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# An Anatomy of U.S. Establishments' Trade Linkages in Global Value Chains*

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**Abstract**

Global value chains (GVC) are a pervasive feature of modern production, but they are hard to measure. Using U.S. Census microdata, we develop novel measures of the linkages between U.S. manufacturing establishments' imports and exports. We document three new GVC patterns. First, for every dollar of exports, imported inputs represent 13 cents in 2002 and 20 cents by 2017, substantially higher than what aggregate data suggests. Second, we find strong complementarities between input and output markets reflected in "round-trip" trade linkages where an establishment sources inputs from and exports output to the same country. Third, we find a strong positive association between regional trade agreements and GVC trade flows. The aggregate data used to build global input-output tables requires proportionality assumptions that we find mute these relationships. Finally, with a global firms model, we show that the roundtrip results are consistent with a notion of country-specific fixed costs that are at least partially common between sourcing (imports) and foreign sales (exports).

**JEL codes:** F1, F14, O51

**Keywords:** global value chains, manufacturing, exports, imports, establishment, microdata

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# 1 Introduction

The ongoing U.S.-China trade war, the COVID-19 pandemic, Russia's invasion of Ukraine, and rising geopolitical tensions are just the latest examples of global shocks that alter prices, employment, income, and output in countries around the world. Understanding and evaluating the consequences of these shocks at both the micro and macro levels are essential for designing and implementing appropriate policies to mitigate and offset negative impacts. An increasingly important element in any such analysis is the propagation of these shocks to other countries through global value chains. Thus, evaluating and improving the accuracy of the measurement of global value chains is a critical starting point.

This paper argues that the appropriate foundation of global value chain (GVC) measurement is connecting imported inputs, output, and exports to individual establishments.[1] Existing research relies primarily on multi-country input-output tables that connect national input-output matrices to international trade flows. Remarkable measurement achievements in their own right, such industry-level tables have been invaluable in providing a portrait of the growth in GVCs across time and space, and in helping calibrate numerous models with inter-sectoral linkages across countries. However, these aggregate resources for monitoring GVCs may provide an incomplete view of global production arrangements for two main reasons. First, integrating domestic input-output tables across countries relies heavily on proportionality assumptions—in connecting source and destination countries, and in allocating a commodity input across using industries—which may distort the true exposure of a country to inputs upstream in the GVC. Second, the use of industry-level data may result in aggregation bias, as the establishment-level connections of exporting and importing are replaced by industry-level assumptions, which may distort the overall degree of vertical specialization, or the true picture of a particular value chain connecting an import source country to an export destination. Combined, these industry-level assumptions can lead to a biased assessment of how GVCs evolve over time and of the key determinants of GVC exposure.

Relaxing these assumptions requires establishment-level GVC measurement, but data limitations have constrained efforts to connect import and export transactions to actual production activities. In the context of the United States, goods trade transactions are collected at the firm level and do not specify the intended use of imports or whether exports were produced by the exporter of record. This complicates classification of imports as in-

[1]The conceptualization of GVC adopted in this paper follows Hummels, Ishii and Yi (2001): a good is produced in two or more sequential stages, at least two countries contribute production value-added, and at least one country uses imported inputs in its production stage and part of the resulting output is exported. Antrás (2020) provides a generalized definition of GVCs along similar dimensions as "a series of stages involved in producing a product or service that is sold to consumers, with each stage adding value, and with at least two stages being produced in different countries".

termediate inputs and classification of exports as manufactured output. The out-sized role of multi-industry firms in U.S. goods trade further complicates ascertaining imported input use and production of exports at individual establishments that are the most dis-aggregated statistical unit of production. We address these well-known measurement challenges by, respectively, linking U.S. firms' exports and imports to their establishment's output and material use.

We measure the source-specific imported input content of an establishment's destination-specific exports in 2002, 2007, 2012, and 2017 by combining two confidential, micro-level datasets maintained by the U.S. Census Bureau. First, the Longitudinal Firm Trade Transactions Database (LFTTD) contains the universe of goods export and import flows for individual U.S. firms (Bernard, Jensen and Schott, 2009; Kamal and Ouyang, 2020). Second, the Census of Manufactures (CMF) contains detailed information on establishment-by-product-level output and input use (U.S. Census Bureau, 2022c) that underlie the U.S. input-output tables (U.S. Bureau of Economic Analysis, 2009). We link the products imported by a firm in the LFTTD to the products reported as inputs by its manufacturing establishments in the CMF. Similarly, we link products exported by a firm in the LFTTD to the products reported as produced or shipped by its manufacturing establishments in the CMF. Overall, our linking methodology identifies about 60 percent of a firm's imports as inputs used in production by its establishments, and about 70 percent of a firm's exports as manufactured by its establishments.

We begin by documenting GVCs for the overall U.S. manufacturing sector constructed by summing up the establishment-level GVC measures normalized by total manufacturing exports. We find that the imported input content of U.S. manufactured exports steadily increases between 2002 and 2012 with slower growth through 2017. Specifically, for every dollar of manufactured exports, imported inputs represented 13 cents in 2002 and 20 cents by 2017. We also document heterogeneity across industries and over time. For example, the imported input content of exports in the motor vehicle industry increased steadily from about 10 to 25 cents from 2002 to 2017; the electrical equipment and machinery industry shows a more dramatic increase: more than quadrupling between 2007 and 2017 to exceed 80 cents in 2017.

Next, we aggregate our establishment-level GVC measure to the source country–U.S.–destination country level to study the role of frictions and policy in these multi-country linkages in a gravity framework. This measure of trade flows within GVCs involve three, not the usual two, countries typically studied in gravity settings and thus provides an opportunity to evaluate the role of multiple measures of frictions, as proxied by estimates of distance. First, the combined distance between the input source country to the United States, and then from the United States to the destination country of exports, captures barriers to the physical flow of goods in a value chain. Second, the direct distance from the input source country to the export destination country may additionally reflect coordination costs of the overall production flow. Finally, magnitudes of trade flows within GVCs may be uniquely affected by the special case of round-trip production—i.e., when the input source and export destination country is the same.

Gravity estimation results pooling all four years and with exporter-year and importer-year fixed effects reveal the relative importance of the combined, direct, and round-trip distance measures. Increases in combined distance, as well as direct distance, are associated with significantly reduced GVC trade flows with the most stark result for the round-trip case. All else equal, the presence of round-trip production is associated with 3.7 times higher GVC flows. This is consistent with strong complementarity effects between source and destination countries in the supply chain.

Our framework allows a unique perspective on the well-studied role that policy plays–specifically, the role of regional trade agreements (RTAs)—in the formation of GVCs. Unlike prior work on this topic, we can examine all combinations of regional trade agreements among the source-U.S.-destination countries in a value chain. We find that bilateral RTAs between the United States and the input source country, and between the United States and the export destination country, are associated with 22 percent higher GVC flows, all else equal. A trilateral RTA between all three countries raises GVC trade by 55 percent, all else equal. Strikingly, even in the presence of RTAs, the round-trip indicator remains both economically and statistically significant, suggesting that the complementarity between source and destination countries extends beyond the effects of trade policy coordination.

