 7 provides further evidence on the direction of switching. The iceberg-cost reduction is one-sided: all switching inputs move from domestic to foreign sourcing. The unbundling reforms are two-sided: under the trade-equivalent reform, 3.34 percent of input–

Figure 5: Sourcing Reallocation and Welfare Decomposition



(a) Sourcing reallocation

(b) Welfare decomposition

Notes: The figure compares three counterfactuals relative to the calibrated economy: a one percent reduction in iceberg trade costs, a trade-equivalent reduction in unbundling costs, and a welfare-equivalent reduction in unbundling costs. The trade-equivalent unbundling counterfactual sets $\lambda = 0.385$, corresponding to a 61.5 percent reduction in unbundling costs, and matches as closely as possible the import response from the one percent reduction in iceberg trade costs. The welfare-equivalent unbundling counterfactual sets $\lambda = 0.835$, corresponding to a 16.5 percent reduction in unbundling costs, and matches as closely as possible the welfare gain from the same trade-cost reduction. Panel A reports the share of input–firm sourcing decisions that change location ("Inputs switched") and the share of firms that change at least one input sourcing decision ("Firms switching"). Panel B decomposes the welfare gain into a fixed-allocation component and a reoptimization component. The fixed-allocation component evaluates each counterfactual while holding baseline sourcing decisions fixed; the reoptimization component is the difference between the full welfare gain and the fixed-allocation gain. Welfare is measured as the percentage change in the inverse of the aggregate price index. The model is simulated using 5,000 firm draws with a common random seed across counterfactuals.

firm decisions are newly offshored while 6.12 percent are reshored. The net import response is nevertheless positive because switching is measured as an unweighted count while imported input use is value-weighted. This two-sided movement is a distinctive implication of the model: when unbundling costs fall, firms break up existing clusters and form new ones, moving some inputs abroad and returning others home.

Table 8 reports the exact welfare decomposition. For the iceberg-cost reduction, reoptimization accounts for only 1.9 percent of the total welfare gain. For the trade-equivalent unbundling reform, it accounts for 43.2 percent. These numbers express the section's central point precisely: conventional trade liberalization changes costs on an existing sourcing organization; unbundling liberalization changes the organization itself.

The reoptimization share is counterfactual-specific rather than a structural invariant. For very small shocks, the envelope effect implies that most gains are fixed-allocation gains unless firms are exactly at switching thresholds; for very large shocks, the baseline allocation becomes less informative. The entries in Tables 7 and 8 should therefore be read as the

Table 7: Sourcing Reallocation Across Counterfactuals

Counterfactual	ΔM pp	ΔW %	Inputs switched	Newly offshored	Reshored	Firms switching
1% lower iceberg trade costs	1.281	0.234	1.367	1.367	0.000	1.944
Trade-equivalent lower unbundling costs	1.286	1.466	9.463	3.339	6.124	30.811
Welfare-equivalent lower unbundling costs	0.062	0.234	1.825	0.564	1.260	5.236

Notes: The table reports changes relative to the calibrated economy. ΔM is the percentage-point change in imported input use, and ΔW is the percentage change in welfare, measured as the inverse of the aggregate price index. "Inputs switched" is the share of input–firm sourcing decisions that change location; "Newly offshored" and "Reshored" distinguish the direction of the switch. "Firms switching" is the share of firms that change at least one input sourcing decision. All switching measures are reported in percent. The trade-equivalent unbundling counterfactual sets $\lambda = 0.385$, corresponding to a 61.5 percent reduction in unbundling costs. The welfare-equivalent unbundling counterfactual sets $\lambda = 0.835$, corresponding to a 16.5 percent reduction in unbundling costs.

composition of gains for the benchmark-sized reforms considered here. Appendix Tables 15 and 16 confirm the same qualitative pattern in sales-weighted terms: unbundling liberalization changes the sourcing decisions of a much larger share of economically important firms than conventional iceberg-cost liberalization.

4.4 Measures of Fragmentation

The previous subsection shows that import exposure does not capture the organizational content of trade liberalization. Two reforms can generate similar import responses while producing different welfare gains and different sourcing reallocations. We now ask which sector-level objects explain this gap. We define two structural measures that use the full model solution and then construct empirical counterparts that require only input shares, sourcing shares, and the complementarity matrix.

The first structural measure is the complementarity cost share, CCS_n. Let $B_{n,z}$ denote the complementarity-cost component of marginal cost for firm z in sector n, evaluated at its equilibrium sourcing allocation. We define

$$\text{CCS}_n = \frac{\sum_z \omega_{n,z} B_{n,z}}{\sum_z \omega_{n,z} MC_{n,z}},$$

where $\omega_{n,z}$ is the firm's sales weight in sector n. This is the share of marginal costs accounted

Table 8: Fixed-Allocation and Reoptimization Decomposition

Counterfactual	Full ΔW	Fixed ΔW	Reopt. ΔW	Reopt. share
1% lower iceberg trade costs	0.234	0.230	0.004	0.019
Trade-equivalent lower unbundling costs	1.466	0.833	0.633	0.432
Welfare-equivalent lower unbundling costs	0.234	0.207	0.026	0.113

Notes: The table reports welfare changes relative to the calibrated economy. Welfare is measured as the percentage change in the inverse of the aggregate price index. "Fixed" evaluates each counterfactual using baseline sourcing decisions. "Full" allows firms to reoptimize sourcing decisions. "Reopt. ΔW" is the difference between the full and fixed-allocation welfare gains, and "Reopt. share" is this difference divided by the full welfare gain. The trade-equivalent unbundling counterfactual sets $\lambda = 0.385$, corresponding to a 61.5 percent reduction in unbundling costs. The welfare-equivalent unbundling counterfactual sets $\lambda = 0.835$, corresponding to a 16.5 percent reduction in unbundling costs.

for by unbundling costs. Holding sourcing allocations fixed, sectors with larger CCS_n receive larger immediate cost reductions when unbundling costs fall.