We show that without the novel establishment-level linkages developed in this paper, U.S. trade within GVCs would be underestimated and the round-trip effect would be significantly muted, driven primarily by biases owing to aggregation and proportionality assumptions, respectively. Aggregation may lead to downward (upward) bias in GVC measurement if establishment-level import and export intensities are positively (negatively) correlated. We document evidence of downward aggregation bias—our establishment-level measures aggregated to the industry level are significantly higher than an industry-level measure constructed from standard input-output table assumptions.[2]

We document the role of two specific proportionality assumptions in GVC measurement. Country pairwise proportionality relates sourcing and destination linkages, and import proportionality assumes that an industry's imports of an input, relative to its total demand, is the same as the economy-wide imports of the input relative to total demand (e.g., imports of steel from Brazil are allocated to steel-using industries in the same proportion as the overall allocation of imported steel to steel-using industries). Import proportionality is commonly used to construct national input-output tables when industry-specific input source country

[2] Flaaen, Kamal, Lee and Yi (2024) show that the aggregation bias is growing over time and driven by increase in export and import intensity at the establishment-level.

information is not readily available. We find the less well-studied pairwise proportionality generates "excess smoothing" in GVC measures. For example, under pairwise proportionality, as long as total imported inputs by a U.S. sector and exports from that sector are positive, the GVC measure at the sector-level will be positive for *all* import-export country-pairs. However, with our newly constructed establishment-level linkages, we show that in several sectors, more than 10 percent of import-export country pairs have zero GVC trade flows, as no single establishment participates in that particular value chain. We further demonstrate that GVC flows based on the these proportionality assumptions exhibit significantly smaller round-trip effects. Thus, in the absence of establishment-level linkages, we would miss the strong complementarities between input and output markets.

Finally, we augment a version of the "global firms" model in Bernard, Jensen, Redding and Schott (2018b) featuring fixed and variable costs of both importing and exporting. We derive the model counterpart to our GVC measure and conduct several numerical experiments with 14 symmetric countries, plus the United States and 1000 firms per country. Each experiment is characterized by a different configuration of fixed costs. We then simulate the model and run gravity regressions on our simulated data. We find that a firm-country-specific fixed cost combined with an adjustment factor that is low when the source and destination countries are the same can generate patterns consistent with our findings on round-trip GVC trade flows from the gravity regression results.

Our paper contributes to three main bodies of literature. The first is GVC measurement which accelerated in the 2000s thanks to the development of multi-country input-output tables. Early work by Hummels, Ishii and Yi (2001) measuring vertical specialization was followed by more intricate efforts to isolate value-added exports or VAX (Johnson and Noguera, 2012; Koopman, Wang and Wei, 2014; Timmer, Erumban, Los, Stehrer and de Vries, 2014; Dietzenbacher, Los, Stehrer, Timmer and de Vries, 2015; Johnson and Noguera, 2017).[3] These developments have been instrumental in providing a comprehensive portrait of GVCs across countries and over time, and the multi-country input-output tables themselves have been used to calibrate a large set of international trade models.[4] Despite their widespread value and use, however, input-output tables, and GVC measures constructed from these tables, reflect biases owing to import proportionality and aggregation. To our knowledge, only Kee and Tang (2016) and Bems and Kikkawa (2021) measure GVCs by employing firm-level data for China and Belgium, respectively, and, in so doing, address both sources of biases. Relatedly, using firm-level trade and industry-level production flows, de Gortari (2019) showed for Mexico that ignoring heterogeneity in input sourcing within an industry

[3]International organizations and partnerships have developed a full suite of trade in value added statistics to facilitate GVC measurement for large number of countries e.g., OECD (2024); WIOD (2023). See Antràs and Chor (2022) for a survey of the GVC measurement literature.

[4]In particular, models based on Caliendo and Parro (2015) have been so calibrated.

that varies by export markets understates GVC trade flows between given bilateral trading partners.

Yet, studies using firm-level data for measurement of GVCs cannot fully account for heterogeneity in industrial activities within firms. The vast majority of U.S. goods trade is mediated by large, multi-industry firms (Bernard, Jensen, Redding and Schott, 2018b; Ding, 2023). While trading firms operate in many industries, each establishment within the firm is classified within a single industry (U.S. Office of Management and Budget, 2024). Our innovation is creating linkages between input and output flows at the most disaggregated statistical economic unit – the establishment — minimizing distortion in constructing value added flows that would otherwise arise owing to the assumptions made to allocate inputs across different industries for multi-sector firms.

Insights from firm-level studies have informed development efforts by statistical agencies to introduce firm-level heterogeneity by making available extended input-output tables that would minimize measurement biases due to aggregation (United Nations, 2018). For example, Fetzer et al. (2023) introduces the multinational production heterogeneity in U.S. input-output tables to create trade in value added statistics. Input-output tables distinguishing processing from non-processing firms have also developed in countries with large processing trade sectors like China (e.g., Koopman et al. (2014)) and Mexico (e.g., De La Cruz et al. (2013)). Our microdata infrastructure can potentially be used to extend input-output tables in additional dimensions such as by the differences in the use of imported intermediate inputs across different firm types.

The second is the literature on input sourcing measurement. Early contributions pioneered use of firm-level data to relax the import proportionality assumption embodied in national input-output tables. Feenstra and Jensen (2012) is one of the first attempts to enhance U.S. input-output tables by linking information in 1997 on firms' total imports from the LFTTD to materials use reported by their establishments in the CMF. Winkler and Milberg (2009) and Puzzello (2012) account for heterogeneity in input sourcing patterns across firms in the case of Germany and a set of Asian countries, respectively. These early contributions underscored the need for micro data to provide a full characterization of production arrangements, generating a rich portrait of firms' global operations. Recent contributions for the United States include Fort (2017), Fort (2023) and Antràs, Fadeev, Fort and Tintelnot (2024). Progress in identifying firms' imported inputs by source linked to U.S. exports has also been made in the context of examining U.S. firms' responses to input shocks (e.g., Boehm, Flaaen and Pandalai-Nayar (2019); Handley, Kamal and Monarch (forthcoming)).[5] We provide the first comprehensive assessment of the imported inputs embodied in U.S. manufacturing establishments' exports.

[5]A recent study for Mexico finds that Mexican GVC firms increased their exports to the United States in response to the U.S.-China tariff war (Utar, Cebreros and Torres, 2023).

The third literature studies the effect of regional trade agreements (RTAs) on measures of GVCs in a gravity framework (e.g., Noguera (2012); Johnson and Noguera (2017); Laget, Osnago, Rocha and Ruta (2020)). We extend this research by leveraging the *trilateral* nature of our GVC measures. In this broader context, we provide direct evidence between relationships in RTAs and their associated GVC flows. In addition, we document a large round-trip effect, and that this effect is significantly muted if GVC measurement is subject to biases arising from aggregation and proportionality assumption. Our findings underscore that, as trade flows and GVCs re-orient within geopolitical blocs centered around the United States and China (Gopinath, Gourinchas, Presbitero and Topalova, 2024), measurement using granular data becomes especially important to capture shifts in global production networks.

The rest of the paper is organized as follows. Section 2 details the data and our methodology for constructing establishment-level GVC measures by linking administrative firm-level data on exports and imports to establishment-level data on products produced and materials consumed. Section 3 presents trends in foreign inputs cost shares and GVCs in the U.S. manufacturing sector, all based on establishment-level linkages. Section 4 reveals the determinants of GVC trade in a gravity framework. Section 5 documents the role of the proportionality assumption in shaping GVC measures and the gravity determinants of GVC trade. Section 6 highlights key assumptions in canonical trade models that can rationalize the observed patterns in the determinants of GVC trade. The final section concludes.

# 2 Measuring Global Value Chains in the United States

In this section, we describe our measure of establishment-level GVCs—imported inputs by source embodied in exports by destination. We then describe the data linking methodology and core datasets used to construct the establishment-level measures of GVC.

## 2.1 Establishment-Level GVC

The central contribution of this paper is moving beyond connecting imported inputs to U.S. production to connecting the full value chain flow through the United States: from imported inputs to U.S. production through to U.S. exports. We construct an establishment-level GVC measure that is based on the concept of vertical specialization (VS) capturing the imported input content of exports (Hummels, Ishii and Yi, 2001).[6] It is defined for an input product $r$ imported from country $m$ and used by a U.S. establishment $e$ in industry $s$ in its

[6]Note that the difference between the imported input content of exports and total gross exports represents value-added trade such that (1-VS) measures the domestic value-added share in exports.

output product $p$ for export to country $n$ in period $t$ as:

$$GVC_{emnrspt} = \frac{IMP^I_{emrt}}{GO_{est}} EXP_{enpt}, \tag{1}$$

where $IMP^I_{emrt}$ denotes imported inputs (see Equation A2), and $EXP_{enpt}$ represents produced outputs (see Equation A3).[7] $GO_{est}$ is gross output of establishment $e$ in industry $s$ in period $t$.

## 2.2 Conceptual Example of Country Pairwise Proportionality

For a conceptual illustration of how true country-pair linkages are lost in aggregation, consider a simple economy composed of two firms that each import an identical commodity and export an identical product, but from and to a different set of countries. The import, export, and gross output values of these two firms are shown below in Table 1a.

Table 1: Conceptual Illustration of GVC Proportionality

(a) Firm-Level and Aggregate Data

| | **Imports** | | **Exports** | | **Gross** |
|---|---|---|---|---|---|
| | Mexico | China | U.K. | Germany | **Output** |
| Firm 1 | \$100 | \$0 | \$150 | \$0 | \$500 |
| Firm 2 | \$0 | \$100 | \$0 | \$300 | \$1000 |
| **Total** | **\$100** | **\$100** | **\$150** | **\$300** | **\$1500** |

(b) GVC Calculations: Reality vs Aggregate

**Bilateral GVC: Reality**

| | U.K. | Germany |
|---|---|---|
| Mexico | \$30 | \$0 |
| China | \$0 | \$30 |

**Bilateral GVC: Aggregated**

| | U.K. | Germany |
|---|---|---|
| Mexico | \$10 | \$20 |
| China | \$10 | \$20 |

The GVC values for the possible country-pair combinations that result from summing equation (1) across the two firms for a given country-pair is shown in the left panel of

[7] At the establishment level, $s$ is measured as a 6-digit NAICS industry. When presenting GVC statistics, we use the $s$ notation to denote 3-digit manufacturing sectors based on industry definitions from the World Input-Output Database (WIOD) (Dietzenbacher, Los, Stehrer, Timmer and de Vries, 2015). We use WIOD definitions to enable comparisons to statistics computed using the WIOD as discussed in Section 5.

Table 1b. In this example, Firm 1 generates \$30 of GVC from Mexico to the UK and Firm 2 generates \$30 of GVC from China to Germany. Absent firm-level data, however, the researcher only observes the area highlighted in blue in Table 1a, representing aggregate country-level import and export data. Hence, the researcher must use pair-wise combinations of import and export values to to construct bilateral GVC values from this data, illustrated in the right panel of Table 1b. This example illustrates the bias that can be introduced from this aggregation and resulting pairwise proportionality assumptions; the next sections describe our methodology for constructing novel GVC linkages to help understand these biases in greater detail.

## 2.3 Data Sources and Sample Construction

The construction of an establishment-level GVC measure in Equation 1 entails combining goods trade and production information from two confidential, micro-level datasets maintained by the U.S. Census Bureau.

First, the Longitudinal Firm Trade Transactions Database (LFTTD) links specific international trade transactions to individual firms in the United States (Bernard et al., 2009; Kamal and Ouyang, 2020). The LFTTD combines merchandise export and import transactions from confidential customs declaration forms with administrative data on the universe of U.S. firms in the non-farm, private sector in the Census Bureau's Business Register. It covers the universe of imported shipments valued over US\$2,000 and exported shipments valued over US\$2,500 of merchandise goods. We utilize the LFTTD to measure a U.S. firm's exports and imports by detailed 10-digit Harmonized System (HS) product and destination and source country, respectively.

Second, we rely on the Census of Manufactures (CMF) to obtain detailed information on establishment-level output and inputs. The CMF is collected quinquennially (every 5 years, in years ending in a 2 or 7) as part of the economic census (U.S. Census Bureau, 2022c). The CMF is a survey sent to the universe of establishments or plants in the manufacturing sector with questions on detailed output, input usage, product-level shipments, energy usage, inventories, and other aspects of production.[8] Specifically, to allocate a firm's exports and imports to their establishments, we use the trailer files of the Census of Manufactures: the Materials Trailer File (CMF-MAT) identifies the individual products used as material inputs in production; and the Product Trailer File (CMF-PROD) identifies the individual products produced and/or shipped.

Given our focus on the linkages in manufacturing production activity in the United States, our sample includes all establishments in the manufacturing sector with product-level information on inputs and output. This restriction eliminates a significant number of

[8]See the full set of questions on the survey forms at U.S. Census Bureau (2022a).

small manufacturing establishments that do not report product-level detail on inputs and output but retains firms accounting for the vast majority of shipments. We further restrict our sample to only those firms with non-negligible manufacturing shares of activity in terms of employment and sales.[9]

## 2.4 Connecting Trade Flows Associated with Production Activity

Measurement of global value chains connecting U.S. manufacturing with the rest of the world is challenging as firms undertake a variety of activities across sectors, a portion of which may be classified outside of manufacturing.[10] A direct implication is that manufacturers may import goods intended for direct sale downstream as part of wholesale and retail activities, and thus such shipments would not be inputs from the perspective of their U.S. production operations; similarly, not all exports by a manufacturer may be produced in-house and therefore should not be considered as manufactured exports.

Even within the manufacturing sector, firms operate across multiple industries. Without detailed industry information, restrictive assumptions would be needed to allocate firm-level inputs and output. We document the number of six and four-digit manufacturing industries (based on NAICS) that firms operate in according to their goods trading status to demonstrate the pervasiveness of multi-sector goods traders. Table 2 shows that manufacturers that both export and import have very diverse industrial footprints operating in roughly 8 six-digit and 5 four-digit industries.

By construction, firms that both export and import contribute the most to measures of GVC and thus ignoring the industry-level heterogeneity within a firm can yield spurious assignment of imported inputs across industries. To illustrate this challenge, suppose a firm imports steel from China and axles from Vietnam, while at the same time exports engines to Mexico and finished cars to Canada. Should some fraction of steel and axles be assigned to both engines and finished cars or should all the steel be assigned to engines and all the axles assigned to finished cars?

Our methodology takes an establishment-level perspective to split the firm's production by distinct industries. To identify imported inputs, we utilize the set of input products reported by establishments in the CMF-MAT. To identify produced exports, we utilize the set of products reported by establishments in the CMF-PROD.[11] Thus, using LFTTD, CMF-

[9] Appendix Section A.1 provides details on sample construction.

[10] For example, many automakers produce some models in the United States with a wide variety of imported input content, while also importing finished cars to be sold to U.S. consumers. Indeed, an extreme form of production fragmentation is captured by so-called "factoryless" goods-producing firms that outsource physical transformation activities while retaining ownership of the intellectual property and control of sales to customers (Bernard and Fort, 2015; Bayard, Byrne and Smith, 2015; Fort, 2017, 2023; Kamal, 2023).

[11] This builds on Boehm, Flaaen, Pandalai-Nayar and Schlupp (2021) to link LFTTD-based exports to individual establishments.

Table 2: Number of Manufacturing Industries by Trader Type and Year

| **Trader Type** | **Year** | **4-digit Industry** | **6-digit Industry** |
|---|---|---|---|
| Exporter-Importer | 2002 | 5.68 | 9.54 |
| Exporter-Importer | 2007 | 4.91 | 8.21 |
| Exporter-Importer | 2012 | 4.74 | 7.56 |
| Exporter-Importer | 2017 | 4.72 | 7.42 |
| Exporter-Only | 2002 | 1.13 | 1.26 |
| Exporter-Only | 2007 | 1.12 | 1.24 |
| Exporter-Only | 2012 | 1.11 | 1.18 |
| Exporter-Only | 2017 | 1.12 | 1.19 |
| Importer-Only | 2002 | 1.32 | 1.52 |
| Importer-Only | 2007 | 1.28 | 1.42 |
| Importer-Only | 2012 | 1.26 | 1.35 |
| Importer-Only | 2017 | 1.49 | 1.77 |
| Non-Trader | 2002 | 1.08 | 1.12 |
| Non-Trader | 2007 | 1.04 | 1.06 |
| Non-Trader | 2012 | 1.03 | 1.04 |
| Non-Trader | 2017 | 1.05 | 1.07 |

**Notes**: This table displays the weighted average number of 4- and 6-digit NAICS industries in the manufacturing sector that firms operate in where weights are the total value of shipments by type of trader and year.
**Source**: Authors' calculations using CMF and LFTTD.