The second structural measure captures the reorganization margin. For each τ, define three benchmark allocations for firm z in sector n:

$$S^0_{n,z}(\tau) = S_{n,z}(\tau, 0), \qquad S^*_{n,z}(\tau, \lambda) = S_{n,z}(\tau, \lambda), \qquad S^\infty_{n,z}(\tau) = S_{n,z}(\tau, \infty).$$

The first is the allocation chosen when splitting complementary inputs is costless; the second is the current allocation; the third is the best fully integrated allocation, where splitting is prohibitively costly. Let $V_{n,z}(\tau, S)$ denote the non-unbundling component of marginal cost, input costs plus iceberg trade costs, excluding unbundling costs, for allocation S at trade cost τ. Realized unbundling gains are

$$\mathrm{RUG}_{n,z}(\tau, \lambda) = 1 - \frac{V_{n,z}\big(\tau, S^*_{n,z}(\tau, \lambda)\big) - V_{n,z}\big(\tau, S^0_{n,z}(\tau)\big)}{V_{n,z}\big(\tau, S^\infty_{n,z}(\tau)\big) - V_{n,z}\big(\tau, S^0_{n,z}(\tau)\big)},$$

with $\mathrm{RUG}_{n,z} = 1$ when the denominator is zero. The sector-level measure is the sales-weighted average $\mathrm{RUG}_n = \sum_z \omega_{n,z} \mathrm{RUG}_{n,z}$. A value of zero means the sector is at the fully integrated benchmark, with no organizational gain yet realized; a value of one means current sourcing already coincides with the frictionless-unbundling allocation. Unlike CCS_n, RUG does not measure the cost currently paid as unbundling costs, instead it measures how far the sector has already reorganized toward the frictionless allocation.

Because both structural measures require solving the model, we construct empirical counterparts from observables. Let θ_{mn} be input m's expenditure share in sector n's input bundle

and C_{mk}^{emp} be the empirical complementarity matrix. Potential complementarity mass is

$$\text{PCM}_n = \sum_{m<k} \theta_{mn}\theta_{kn}C_{mk}^{emp}.$$

This captures latent organizational complexity: sectors with high PCM_n use bundles of inputs that are strongly complementary. The empirical co-location index is

$$\text{ECI}_n = 1 - \frac{\sum_{m<k} \theta_{mn}\theta_{kn}C_{mk}^{emp}\left[\pi_{mn}(1-\pi_{kn}) + (1-\pi_{mn})\pi_{kn}\right]}{\sum_{m<k} \theta_{mn}\theta_{kn}C_{mk}^{emp}},$$

where π_{mn} is the domestic sourcing share for input m used by sector n. ECI is high when complementary inputs have similar sourcing patterns and low when they are split across locations.

RUG and ECI are related but conceptually distinct. High ECI means complementary inputs are co-located in observed sourcing patterns; high RUG means the current allocation is already close to what firms would choose if unbundling costs were zero. These objects can move in opposite directions: co-location reduces unbundling costs but can also prevent firms from exploiting cross-country cost differences, while a sector with low co-location may have already split complementary inputs in a way that resembles the zero-unbundling allocation.

To evaluate the four measures, we use the calibrated model as a laboratory. We solve the 2019 economy on a 60×60 grid over iceberg trade costs and complementarity intensity,

$$\tau(\rho) = 1 + \rho(\hat{\tau} - 1), \quad \rho \in [0.05, 4], \qquad C(\lambda) = \lambda\widehat{C}, \quad \lambda \in [0, 2],$$

and at each grid point compute sectoral fragmentation measures and the sector-level responses to trade-cost and unbundling-cost reductions. This is an internal diagnostic, not an external empirical test: if a measure captures the relevant mechanism, it should predict which sectors respond most strongly across model-generated policy environments.

Table 9 reports the results. First, import exposure is useful but incomplete. It predicts import elasticities well, the import-only R^2 for a 10 percent reduction in iceberg trade costs is 0.686, but performs poorly for the outcomes that motivated this section: 0.125 for welfare elasticity, 0.109 for input switching, and 0.009 for firm switching. Import exposure captures the trade-volume response, not the value or organizational content of that response.

Second, the structural measures validate the two model mechanisms. Adding RUG and CCS to import exposure increases the R^2 from $R^2 = 0.009$ to $R^2 = 0.706$ for firm switching after a trade-cost reduction, which shows that these measures identify which sectors are close to reallocation thresholds. For welfare responses to lower unbundling costs, the structural

specifications reach $R^2 \simeq 0.998$: CCS captures the direct cost wedge while RUG captures the sector's position on the organizational margin.

Third, the empirical measures recover meaningful information without solving the model. Adding PCM and ECI to import exposure raises the R^2 for welfare elasticity from 0.125 to 0.507; adding interactions raises it to 0.743. For input switching, the corresponding values rise from 0.109 to 0.470 and then to 0.570. PCM and ECI thus change the mapping from import exposure to welfare and reallocation responses by identifying whether imported inputs belong to complementary bundles and whether those bundles are already co-located.

Fourth, a simple taxonomy preserves much of this information. Allowing the import-exposure slope to vary across high/low PCM–ECI regimes raises the R^2 for welfare elasticity to 0.687 and for input switching to 0.481. The fit is somewhat below the full interaction specification, but the taxonomy is substantially easier to interpret. The next subsection uses these regimes to characterize the organizational environments in which trade-cost and unbundling-cost shocks operate.[24]

Table 9: Predictive Content of Structural and Empirical Fragmentation Measures

Outcome	Import only	Import + RUG + CCS	Structural interactions	Import + PCM + ECI	Empirical interactions	Import + quadrant dummies	Quadrant import slopes
Import elasticity, 10% lower τ	0.686	0.691	0.701	0.711	0.711	0.700	0.708
Welfare elasticity, 10% lower τ	0.125	0.219	0.299	0.507	0.743	0.437	0.687
Welfare/import, 10% lower τ	0.044	0.269	0.291	0.129	0.134	0.114	0.123
Input switching, 10% lower τ	0.109	0.133	0.166	0.470	0.570	0.379	0.481
Firm switching, 10% lower τ	0.009	0.706	0.776	0.177	0.254	0.144	0.235
Welfare elasticity, lower φ	0.095	0.998	0.998	0.369	0.414	0.273	0.311
Firm switching, lower φ	0.086	0.574	0.575	0.198	0.229	0.191	0.203

Notes: Entries are unweighted R^2 values from no-fixed-effect regressions over sector–grid observations. The trade-cost outcomes correspond to a 10 percent reduction in iceberg trade costs. The unbundling outcomes correspond to a one percent reduction in complementarity intensity. The structural variables are RUG and CCS. The structural-interaction specification adds interactions of import exposure with RUG and CCS. The empirical variables are import exposure, PCM, and sectoral ECI. The empirical-interaction specification adds interactions of import exposure with PCM and ECI. Low PCM/low ECI is the omitted group in the quadrant specifications.