MAT, and CMF-PROD, we build a comprehensive picture of establishment-level production with links to global input usage and global market access. Appendix A.1 provides the methodological details.

Table 3: Aggregate Match Statistics (%)

| | Intermediate Share | | Produced Export Share | |
|---|---|---|---|---|
| | of Firm Imports | of Firm Cost | of Firm Exports | of Firm Shipments |
| 2002 | 56.9 | 14.0 | 69.8 | 7.7 |
| 2007 | 60.9 | 17.8 | 70.6 | 9.1 |
| 2012 | 62.9 | 16.9 | 69.8 | 10.3 |
| 2017 | 58.5 | 18.4 | 68.9 | 10.4 |

**Notes**: This table displays imports identified as inputs as a share of total firm imports (column 1) and as a share of total firm material cost (column 2); exports identified as being produced by manufacturing establishments as a share of total firm exports (column 3) and as a share of total firm shipments (column 4).
**Source**: Authors' calculations using CMF and LFTTD.

Consistent with the complexity of modern U.S. manufacturers' activities, our methodology assigns part of firms' imports and exports as intermediate inputs and manufactured output, respectively. Table 3 reports the matching results over the sample years. Our methodology allocates about 60% of the average firm's imports to its establishments as intermediate inputs (column 1). This share is similar to Boehm, Flaaen and Pandalai-Nayar (2019) who classify 64% of manufacturing imports as intermediates in 2007.[12] For the representative manufacturing establishment, imported inputs are about 17% of the total material costs (column 2). Our methodology allocates about 70% of the average firm's exports to its establishments as being produced (column 3). A similar finding for Belgium attributes about a third of export value to so-called carry-along trade (Bernard, Blanchard, Beveren and Vandenbussche, 2018a). For the representative manufacturing establishment, produced exports are about 9% of the total value of shipments (column 4).[13]

There are two important data limitations we confront. First, while we have detailed product-level information on establishments' output and input in the CMF, these data do not indicate whether input usage differs by the output market. Thus, we rely on a proportionality assumption that a particular establishment's imported input use for its exported products is in proportion to overall input use. Second, while we have micro-level data for a firm's direct import and export activities, we cannot track firm-to-firm transactions within the United States—unlike countries that collect such data through VAT reporting guidelines (e.g., Belgium (Dhyne, Kikkawa, Mogstad and Tintelnot, 2021))—and thus are unable to account for indirect import and export activities through domestic supply linkages.[14] Of course, one of the main contributions of global input-output tables is their convenient calculation of these indirect activities via the Leontief inverse. Hence, we view our measures as *direct* GVC measures and a lower bound of the true degree of foreign input usage in U.S. production activity.

# 3 Trends in GVC Activity within U.S. Manufacturing

This section derives industry-level GVC statistics based on the establishment-level linkages described in Section 2.4 that are novel in their detail and scope. We begin by reporting the imported input share in total material cost for the U.S. manufacturing sector over our sample years. We then derive industry level measures of imported input content embedded in U.S. export to highlight how aggregation bias mutes both the level and trend in the U.S. manufacturing sector's participation in global value chains.

[12]Their methodology differs somewhat as they classify goods as intermediate inputs or capital investment goods if they are not on the list of products on the CMF-PROD.

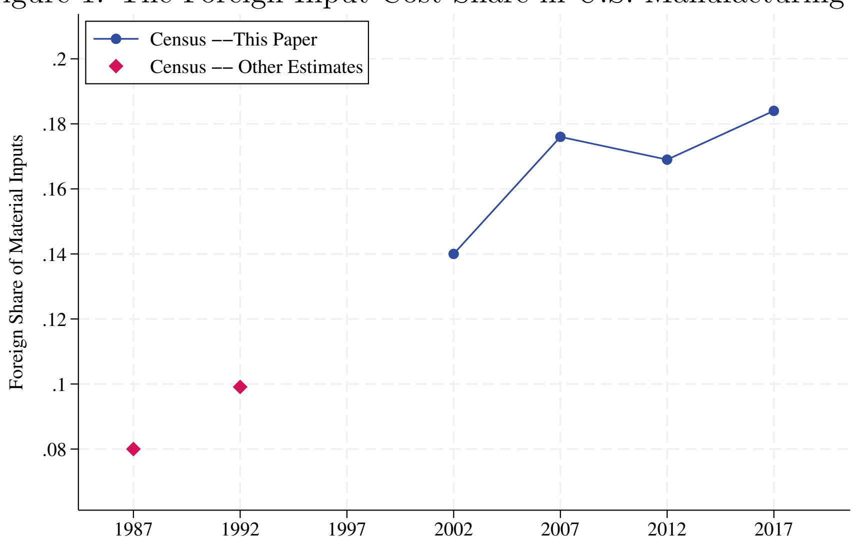
[13]This is smaller than the 14% share of exports to gross output reported for the manufacturing sector in Bernard, Jensen, Redding and Schott (2007, Table 2), but the authors rely solely on the exports reported by establishments in the 2002 CMF and do not utilize the LFTTD or CMF-PROD.

[14]The Commodity Flow Survey (U.S. Census Bureau, 2023) tracks a select set of domestic shipments from a sending establishment to a destination zip code. However, strong assumptions are required to construct flows between establishments. For example, Atalay, Hortaçsu and Syverson (2014) use information on zip codes and industry for all establishments of a firm to probabilistically determine the receiving establishment.

## 3.1 Share of Imported Inputs in U.S. Material Costs

A large literature measuring the extent of offshoring in U.S. manufacturing has focused on the share of material inputs sourced from abroad. Houseman, Kurz, Lengermann and Mandel (2011) describe how the increase of foreign-sourced inputs could lead to upward bias in manufacturing productivity statistics, as the price declines from foreign substitution are systematically under-measured due to the well-known outlet-substitution bias in price index measurement. In another strand, many papers (including, for example Feenstra and Hanson (1996b), Feenstra and Hanson (1996a)) explore the specific role "outsourcing" of inputs abroad has had in labor market developments within the U.S. manufacturing sector.

Figure 1: The Foreign Input Cost Share in U.S. Manufacturing




**Notes:** This figure plots estimates of the foreign input cost share for U.S. manufacturing.

**Source:** Authors' calculations using CMF and LFTTD (blue line) and Berman, Bound and Griliches (1993) and Kurz (2006) (red diamonds).

Despite the importance of this statistic, the data limitations identified in this paper have made it difficult to quantify this basic measure of the dependence of U.S. manufacturers on foreign inputs. The blue line in Figure 1 represent new estimates of this statistic for years 2002-2017, while the red diamonds display estimates for 1987 (Berman, Bound and Griliches, 1993) and 1992 (Kurz, 2006).[15] Our establishment-level linkages indicate that foreign sources of material costs increased during the sample period, most notably between 2002 and 2007.

## 3.2 Imported Input Content in U.S. Exports

We construct sector level measures of GVC from the establishment-level linkages between imports and exports by summing over all country-sector sources of imports and country

[15]The 1987 and 1992 CMF included a question on the cost of the foreign content of materials used in production. The question asked: "Does this establishment use materials purchased or transferred from foreign sources?".

destinations for exports to arrive at a measure for an individual establishment $e$ operating in industry $s$ in period $t$ as:

$$GVC_{est} = \frac{\sum_{m,r} IMP^{I}_{emrt}}{GO_{est}} \sum_{n,p} EXP_{enpt}, \tag{2}$$

and then sum across establishments of a sector. We then scale $GVC_{est}$, which is in units of dollars, by sectoral exports to arrive at a ratio as follows:

$$gvc^{E}_{st} = \frac{\sum_{e \in E_{st}} \left[ \frac{\sum_{m,r} IMP^{I}_{emrt}}{GO_{est}} \sum_{n,p} EXP_{enpt} \right]}{\sum_{e \in E_{st}} \sum_{n,p} EXP_{enpt}}, \tag{3}$$

where $E_{st}$ is the set of establishments that are producing in industry $s$ in year $t$.

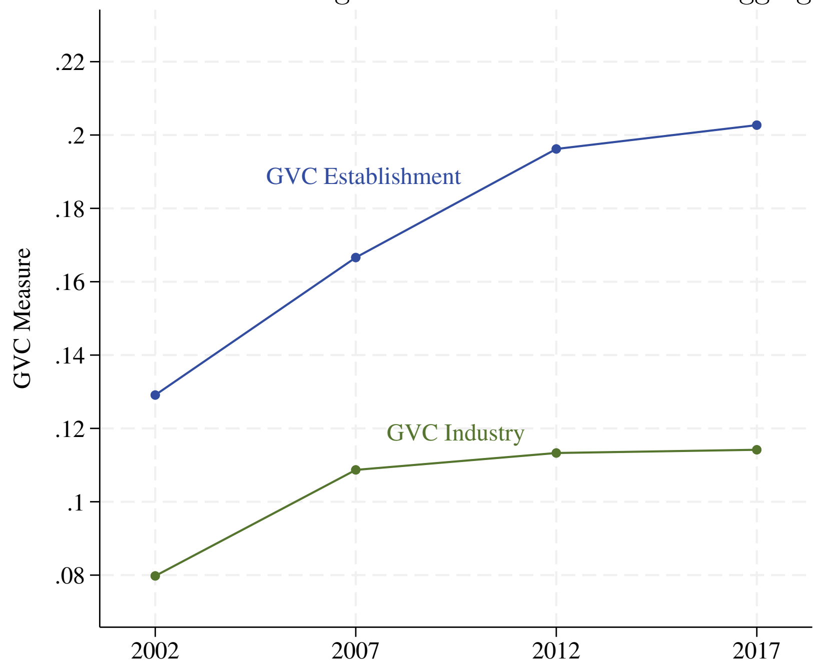
The $GVC$ and $gvc$ measures are closely related to well-known measures of value-added exports (hereafter, VAX) (Johnson and Noguera, 2012, 2017; Koopman, Wang and Wei, 2014). VAX captures the domestic value-added embodied in a country's exports. Over the past decade, these measures have become widely used for capturing global value chain behavior. There are three points worth mentioning. First, as with our measure, VAX is a useful way to measure international production chains in which a good-in-process crosses multiple borders. Second, when aggregate VAX is reported as a share, i.e., total value-added exports as a share of total exports, then it is roughly equivalent to $1 - gvc$.[16] From these first two points, it is clear that VAX and GVC are "cousins", in some sense. Third, VAX can be split into components by destination country, by sector, and even by sector and destination. However, by its nature, its focus is on the export side, while our measure captures both the imported inputs and exports. This motivates much of our regression analysis in Section 4.

We plot the $gvc^{E}_{st}$ measures for U.S. manufacturing as a whole—i.e., where $s$ denotes the entire U.S. manufacturing sector—as the blue line in Figure 2. There are steady gains in the reliance on global value chains in the United States between 2002 and 2012 such that by the year 2012 there were nearly 20 cents of imported inputs embodied in each dollar of exported output. In 2017 the increase in GVC activity moderates somewhat, to slightly over 20 cents, relative to the trend in previous years.

Our measure stands in contrast to what would be calculated solely from industry-level aggregates of imports, output, and exports. As previously demonstrated by Kee and Tang (2016), using data on Chinese firms, and Bems and Kikkawa (2021), using data on Belgian firms, estimates of GVC from industry-level aggregates are subject to non-trivial aggregation

[16] The term $1 - gvc$ captures the domestic value-added embodied in exports as a share of total exports, subject to one caveat. If there is a great deal of back-and-forth trade, then some imports by U.S. firms may embody U.S. value-added. Hence, in this case $1 - gvc$ will underestimate the VAX share. This is relevant if goods are produced in more than two stages.

Figure 2: GVC in Manufacturing: Establishment-based vs. Aggregate




**Notes:** This figure plots GVC measures for the manufacturing sector as a whole.

**Source:** Authors' calculations using CMF and LFTTD.

bias that can distort trends in the fragmentation of global production.[17] To highlight such aggregation bias, we calculate industry-level GVCs using industry-level aggregates from our newly linked data (essentially ignoring the establishment-level mappings between imports and exports) as in:

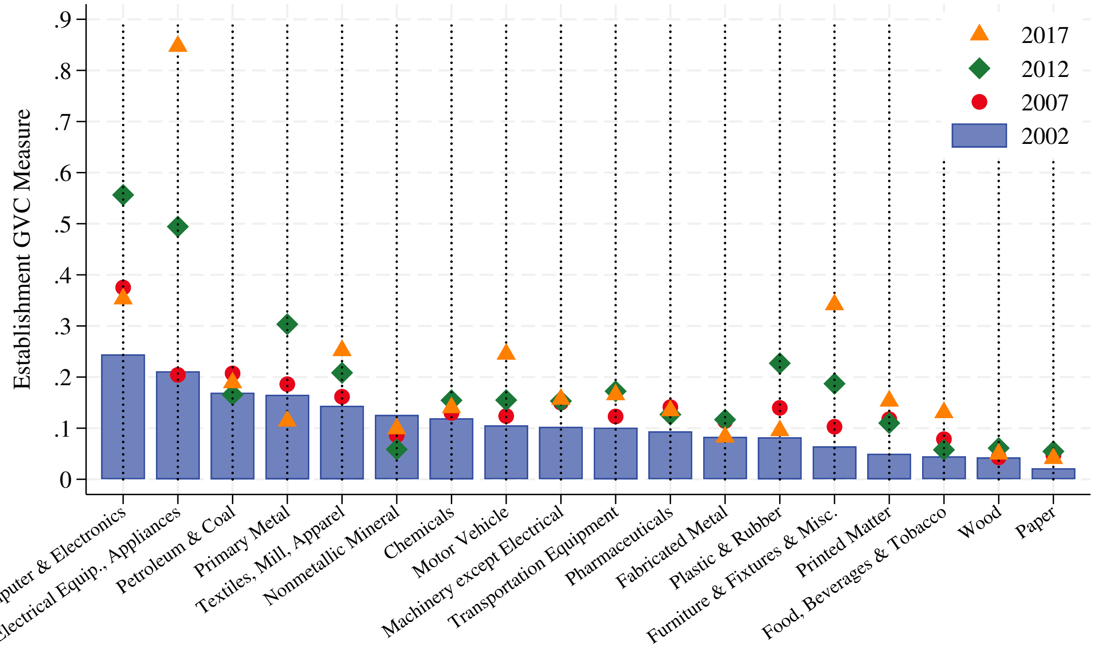
$$gvc^I_{st} = \frac{\left(\sum\limits_{e \in E_{st}} \sum_{n,p} EXP_{enpt}\right)\left(\frac{\sum\limits_{e \in E_{st}} \sum_{m,r} IMP^I_{emrt}}{\sum\limits_{e \in E_{st}} GO_{est}}\right)}{\sum\limits_{e \in E_{st}} \sum_{n,p} EXP_{enpt}}. \tag{4}$$

The green line in Figure 2 plots this aggregate-based measure, highlighting the important role that aggregation bias plays in this measure. Indeed, it is not only the level of GVC that would be mis-measured without establishment-level links, but also the trends. As shown in the green line, the aggregate-based measure slowed considerably in 2012, and then remained flat in 2017. Flaaen, Kamal, Lee and Yi (2024) provides extensive discussion of the components and further interpretation of this aggregation bias.