4.5 Regimes of International Organization

The previous subsection shows that PCM and ECI are informative because they clarify what a given import share represents. A high imported-input share may arise in sectors whose imported inputs are only weakly related to the rest of the input bundle, or in sectors where imported inputs are part of tightly complementary production clusters, complementary in-

[24]The predictive results are not driven only by variation over the policy grid. Appendix Table 19 repeats the same specifications in the calibrated 2019 cross-section of sectors and finds the same qualitative pattern.

puts may already be co-located or split across locations. The same import share can therefore correspond to very different welfare and reallocation responses. We use PCM and ECI to organize these differences into a simple taxonomy of international organization.

We divide sector–grid observations into four regimes according to whether PCM and sectoral ECI are above or below their sample medians. The two axes have distinct interpretations: PCM measures the amount of latent complementarity in the sector's input bundle, while ECI measures whether complementary inputs are already co-located. The resulting regimes are not a ranking from low to high fragmentation; they describe four qualitatively different organizational environments. Low-PCM, low-ECI sectors are closest to conventional trade environments, where import exposure mainly captures the use of foreign inputs. High-PCM, low-ECI sectors are latent-complexity environments: complementary inputs are important but currently fragmented, leaving substantial scope for reorganization. Low-PCM, high-ECI sectors are simpler co-located environments, where bundling is present but complementarity is limited. High-PCM, high-ECI sectors are complex bundled-sourcing environments, where import sourcing is embedded in co-located complementary input clusters.

This coarse classification preserves much of the information in the continuous measures. Adding high/low PCM–ECI regime dummies to import exposure raises the R^2 for the welfare elasticity to a 10 percent reduction in iceberg trade costs from 0.125 to 0.437; allowing the import-exposure slope to vary across regimes raises it further to 0.687. For input switching, the corresponding values are 0.109, 0.379, and 0.481. The regimes therefore change the marginal relationship between import exposure and the response to a trade-cost shock.

Table 10 describes the average response in each regime. The high-PCM, low-ECI regime has the largest average firm-switching response to a trade-cost reduction and the largest average response to lower unbundling costs, the regime where complementarity mass is present but not yet co-located, leaving the most scope for organizational adjustment. The high-ECI regimes have larger import elasticities but lower average switching and welfare responses to trade-cost reductions: complementary inputs are already more strongly bundled, so import exposure is associated with larger foreign-sourcing movements but less organizational reconfiguration. PCM and ECI therefore separate economically different environments rather than relabeling sectors by their import shares.

Table 11 goes further by reporting how import exposure operates *within* each regime. It reports the predicted change in each outcome associated with a 10 percentage point increase in import exposure, using the quadrant import-slope specification in column (7) of Table 9. A positive entry means that higher import exposure predicts a stronger response to the trade-cost reduction within that regime; a negative entry means the opposite.

Table 10: Average Responses by PCM–ECI Regime

Regime	Import elast.	Welfare elast.	Input sw.	Firm sw.	Unbundling welfare	Unbundling firm sw.
Low PCM / Low ECI	1.009	0.0363	1.776	3.724	0.0076	0.249
High PCM / Low ECI	1.048	0.0320	1.772	5.341	0.0146	0.477
Low PCM / High ECI	2.064	0.0196	0.742	2.205	0.0042	0.094
High PCM / High ECI	2.136	0.0147	0.669	2.735	0.0085	0.221

Notes: Entries are unweighted trimmed means. The first four outcome columns refer to a 10 percent reduction in iceberg trade costs. The last two columns refer to a one percent reduction in complementarity intensity. Regimes are defined using high and low values of PCM and sectoral ECI over the sector–grid sample.

Table 11: Predicted Response to Higher Import Exposure, by PCM–ECI Regime

Outcome	Low PCM Low ECI	High PCM Low ECI	Low PCM High ECI	High PCM High ECI
Welfare elasticity	-0.005	-0.003	0.036	0.032
Input switching	-0.296	-0.155	1.266	1.347
Firm switching	-0.813	-0.989	4.038	5.577

Notes: Entries report the predicted change in the outcome associated with a 10 percentage point increase in import exposure within each PCM–ECI regime. Predictions are based on the quadrant import-slope specification in column (7) of Table 9. Import exposure is measured in percentage points. The trade-cost shock is a 10 percent reduction in iceberg trade costs.

In the two low-ECI regimes, higher import exposure predicts slightly smaller welfare and reallocation responses: a 10 percentage point increase in import exposure is associated with about 0.8–1.0 percentage points less firm switching. In the two high-ECI regimes, the relationship reverses: the same increase predicts higher welfare elasticities, 1.3–1.4 percentage points more input switching, and 4.0–5.6 percentage points more firm switching. ECI therefore changes not only the average level of responsiveness but the sign of the relationship between import exposure and organizational adjustment.

Taken together, the two tables show that import exposure is a conditional object. The regime means establish that fragmented high-complementarity sectors are most responsive to unbundling-cost reductions, while co-located regimes have larger import elasticities but lower average reallocation. The regime-specific slopes show that when complementary inputs are co-located, a higher import share predicts much stronger welfare and reallocation responses to trade-cost shocks. The economic content of an import share therefore depends on whether the imported inputs belong to complementary bundles and whether those bundles are already organized across locations. PCM and ECI are useful because they reveal these organizational differences through observable data.

5 Conclusion

This paper develops a quantitative model of international production in which firms choose not only how much to source from abroad, but which inputs to locate together. The key departure from standard sourcing models is pairwise complementarity: splitting two related inputs across countries raises production costs. This structure nests simultaneous sourcing and sequential production as special cases, while allowing richer patterns of clustering among inputs that are not naturally ordered along a single production chain.