Our GVC estimates, $gvc^E_{st}$, for manufacturing as a whole masks significant heterogeneity across industries. We plot the industry-level GVC values from Equation (3) in Figure 3,

[17] Another source of aggregation bias may arise from using *firm* versus *establishment* level data. GVC estimates using firm-level aggregates indicate that they align closely with GVC estimated from establishment-level information at both the national (correlation of 0.99) and sub-sector (correlation of 0.97) levels. See discussion in Appendix Section B.4.

Figure 3: GVC Estimates for Manufacturing and sub-sectors, 2002, 2007, 2012, 2017




**Notes:** This figure plots GVC for 3-digit sectors consistent with industry definitions in WIOD.

**Source:** Authors' calculations using CMF and LFTTD.

where the bars signify values from 2002, the red dots values for 2007, the green diamonds for 2012, and the orange triangles for 2017. The industries experiencing the greatest growth in foreign linkages during this period include computer and electronics, electrical equipment, plastics and rubber, and furniture. Conversely, those industries experiencing little or negative growth in foreign linkages are non-metallic minerals, petroleum and coal, and wood products.

# 4 Determinants of GVC Trade Patterns

We now turn to a systematic analysis of the integrated flows of imports, domestic production, and foreign exports. Because the data provide a complete accounting of how import countries are linked to export countries through the United States – all coming from a granular, establishment-level production basis, rather than industry-level input-output tables – we can, for the first time, explore the determinants of global value chain connections across multiple trading partners. This analysis sheds light on the trends in the broad patterns of global value chains in the United States shown in Figure 2.

For this analysis, we define a bilateral GVC measure for import source country $m$ and export destination country $n$ in year $t$ as follows:

$$GVC_{mnt} = \sum_{e \in E_{mnt}} \left( \frac{\sum_r IMP^I_{emrt}}{GO_{est}} \sum_p EXP_{enpt} \right), \tag{5}$$

where $E_{mnt}$ is the set of all manufacturing establishments that import inputs from country $m$ and export their products to country $n$ in year $t$. Thus, we first compute bilateral GVC measures for each establishment and then aggregate them across all establishments participating in a given supply chain $(m, US, n)$.

We examine the determinants of $GVC_{mnt}$ in a gravity framework, which typically relates bilateral gross trade flows to bilateral determinants that include proxies for trade costs such as distance. $GVC_{mnt}$ captures country-pairs connected via the the United States, and thereby enables an examination of the role of distance and policy-measures such as regional trade agreements in a three-country setting. We implement the gravity estimation by linking our bilateral GVC measures to information on country attributes (distance, trade agreements, etc.) sourced from the Centre d'Etudes Prospectives et d'Informations Internationales or CEPII (Conte, Cotterlaz and Mayer, 2022). For each combination of the bilateral GVC, the country-level information can vary according to the pairs of countries involved (import country to U.S., U.S. to export country, and import country to export country).

## 4.1 Gravity in Global Value Chains

In our context, the traditional measure of distance between two non-U.S. countries does not capture any direct trade flow; here, the analog proxy measure of trade frictions for GVC flows would be the *combined* distance of each country to the United States, capturing the flow of inputs and output in the three countries involved in production. Formally, this is defined as $d_{m,US,n} = d_{m,US} + d_{US,n}$ for imports from country $m$ and exports to country $n$.

While the combined distance is more directly linked to GVC flows, the *direct* distance between import (input) and export (sale) countries (that is, $d_{m,n}$)—ignoring the location of the United States in the production chain—may also have an impact on GVC flows. This measure of distance should be interpreted differently than traditional measures, in particular when included on top of the combined distance measure.[18] Whether the proximity of input and output markets increases or decreases the scale of global value chain activity may also depend on their joint distance away from the United States. For example, Italy and Spain are relatively proximate, but a middle stage of production in the United States substantially increases the total distance and complexity of the value chain. Hence, including both resistance terms may yield important insights on a number of questions, such as whether the strength of regional factors linking input and output markets outweighs the cost of processing outside the region (a negative coefficient on $d_{m,n}$), or whether value chains of such proximate input-output countries would be unlikely to be paired with a country that adds significant cost (a positive coefficient on $d_{m,n}$). Returning to our example, are the

[18]Note that the distance measure for round-trip production (for $d_{m,m}$) is not measured as zero in gravity datasets such as CEPII. For population-weighted, within-country distance measures, the CEPII methodology is to take all possible combinations of *city-pair* distances within a country and calculate a weighted average.

regional factors of a particular product chain similar enough between Spain and Italy to overcome the added cost of U.S. processing, or could such processing just as easily occur in a different (more proximate) country to that bilateral pair (e.g., Germany, rather than the United States)?

A special case of the direct distance arises when country $m$ equals country $n$. This illustrates another non-traditional factor affecting GVC flows — the prominence of "round-trip" production, in which a U.S. establishment imports an input from a given country and subsequently exports output to the same country.[19] In addition to the overall impact of the direct distance, we capture the round-trip effect on GVC flows by including an indicator term $\mathbb{I}(m = n)$ in the gravity specification. After controlling for both distance measures, the estimated round-trip coefficient will capture the effect of having the same country as the input source and the export destination, which is not captured by proximity in input and output markets.

To explore these ideas, we estimate a novel form of the gravity model connecting these bilateral pairs of production flows through the United States as below:

$$\log(GVC_{mnt}) = \alpha + \delta_{m,t} + \eta_{n,t} + \beta\mathbb{I}(m = n) + \gamma d_{m,US,n} + \lambda d_{m,n} + \varepsilon_{mnt}, \tag{6}$$

where the dependent variable is $\log(GVC_{mnt}) \equiv \log(\sum_s GVC_{mnst})$.[20] All specifications also include exporter-year ($\eta_{n,t}$) and importer-year ($\delta_{m,t}$) fixed effects. As discussed above, the foreign value content of U.S. exports captured in our measure is similar but distinct from the VAX measure considered in the gravity model results in Noguera (2012). It is important to note, however, that the results in Noguera (2012), Johnson and Noguera (2017), and others rely on the industry-level proportionality assumptions to back out VAX measures that we evaluate in Section 5.

We report the gravity results in the first six columns of Table 4, beginning with bi-variate regressions of the key variables of interest.[21] The coefficient on the round-trip indicator is large and highly significant, and coefficients on the combined and direct distance variables exhibit the expected negative sign, with the direct trade cost proxy (combined distance) exhibiting a far greater magnitude. Columns (4) through (6) show results when these variables are included in combination (we discuss results in column (7) in Section 5.4). The coefficient on the round-trip indicator is attenuated somewhat when controlling for direct distance, but remains large and highly significant. Given that the $m$ to $n$ distance measure is comparatively very small for the round-trip country pairs (reflecting CEPII's within-country

[19]This feature was highlighted in the model constructed in Johnson and Moxnes (2023), though it is not considered prominent in the data in Johnson and Noguera (2017).

[20]$GVC_{mnst}$ is defined in Equation A4. See Appendix Section B.1 for summary statistics.

[21]The results in Table 4 are pooled across all years in our sample i.e., every five years from 2002 to 2017; Appendix Table A8 provides estimates by year.