The central quantitative finding is that unbundling liberalization and conventional trade liberalization are distinct in their welfare implications, even when they generate similar import responses. A one percent reduction in iceberg trade costs raises imported input use more in the calibrated economy than in a no-complementarity benchmark, yet delivers smaller welfare gains because the additional imports occur in an economy where complementary inputs remain costly to split. By contrast, a reduction in unbundling costs reorganizes the structure of production, inducing both offshoring and reshoring, and can generate welfare gains more than six times larger than a reform that moves the same volume of imports through lower iceberg costs. The welfare decomposition shows why: conventional trade liberalization mostly changes costs on an existing sourcing organization, while unbundling liberalization changes the organization itself.

The fragmentation measures developed in the paper translate this distinction into observables. Structural measures, the complementarity cost share and realized unbundling gains, identify which sectors bear the direct cost of maintaining production clusters and how far they have already reorganized toward the frictionless-unbundling allocation. Empirical counterparts based on input-output shares, sourcing shares, and the complementarity matrix recover much of this information without solving the full model, and a simple PCM–ECI taxonomy of organizational regimes substantially improves the prediction of welfare and reallocation responses relative to import exposure alone.

Several limitations are worth emphasizing. We follow the economic geography literature and use occupational similarity, R&D flows, and patent citation patterns to capture labor and technological complementarity. These measures are useful because they are observable and discipline the model with external information, but they are necessarily incomplete. Production complementarity can arise from other sources that are harder to measure, including managerial expertise, tacit production knowledge, supplier-specific relationships, regulatory compatibility, engineering standards, software integration, and the need to coordinate design and assembly. Our complementarity matrices should therefore be interpreted as disciplined empirical proxies rather than exhaustive measures of all organizational links among inputs.

Our framework is also intentionally stylized in two respects. We model unbundling costs as part of marginal production costs, which captures ongoing coordination costs and compatibility risks but abstracts from fixed costs of establishing cross-border supplier relationships. And the quantitative model is also a two-country framework, which keeps the firm's sourcing decision binary for each input and makes estimation feasible with the current algorithm. Extending the model to many countries is conceptually straightforward but computationally demanding. Both extensions are natural directions for future work.

The broad message of this paper is that trade liberalization and organizational liberalization are distinct. Tariffs, transportation costs, communication technologies, standards harmonization, and managerial improvements may all increase international production fragmentation, but they need not have the same welfare implications. When inputs are complementary, the value of a reform depends on how it changes the feasible organization of production, not only on how much it changes import volumes. Accounting for the structure of input complementarity therefore helps explain why two reforms that look similar through the lens of import exposure can have very different consequences, and why import exposure alone may miss an important dimension of globalization.

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A Properties of the Model

A.1 General Properties

We consider the effects of non-tariff trade liberalization for the case of a uniform decrease in the unbundling costs, or equivalently, a decrease in the complementarity cost multiplier φ. The proofs of Propositions 1-5 and 8 from Tyazhelnikov (2022) rely on the revealed preferences argument and do not depend on the sequentiality of the production process, so they also hold for this model.[25] In particular, the following propositions hold:

Proposition 1. *The firm's marginal costs are non-decreasing in φ and increasing if a firm is engaged in international production.*

This proposition is relatively straightforward: a firm cannot be worse off when facing lower unbundling costs. If the firm does not change its previous allocation and is not engaged in international production, its marginal costs will not change. In the case in which a firm produces internationally, its marginal costs will decrease.

Proposition 2. *The firm's quantity of complementarity activities $\sum_{m=1}^{N}\sum_{k=1}^{N}|s_{mn,z}-s_{kn,z}|\,\mathbf{C}_{mk}$ is non-decreasing in φ.*

This is another proposition based on a revealed preferences argument: if a firm chose to engage in international production, it would not choose to integrate less when the costs of integration are lower.

Proposition 3. *The value of firm's complementarity activities is non-monotonic in φ: in the case of lower φ, it directly reduces unbundling costs, but also encourages increased degree of fragmentation that can increase unbundling costs.*

This proposition indicates that firms' expenditure on supporting international activity can depend non-monotonically on the costs of such activity. For example, a decrease in the cost of telecommunication services will lead to an increase in the usage of these services, while the effect on the telecommunication expenditure will be ambiguous. Furthermore, the expenditure on telecommunication services will be equal to zero in both cases when the services are free and prohibitively expensive.

With the decrease of costs of complementarity φ, the quantity of complementarity activities $\sum_{m=1}^{N}\sum_{k=1}^{N}|s_{mn,z}-s_{kn,z}|\,\mathbf{C}_{mk}$ does not change or increases, so their product $\varphi\sum_{m=1}^{N}\sum_{k=1}^{N}|s_{mn,z}-s_{kn}$ can either decrease or increase depending on which effect is stronger. Note that both for

[25] Note that these properties hold both for Tyazhelnikov (2022) and our framework despite drastically different technological assumptions and dissimilar clustering patterns.

the cases of autarky $\varphi = \infty$ and free trade $\varphi = 0$, $\varphi \sum_{m=1}^{N} \sum_{k=1}^{N} |s_{mn,z} - s_{kn,z}| \, \mathbf{C}_{mk} = 0$ and $\varphi \sum_{m=1}^{N} \sum_{k=1}^{N} |s_{mn,z} - s_{kn,z}| \, \mathbf{C}_{mk} > 0$ for some $0 < \varphi < \infty$ if a firm chooses to engage in international production for any value of φ.

Proposition 4. *If the firm changes its unique optimal allocation due to decreases in φ, this firm's per-unit non-unbundling costs will decrease as production costs savings are prioritized.*

This proposition follows from the previous propositions and states that the reason why a firm may choose to reallocate its production is driven by production efficiency considerations, not potential cost savings on the costs of complementarity activities, which is $\sum_{m=1}^{N} [s_{mn,z} c^1_{mn,z} + (1 - s_{mn,z}) c^2_{mn,z} + T(s_{mn,z}, c^1_{mn,z}, c^2_{mn,z})]$ for each unit. Trade liberalization always leads to a more efficient allocation of resources across countries, so unbundling costs can be interpreted as frictions preventing firms from allocating their resources.