Table 4: Gravity Model of GVC, 2002-2017

| | Dependent Variable: Log Bilateral GVC | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Round-trip ($m$=$n$) | 2.33*** | | | 2.24*** | 1.32*** | 1.39*** | 0.08*** |
| | (0.112) | | | (0.111) | (0.119) | (0.121) | (0.020) |
| Log Distance ($m$ →US→ $n$) | | -1.64*** | | -1.42*** | | -0.414*** | -0.01 |
| | | (0.106) | | (0.104) | | (0.118) | (0.061) |
| Log Distance ($m$ to $n$) | | | -0.26*** | | -0.194*** | -0.175*** | 0.00 |
| | | | (0.009) | | (0.009) | (0.002) | (0.004) |
| Data | Census | Census | Census | Census | Census | Census | WIOD |
| Exporter-Year F.E. | yes | yes | yes | yes | yes | yes | yes |
| Importer-Year F.E. | yes | yes | yes | yes | yes | yes | yes |
| Observations | 117,000 | 117,000 | 117,000 | 117,000 | 117,000 | 117,000 | 7,100 |
| R-squared | 0.861 | 0.860 | 0.861 | 0.861 | 0.861 | 0.861 | 0.99 |

**Notes**: The Census sample consists of years 2002, 2007, 2012, and 2017. The WIOD sample consists of the same years except the last which is given by the end year, 2014, in the WIOD. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
**Source:** Authors' calculations using the CMF, LFTTD, CEPII (Columns 1-6); WIOD and CEPII (Column 7).

distance calculation), it follows that some of the effect attributed specifically to a round-trip effect would fall instead on this distance measure. The coefficients on both distance measures are significantly negative, with the combined distance measure having roughly double the magnitude of the direct ($m \rightarrow n$) distance.

These results reveal two novel features of international supply chains connected through the U.S. manufacturing sector. First, the negative relationship between the combined distance ($m$ →US→ $n$) and bilateral GVC flows suggests that trade frictions operate along the multi-country supply chain, with the degree of production spanning three countries being attenuated as the frictions of the production chain accumulate. Second, the negative coefficient on the direct ($m \rightarrow n$) distance after accounting for combined distance implies that greater proximity between input and output markets supports higher GVC flows. This result points to strong complementarities between input and output markets. The large coefficient on the round-trip indicator is an extreme example of this complementarity, highlighting the importance of back-and-forth production sharing by establishments within a given country. It also indicates that this round-trip behavior extends beyond the complementarity effects captured solely by the direct ($m \rightarrow n$) distance between source and destination countries. This complementarity between input and output markets is an under-explored topic, which we return to in greater detail in Section 5.4, in the context of biases that arise when measuring GVCs with aggregate input-output tables.

## 4.2 The Impact of Regional Trade Agreements on Value Chains

The last few decades have been marked by a proliferation of regional trade agreements (RTAs) and production chains increasingly crossing multiple borders before final consumption (Ruta, 2017). Hence, it is increasingly difficult to connect the effects of a specific regional trade agreement to a particular trade flow when that shipment is only one part of a broader value chain encompassing other countries. For example, the extent to which a trade agreement between the United States and any particular country, say the Republic of Korea, enhances GVC flows between the United States, Korea, and any third country (say Canada) may also depend on the state of bilateral trade agreements between the United States and Canada, the Republic of Korea and Canada, or all three countries. The structure of our data allows a first exploration of the complex impacts of RTAs on global supply chains.

The study of the impacts of RTAs on gross trade flows in a gravity framework has a long history with estimates of a bilateral RTA indicator generally ranging from 0.1 to 0.3 (Larch and Yotov, 2024). The impact of regional trade agreements on value added trade has also received close attention. For example, Noguera (2012) and Johnson and Noguera (2017) find a negative relationship between RTAs and VAX (the domestic value-added embodied in a country's exports) consistent with RTAs facilitating increased production sharing between RTA partners. Our establishment-level links provide the opportunity to extend this finding beyond a relationship between RTAs and overall production sharing in a country's exports, to specific trilateral supply chain linkages.

Hence, we construct several indicator variables for whether regional trade agreements are in place between all possible combinations of the GVC countries. Using data from CEPII, we construct indicators for whether countries $m$ and $n$ have an RTA, whether both countries $m$ and $n$ have RTAs with the United States, and finally whether all three countries ($m$, $n$, and the U.S.) are all under an RTA.[22] We add these variables to the existing gravity regression variables in Equation (6), and present the results in columns (1) - (4) of Table 5.

We display results in columns (1) - (4) of Table 5, where we continue to include the round-trip indicator and combined distance as controls.[23] Perhaps unsurprisingly, there is only a small positive coefficient on GVC flows from an RTA indicator that includes the import and export countries but not the United States.[24] But the coefficient increases substantially once we focus instead on an RTA indicator capturing those importers and exporters (separately) that have an RTA with the United States (column 2), and even further when the RTA indicator includes all three countries (column 3).[25] In terms of magnitudes, we find that the

[22] Note that the third indicator is a linear combination of the other two RTA indicators.

[23] Since CEPII also records a country as having an RTA with itself, the round-trip indicator will soak up this portion of any effect from the RTA ($m$ and $n$) coefficient.

[24] The European Union plays an important role in this indicator.

[25] See Appendix Table A7 for a listing of all countries included in these RTAs.

Table 5: The Impact of RTAs on GVC Linkages, 2002-2017

| | Dependent Variable: Log Bilateral GVC | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Round-trip ($m$=$n$) | 2.20*** | 2.23*** | 2.21*** | 2.19*** | 0.08*** |
| | (0.112) | (0.111) | (0.112) | (0.112) | (0.015) |
| Log Distance ($m$ →US→ $n$) | -1.38*** | -1.39*** | -1.36*** | -1.36*** | -0.04 |
| | (0.105) | (0.104) | (0.104) | (0.105) | (0.083) |
| RTA ($m$ & $n$) | 0.044** | | | 0.042** | |
| | (0.020) | | | (0.204) | |
| RTA ($m$ & US, $n$ & US) | | 0.198*** | | 0.191*** | |
| | | (0.059) | | (0.059) | |
| RTA ($m$, $n$, US) | | | 0.438*** | | -0.03 |
| | | | (0.112) | | (0.061) |
| Data | Census | Census | Census | Census | WIOD |
| Exporter-Year F.E. | yes | yes | yes | yes | yes |
| Importer-Year F.E. | yes | yes | yes | yes | yes |
| Observations | 117,000 | 117,000 | 117,000 | 117,000 | 7,056 |
| R-squared | 0.861 | 0.861 | 0.861 | 0.861 | 0.997 |

**Notes**: The Census sample consists of years 2002, 2007, 2012, and 2017. The WIOD sample ends in 2014, and so we substitute 2014 in for 2017 to replicate a similar number of years. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
**Source:** Authors' calculations using the CMF and LFTTD (Columns 1-4) and WIOD (Column 5).

imported input content from country $m$ of a U.S. manufacturing firm's exports to country $n$ is nearly 44 percent higher when the three countries are collectively in an RTA (controlling for other factors) than otherwise.

While we find a strong role for RTAs in increasing GVC activities, the round-trip effect remains robust. For instance, the estimated coefficient on the round-trip indicator shows virtually no change between column (4) of Table 4 and columns (1)-(4) of Table 5, where combined distance is controlled. This finding suggests that the back-and-forth trading behavior of establishments is driven by factors affecting the coordination of overall production flows, extending beyond the influence of trade policy coordination between countries.

Further evidence in support of a causal interpretation to our RTA results would leverage *changes* in RTA status and the corresponding changes in GVC activity. Although our sample period is relatively short for such an analysis, we operationalize this strategy in Table 6 by adding a country-pair fixed effect, thereby controlling for the endogenous adoption of RTAs based on historical ties or time-invariant features (Baier and Bergstrand, 2007). Using this approach, the magnitude of the effect of RTAs on GVCs is somewhat reduced relative to Table 5; indeed, the RTA indicator without any U.S. involvement actually switches from mildly positive to mildly negative. Yet, for those RTAs including the United States–despite the small sample and relatively few RTAs initiated during our sample period–our results suggest a positive impact of RTAs on GVC flows of between 14 and 20 percent.