The reason behind this reallocation is a fall in unbundling costs decreases the relative importance of complementarity considerations and, thus, increases the importance of production costs in the cost function. For instance, when unbundling costs are equal to zero, a firm would make a decision based exclusively on the difference in production costs between the two countries.

Proposition 5. *The production of a single part in a given country can depend non-monotonically on φ. Reshoring is possible.*

Due to the presence of unbundling costs, firms choose to organize their production in clusters of technologically similar inputs. Lower unbundling costs mean that the incentives to cluster production are also lower. As a result, a situation called reshoring is possible: an input that a firm chose to produce internationally as part of a cluster can be again produced domestically for a lower value of φ when the firm de-clusters its production.

All of these results hold at the firm, industry, and economy level.

B Labor and Technology Complementarity Matrixes

C Additional Quantitative Results and Diagnostics

This appendix collects quantitative results and diagnostics from the full counterfactual write-up that are not included in the main Results section. The main text reports the core narrative and the figures needed to interpret the mechanism. The appendix reports supplementary numerical tables, additional reallocation and sectoral-incidence results, shock-size diagnostics for the measurement exercises, and global/local policy-frontier checks.

Table 12: labor Complementarity Matrix

Sectors	113	311-312	313-314	315-316	321	322	323	324	325	326	327	331	332	333	334	335	336	337	339	511	512	811
113	0	0.1398	0.1130	0.1031	0.1813	0.1095	0.1275	0.1479	0.1217	0.1034	0.2904	0.1013	0.1263	0.1104	0.0861	0.0991	0.0946	0.1400	0.1323	0.1282	0.0945	0.1635
311-312	0.1398	0	0.4030	0.3315	0.4782	0.5064	0.3575	0.3909	0.4743	0.4919	0.4905	0.4064	0.3578	0.3256	0.2554	0.3420	0.3105	0.3533	0.3652	0.2004	0.1672	0.2910
313-314	0.1130	0.4030	0	0.6193	0.4168	0.4756	0.4028	0.3706	0.4448	0.4952	0.4584	0.4278	0.4264	0.3912	0.3084	0.4039	0.3577	0.4868	0.4514	0.2312	0.1554	0.2684
315-316	0.1031	0.3315	0.6193	0	0.3308	0.3777	0.4128	0.2821	0.3682	0.3933	0.3725	0.3225	0.3612	0.3465	0.2969	0.3581	0.2904	0.4248	0.4226	0.2535	0.1768	0.2304
321	0.1813	0.4782	0.4168	0.3308	0	0.4997	0.3693	0.3765	0.3931	0.5385	0.5348	0.4135	0.4577	0.4522	0.3014	0.4704	0.4251	0.6222	0.4978	0.2066	0.1452	0.3060
322	0.1095	0.5064	0.4756	0.3777	0.4997	0	0.4669	0.4390	0.5084	0.6126	0.5688	0.5051	0.4522	0.4177	0.3302	0.4349	0.3887	0.4333	0.4692	0.2613	0.1470	0.2849
323	0.1275	0.3575	0.4028	0.4128	0.3693	0.4669	0	0.2993	0.3789	0.4198	0.4048	0.3341	0.3856	0.3546	0.2917	0.3495	0.2808	0.4046	0.4622	0.3929	0.2092	0.2640
324	0.1479	0.3909	0.3706	0.2821	0.3765	0.4390	0.2993	0	0.5933	0.4258	0.4731	0.4550	0.3996	0.4069	0.3586	0.4013	0.4020	0.3396	0.4015	0.2361	0.1608	0.2479
325	0.1217	0.4743	0.4448	0.3682	0.3931	0.5084	0.3789	0.5933	0	0.5185	0.5043	0.4747	0.4610	0.4791	0.4346	0.4872	0.4315	0.4020	0.5198	0.3005	0.1967	0.2612
326	0.1034	0.4919	0.4952	0.3933	0.5385	0.6126	0.4198	0.4258	0.5185	0	0.6034	0.6955	0.6028	0.5603	0.3902	0.5957	0.5357	0.5179	0.6146	0.2186	0.1437	0.2800
327	0.2904	0.4905	0.4584	0.3725	0.5348	0.5688	0.4048	0.4731	0.5043	0.6034	0	0.4621	0.4800	0.4341	0.3414	0.4381	0.3987	0.4654	0.4850	0.2334	0.1566	0.3118
331	0.1013	0.4064	0.4278	0.3225	0.4135	0.5051	0.3341	0.4550	0.4747	0.6955	0.4621	0	0.6276	0.5381	0.3565	0.5410	0.5364	0.4070	0.5115	0.1826	0.1333	0.2435
332	0.1263	0.3578	0.4264	0.3612	0.4577	0.4522	0.3856	0.3996	0.4610	0.6028	0.4800	0.6276	0	0.7493	0.4146	0.6093	0.6107	0.5180	0.6071	0.2376	0.1713	0.2870
333	0.1104	0.3256	0.3912	0.3465	0.4522	0.4177	0.3546	0.4069	0.4791	0.5603	0.4341	0.5381	0.7493	0	0.5346	0.7325	0.7357	0.5031	0.6726	0.2644	0.1883	0.2589
334	0.0861	0.2554	0.3084	0.2969	0.3014	0.3302	0.2917	0.3586	0.4346	0.3902	0.3414	0.3565	0.4146	0.5346	0	0.6405	0.5070	0.3488	0.4924	0.3997	0.1914	0.1982
335	0.0991	0.3420	0.4039	0.3581	0.4704	0.4349	0.3495	0.4013	0.4872	0.5957	0.4381	0.5410	0.6093	0.7325	0.6405	0	0.6937	0.5109	0.6901	0.2542	0.1721	0.2379
336	0.0946	0.3105	0.3577	0.2904	0.4251	0.3887	0.2808	0.4020	0.4315	0.5357	0.3987	0.5364	0.6107	0.7357	0.5070	0.6937	0	0.4535	0.6064	0.2055	0.1509	0.2330
337	0.1400	0.3533	0.4868	0.4248	0.6222	0.4333	0.4046	0.3396	0.4020	0.5179	0.4654	0.4070	0.5180	0.5031	0.3488	0.5109	0.4535	0	0.5802	0.2353	0.1612	0.2795
339	0.1323	0.3652	0.4514	0.4226	0.4978	0.4692	0.4622	0.4015	0.5198	0.6146	0.4850	0.5115	0.6071	0.6726	0.4924	0.6901	0.6064	0.5802	0	0.3405	0.2219	0.2786
511	0.1282	0.2004	0.2312	0.2535	0.2066	0.2613	0.3929	0.2361	0.3005	0.2186	0.2334	0.1826	0.2376	0.2644	0.3997	0.2542	0.2055	0.2353	0.3405	0	0.2873	0.2202
512	0.0945	0.1672	0.1554	0.1768	0.1452	0.1470	0.2092	0.1608	0.1967	0.1437	0.1566	0.1333	0.1713	0.1883	0.1914	0.1721	0.1509	0.1612	0.2219	0.2873	0	0.1730
811	0.1635	0.2910	0.2684	0.2304	0.3060	0.2849	0.2640	0.2479	0.2612	0.2800	0.3118	0.2435	0.2870	0.2589	0.1982	0.2379	0.2330	0.2795	0.2786	0.2202	0.1730	0

Table 13: Technology Complementarity Matrix

Sectors	113	311-312	313-314	315-316	321	322	323	324	325	326	327	331	332	333	334	335	336	337	339	511	512	811
113	0	0.0017	0.0043	0.0010	0.4224	0.0129	0.0001	0.0004	0.0155	0.0201	0.0086	0.0019	0.0421	0.1395	0.0102	0.0064	0.0109	0.0235	0.0283	0.0005	0.0000	0.0000
311-312	0.0017	0	0.0011	0.0007	0.0014	0.0790	0.0010	0.0005	0.0395	0.0136	0.0009	0.0008	0.0352	0.1763	0.0259	0.0080	0.0305	0.0010	0.0119	0.0019	0.0016	0.0003
313-314	0.0043	0.0011	0	0.3874	0.0048	0.0156	0.0055	0.0007	0.0665	0.1044	0.0057	0.0022	0.0302	0.0777	0.0596	0.0080	0.0141	0.0053	0.0462	0.0062	0.0060	0.0014
315-316	0.0010	0.0007	0.3874	0	0.0019	0.0137	0.0012	0.0001	0.0147	0.0856	0.0017	0.0008	0.0190	0.0262	0.0261	0.0059	0.0102	0.0033	0.0326	0.0027	0.0023	0.0007
321	0.4224	0.0014	0.0048	0.0019	0	0.0224	0.0075	0.0006	0.0126	0.0282	0.0086	0.0020	0.0440	0.0601	0.0206	0.0075	0.0356	0.0663	0.0267	0.0047	0.0054	0.0015
322	0.0129	0.0790	0.0156	0.0137	0.0224	0	0.0310	0.0012	0.0479	0.0625	0.0098	0.0069	0.0408	0.0920	0.0447	0.0069	0.0142	0.0109	0.0302	0.0182	0.0214	0.0025
323	0.0001	0.0010	0.0055	0.0012	0.0075	0.0310	0	0.0002	0.0197	0.0282	0.0039	0.0021	0.0313	0.0948	0.0508	0.0080	0.0162	0.0189	0.0427	0.1829	0.2118	0.0000
324	0.0004	0.0005	0.0007	0.0001	0.0006	0.0012	0.0002	0	0.1233	0.0082	0.0023	0.0057	0.0349	0.1515	0.0300	0.0017	0.0210	0.0014	0.0130	0.0004	0.0003	0.0001
325	0.0155	0.0395	0.0665	0.0147	0.0126	0.0479	0.0197	0.1233	0	0.1779	0.0551	0.0346	0.0376	0.0860	0.0518	0.0138	0.0331	0.0098	0.0524	0.0185	0.0136	0.0037
326	0.0201	0.0136	0.1044	0.0856	0.0282	0.0625	0.0282	0.0082	0.1779	0	0.0219	0.0204	0.0318	0.0646	0.0316	0.0119	0.0265	0.0213	0.0724	0.0254	0.0263	0.0116
327	0.0086	0.0009	0.0057	0.0017	0.0086	0.0098	0.0039	0.0023	0.0551	0.0219	0	0.0369	0.0403	0.1051	0.0321	0.0122	0.0243	0.0034	0.0184	0.0042	0.0041	0.0018
331	0.0019	0.0008	0.0022	0.0008	0.0020	0.0069	0.0021	0.0057	0.0346	0.0204	0.0369	0	0.0962	0.1991	0.0787	0.0983	0.0128	0.0023	0.0230	0.0016	0.0018	0.0015
332	0.0421	0.0352	0.0302	0.0190	0.0440	0.0408	0.0313	0.0349	0.0376	0.0318	0.0403	0.0962	0	0.1751	0.0649	0.0550	0.1306	0.0307	0.0385	0.0360	0.0285	0.0239
333	0.1395	0.1763	0.0777	0.0262	0.0601	0.0920	0.0948	0.1515	0.0860	0.0646	0.1051	0.1991	0.1751	0	0.0827	0.0920	0.1795	0.0421	0.0547	0.0853	0.0513	0.0674
334	0.0102	0.0259	0.0596	0.0261	0.0206	0.0447	0.0508	0.0300	0.0518	0.0316	0.0321	0.0787	0.0649	0.0827	0	0.1181	0.1103	0.0421	0.1192	0.0475	0.0435	0.0087
335	0.0064	0.0080	0.0080	0.0059	0.0075	0.0069	0.0080	0.0017	0.0138	0.0119	0.0122	0.0983	0.0550	0.0920	0.1181	0	0.0696	0.0088	0.0282	0.0128	0.0116	0.0064
336	0.0109	0.0305	0.0141	0.0102	0.0356	0.0142	0.0162	0.0210	0.0331	0.0265	0.0243	0.0128	0.1306	0.1795	0.1103	0.0696	0	0.0234	0.0333	0.0176	0.0122	0.1471
337	0.0235	0.0010	0.0053	0.0033	0.0663	0.0109	0.0189	0.0014	0.0098	0.0213	0.0034	0.0023	0.0307	0.0421	0.0421	0.0088	0.0234	0	0.0367	0.0110	0.0126	0.0010
339	0.0283	0.0119	0.0462	0.0326	0.0267	0.0302	0.0427	0.0130	0.0524	0.0724	0.0184	0.0230	0.0385	0.0547	0.1192	0.0282	0.0333	0.0367	0	0.0536	0.0466	0.0165
511	0.0005	0.0019	0.0062	0.0027	0.0047	0.0182	0.1829	0.0004	0.0185	0.0254	0.0042	0.0016	0.0360	0.0853	0.0475	0.0128	0.0176	0.0110	0.0536	0	0.1051	0.0001
512	0.0000	0.0016	0.0060	0.0023	0.0054	0.0214	0.2118	0.0003	0.0136	0.0263	0.0041	0.0018	0.0285	0.0513	0.0435	0.0116	0.0122	0.0126	0.0466	0.1051	0	0.0000
811	0.0000	0.0003	0.0014	0.0007	0.0015	0.0025	0.0000	0.0001	0.0037	0.0116	0.0018	0.0015	0.0239	0.0674	0.0087	0.0064	0.1471	0.0010	0.0165	0.0001	0.0000	0

Table 14: Panel Co-location Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labor complementarity	0.0354***	0.0340***	0.0399***	0.0406***	0.0399***	0.0102**	0.0091*	-0.0045
	(0.0007)	(0.0007)	(0.0013)	(0.0013)	(0.0013)	(0.0049)	(0.0048)	(0.0054)
Technology complementarity	-0.0050***	-0.0046***	0.0023***	0.0021***	0.0023***			
	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)			
Year FE, t	Y	Y	Y	N	N	Y	N	N
Using-sector FE, n	N	Y	Y	Y	N	N	N	N
Input m FE	N	N	Y	N	Y	N	N	N
Input k FE	N	N	Y	N	Y	N	N	N
Input-year FE, mt	N	N	N	Y	N	N	N	N
Input-year FE, kt	N	N	N	Y	N	N	N	N
Using-sector-year FE, nt	N	N	N	N	Y	N	Y	N
Input-pair FE, mk	N	N	N	N	N	Y	Y	Y
Input–using-year FE, mnt	N	N	N	N	N	N	N	Y
Input–using-year FE, knt	N	N	N	N	N	N	N	Y
R^2	0.044	0.078	0.282	0.304	0.296	0.394	0.430	0.739
Observations	60536	60536	60536	60536	60536	60536	60536	60536

Notes: Dependent variable: empirical co-location, $1 - |\pi_{mn,t} - \pi_{kn,t}|$, for unordered input pairs $m < k$ used by sector n. The regressors are lagged labor complementarity and lagged technology complementarity between inputs m and k. Regressions are unweighted. Both regressors are standardized within each regression sample. Rows indicate which fixed effects are included in each specification. If technology complementarity is time-invariant, input-pair fixed effects absorb it. Standard errors are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent levels. Blank entries indicate that the corresponding regressor is absorbed by the fixed effects.

C.1 Panel Co-location Regressions

Appendix Table 14 repeats the co-location validation in a panel using annual domestic sourcing shares and lagged complementarity measures. The dependent variable is

$$\text{Coloc}_{mknt} = 1 - |\pi_{mn,t} - \pi_{kn,t}|,$$

defined for unordered input pairs $m < k$ used by sector n. The regressors are lagged labor complementarity and lagged technology complementarity between inputs m and k. Both regressors are standardized within the regression sample, and all regressions are unweighted. Relative to the baseline cross-section in Table 3, the panel allows for richer fixed effects, including year, using-sector-year, input-year, input-pair, and input-by-using-sector-year fixed effects.

The panel results reinforce the baseline finding. Lagged labor complementarity is positive and highly significant in the specifications that control for year effects, using-sector-year effects, input-side effects, and input-year effects. The coefficient remains positive, though

smaller, in columns with input-pair fixed effects, which identify the relationship from within-pair time variation. Technology complementarity is less stable: it changes sign across specifications and is absorbed by input-pair fixed effects when treated as time invariant. The panel evidence therefore supports the main-text conclusion that the robust reduced-form co-location pattern is driven primarily by labor complementarity.

C.2 Input Switching and Welfare Decomposition

Table 15: Detailed Sourcing Reallocation Across Counterfactuals

Counterfactual	τ	λ	Unbund. red.	ΔM	ΔW	ΔP	ΔC	ΔT	Inputs sw.	Newly off.	Reshored	Firms sw.
1% lower iceberg trade costs	1.1957	1.000	0.0	1.281	0.234	-0.234	-0.002	0.032	1.367	1.367	0.000	1.944
Trade-equivalent lower unbundling costs	1.2078	0.385	61.5	1.286	1.466	-1.444	0.539	0.269	9.463	3.339	6.124	30.811
Welfare-equivalent lower unbundling costs	1.2078	0.835	16.5	0.062	0.234	-0.233	0.146	0.012	1.825	0.564	1.260	5.236

Notes: The table reports changes relative to the calibrated economy. Unbundling reduction is $100(1-\lambda)$, where $C(\lambda) = \lambda\hat{C}$. ΔM is the percentage-point change in imported input use; ΔW is the percentage change in welfare; ΔP is the percentage change in the aggregate price index; ΔC is the percentage-point change in the complementarity cost share; and ΔT is the percentage-point change in the trade-cost share. Switching variables are unweighted percentages of input–firm decisions or firms.

Table 16: Sales-Weighted Reallocation and Welfare Decomposition

Counterfactual	Sales-wtd. inputs sw.	Sales-wtd. newly off.	Sales-wtd. reshored	Sales-wtd. firms sw.	Avg. inputs sw.	Full ΔW	Fixed ΔW	Reopt. ΔW	Reopt. share
1% lower iceberg trade costs	0.883	0.883	0.000	1.210	12.938	0.234	0.230	0.004	0.019
Trade-equivalent lower unbundling costs	8.471	2.472	5.999	27.205	5.654	1.466	0.833	0.633	0.432
Welfare-equivalent lower unbundling costs	1.517	0.365	1.153	3.893	6.415	0.234	0.207	0.026	0.113

Notes: Sales-weighted switching variables weight firms by their baseline sales shares within sectors and sectors by baseline output shares. "Avg. inputs sw." is the average number of switched inputs among firms that switch at least one input. Fixed-allocation welfare evaluates each counterfactual using baseline sourcing decisions; full welfare allows firms to reoptimize. The reoptimization component is the difference between full and fixed-allocation welfare gains. Welfare gains are measured as percentage changes in the inverse of the aggregate price index.

Table 17: Sales-Weighted Sourcing Reallocation

Counterfactual	Inputs switched	Newly offshored	Reshored	Firms switching	Inputs per switcher
1% lower iceberg trade costs	0.883	0.883	0.000	1.210	12.938
Trade-equivalent lower unbundling costs	8.471	2.472	5.999	27.205	5.654
Welfare-equivalent lower unbundling costs	1.517	0.365	1.153	3.893	6.415

Notes: All shares are reported in percent. Sales-weighted measures weight firms by their baseline sales shares within sectors and sectors by expenditure shares. "Inputs per switcher" reports the average number of switched inputs among firms that change at least one input sourcing decision.

Table 18: Fragmentation Measures by Sector

Sector	Description	Import exp.	PCM	Sectoral ECI	Regime	RUG	CCS	TCS	Firm ECI
113	Forestry and Logging	27.184	0.0003	0.635	Low PCM / Low ECI	0.211	0.661	4.468	0.823
311	Food, Beverage, and Tobacco Product Manufacturing	21.982	0.0011	0.664	Low PCM / High ECI	0.048	0.450	3.601	0.957
313	Textile Mills and Textile Product Mills	28.610	0.0012	0.594	Low PCM / Low ECI	0.224	2.073	4.763	0.808
315	Apparel, Leather, and Allied Product Manufacturing	22.562	0.0015	0.646	High PCM / Low ECI	0.201	1.545	3.713	0.823
321	Wood Product Manufacturing	23.867	0.0010	0.642	Low PCM / Low ECI	0.208	1.118	3.985	0.894
322	Paper Manufacturing	20.109	0.0013	0.691	Low PCM / High ECI	0.102	0.974	3.341	0.920
323	Printing and Related Support Activities	13.100	0.0016	0.780	High PCM / High ECI	0.132	1.467	2.145	0.912
324	Petroleum and Coal Products Manufacturing	24.914	0.0014	0.628	Low PCM / Low ECI	0.203	1.818	3.988	0.820
325	Chemical Manufacturing	25.063	0.0009	0.636	Low PCM / Low ECI	0.000	0.002	3.457	1.000
326	Plastics and Rubber Products Manufacturing	20.962	0.0014	0.679	High PCM / High ECI	0.090	1.030	3.424	0.924
327	Nonmetallic Mineral Product Manufacturing	19.916	0.0014	0.689	High PCM / High ECI	0.071	0.799	3.217	0.942
331	Primary Metal Manufacturing	31.779	0.0009	0.554	Low PCM / Low ECI	0.000	0.000	5.450	1.000
332	Fabricated Metal Product Manufacturing	27.330	0.0016	0.601	High PCM / Low ECI	0.167	1.727	4.601	0.866
333	Machinery Manufacturing	10.066	0.0022	0.821	High PCM / High ECI	0.167	1.985	1.640	0.914
334	Computer and Electronic Product Manufacturing	24.738	0.0012	0.650	Low PCM / Low ECI	0.137	1.259	4.063	0.883
335	Electrical Equipment, Appliance, and Component Manufacturing	10.462	0.0020	0.815	High PCM / High ECI	0.215	2.203	1.730	0.879
336	Transportation Equipment Manufacturing	24.709	0.0019	0.639	High PCM / Low ECI	0.137	1.517	3.956	0.894
337	Furniture and Related Product Manufacturing	26.083	0.0019	0.613	High PCM / Low ECI	0.296	3.598	4.213	0.875
339	Miscellaneous Manufacturing	14.464	0.0020	0.752	High PCM / High ECI	0.111	1.547	2.358	0.948
511	Publishing Industries	19.479	0.0006	0.693	Low PCM / High ECI	0.034	0.290	3.126	0.966
512	Motion Picture and Sound Recording Industries	0.889	0.0002	0.982	Low PCM / High ECI	0.000	0.001	0.145	0.999
811	Repair and Maintenance	12.872	0.0018	0.794	High PCM / High ECI	0.304	3.425	2.052	0.915

Notes: Measures are evaluated at the calibrated 2019 steady state, not averaged over the policy grid. Import exposure is the empirical imported-input share. PCM is potential complementarity mass. Sectoral ECI is computed from sector-input domestic sourcing shares. Regimes use high/low PCM and sectoral ECI relative to their calibrated cross-sectional medians. RUG is the cost-based structural cost-allocation measure. CCS is the complementarity-cost share. TCS is the trade-cost share. Firm ECI is computed from simulated firm-level joint sourcing decisions and aggregated using firm sales weights.

Table 19: Predictive Content of Fragmentation Measures in Sectoral Cross-Section

Outcome	Import only	Import + RUG + CCS	Structural interactions	Import + PCM + ECI	Empirical interactions	Import + quadrant dummies	Quadrant import slopes
Import elasticity, 10% lower τ	0.318	0.696	0.828	0.666	0.687	0.488	0.616
Welfare elasticity, 10% lower τ	0.998	0.998	0.998	0.998	0.999	0.998	0.999
Welfare/import, 10% lower τ	0.364	0.750	0.779	0.680	0.703	0.497	0.598
Input switching, 10% lower τ	0.163	0.542	0.543	0.503	0.565	0.263	0.482
Firm switching, 10% lower τ	0.075	0.792	0.793	0.423	0.465	0.228	0.460
Welfare elasticity, lower unbundling costs	0.005	1.000	1.000	0.623	0.642	0.405	0.548
Firm switching, lower unbundling costs	0.015	0.671	0.725	0.307	0.363	0.145	0.238

Notes: Entries are unweighted R^2 values from regressions across the 22 calibrated sectors. Measures and outcomes are evaluated at the calibrated 2019 steady state. This table is intended as a cross-sectional diagnostic, complementary to the sector–grid results in Table 9. With only 22 observations, the cross-sectional exercise is low-powered and should not be read as a replacement for the grid-based diagnostic. Its role is to show that the empirical and structural measures also contain information about differences across sectors at the calibrated steady state.