Table 6: Additional Results on the Impact of RTAs on GVC Linkages, 2002-2017

| | Dependent Variable: Log Bilateral GVC | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| RTA ($m$ & $n$) | -0.08** | | |
| | (0.036) | | |
| RTA ($m$ & US, $n$ & US) | | 0.14* | |
| | | (0.075) | |
| RTA ($m$, $n$, US) | | | 0.20** |
| | | | (0.099) |
| Data | Census | Census | Census |
| Exporter-Year F.E. | yes | yes | yes |
| Importer-Year F.E. | yes | yes | yes |
| Exporter-Importer F.E. | yes | yes | yes |
| Observations | 112,000 | 112,000 | 112,000 |
| R-squared | 0.920 | 0.920 | 0.920 |

**Notes**: The sample consists of years 2002, 2007, 2012, and 2017. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
**Source:** Authors' calculations using CMF and LFTTD .

At face value, this approach looks similar to the findings in Johnson and Noguera (2017) that examines the role of RTAs in value-added trade. While the results in that paper are complementary to this work– the authors find that the overall value-added share of gross exports declines (overall foreign inputs usage increase) between a bilateral pair when they are engaged in an RTA–our results directly link the adoption of RTAs between a three-country pair to the actual GVC activity among those same countries. Such direct evidence for the increased supply chain integration accompanying regional trade agreements is useful for policymakers considering efforts to sign new agreements or modify existing agreements.

# 5 Assessing Biases in GVC Measurement from Proportionality Assumptions

This section explores in greater depth the multiple proportionality assumptions that are used in traditional measurement of global value chains using aggregate data. Section 2.2 illustrated proportionality assumptions in linking source and destination countries through a third country, but when evaluating industry-level estimates one must also recognize the more well-known import proportionality assumption—an individual country's imports are allocated as inputs across industries in the same proportion as their overall imports. While this assumption has received recent attention in research such as de Gortari (2019), evidence to quantify potential biases, at least for the United States, has been limited. The work highlighted in Feenstra and Jensen (2012) is similar in spirit to our empirical methodology using similar datasets, and the results we find below on import proportionality largely aligns with their results from earlier data.

To explore these multiple proportionality assumptions, we compare the imported input cost share and imported input content of exports (i.e. imported inputs from Mexico in exports to France) derived from establishment-level linked data to those measures derived from aggregate input-output data harmonized across countries. Specifically, we rely on the World Input-Output Database or WIOD (Dietzenbacher, Los, Stehrer, Timmer and de Vries, 2015; Timmer, Los, Stehrer and de Vries, 2016) spanning 43 countries and 56 sectors (18 in manufacturing) between 2000-2014.[26] To compare the Census-basis estimates with what would be generated using the WIOD, we isolate the imports of inputs into the United States. We convert the NACE (Nomenclature of Economic Activities) industry classification to NAICS and then drop all inputs of services to align with our focus on only the manufacturing activities of U.S. firms. We then collapse the Census-basis data to match the 43 countries and a Rest of World (RoW) aggregate and at the same level of NAICS classification.

## 5.1 Imported Input Cost Shares by Source

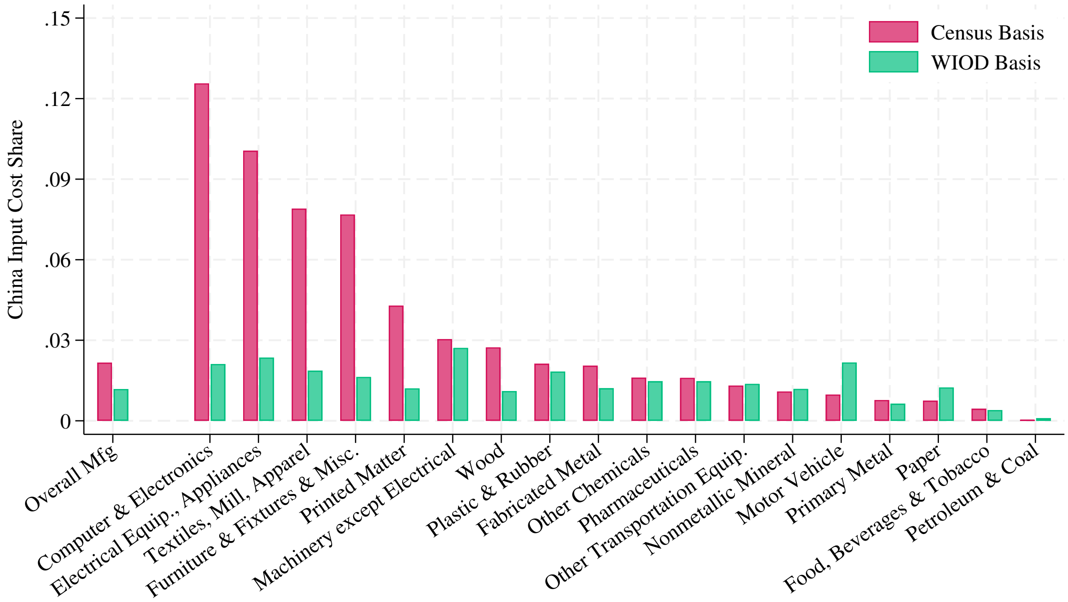
We begin by comparing the imported input cost shares for the manufacturing sector derived from establishment-level linked data from the Census and compare these estimates to those derived from the WIOD. The Census-based estimates (shown in Figure 1) show steady increases in the usage of foreign inputs through 2007 with a leveling off in 2012 and 2017. This contour is broadly similar to what one would obtain from the WIOD (not shown), though the level in WIOD is typically a few percentage points lower.

There is particular interest in the dependence of U.S. manufacturers on inputs sourced from China. In Figure 4, we plot the fraction of Chinese inputs in total material inputs across all broad manufacturing industries using the newly created links from Census data (red bars) compared to analogous estimates derived from the WIOD (green bars), using data from 2012. Based on the Census estimates, Chinese imported inputs represent 2.2% of total cost of materials in the manufacturing sector. However, reliance on Chinese imported inputs varies widely by industry: "Computer & Electronics" and "Electrical Equipment & Appliances" have the highest shares, 13% and 10%, respectively; "Food, Beverage, & Tobacco" and "Petroleum & Coal" have the lowest shares, 0.46% and 0.04%, respectively. In contrast, the WIOD estimates indicate much lower dependence on China as a source of inputs across most manufacturing industries, except "Motor Vehicles" and "Paper" where the WIOD estimates are about double that of the Census estimates. This comparison highlights the potential role of biases in the import proportionality assumption, along with other measurement issues (such as the classification of imports by intended use). An accurate picture of the true

[26]The current available version is the November 2016 release and includes a rest of world aggregate.

dependence of U.S. manufacturers on Chinese inputs is another useful application of this data.

Figure 4: Chinese Input Cost Share in U.S. Manufacturing, 2012




**Notes:** This figure displays inputs imported from China as a share of material costs in U.S. manufacturing industries.

**Source:** Authors' calculations using CMF, LFTTD, WIOD.

## 5.2 Correlations between Census and WIOD Measures

For a systematic assessment of these proportionality assumptions, we calculate correlations between various measures from the Census data and the WIOD equivalents. Beginning with the import proportionality assumption operative in the country import cost shares, we report a summary of the alignment between Census estimates and WIOD estimates in the first column of Table 7, using simple correlations across country shares for given industries.[27] For manufacturing as a whole, the correlation is 0.64 – a strong positive correlation indicating that the WIOD and its inherent proportionality assumption do indeed capture significant features of U.S. global value chains. Nonetheless, a correlation well below 1 reveals that there are patterns in foreign input sourcing that are not well-represented by the import proportionality assumption. All broad industries within manufacturing show a correlation well above zero. High correlations above 0.9 are seen in sectors such as "Basic Metals" and "Motor Vehicles and Trailers"; the correlation is lowest at 0.3 for "Pharmaceuticals".[28]

[27] Imported input cost share measured as $IC_{st} = \frac{\sum_{e \in E_{st}} IMP^{I}_{est}}{\sum mc_{est}}$, which we replicate using the WIOD.

[28] Our finding of a correlation of 0.64 across (roughly) three-digit NAICS industries is in fact remarkably close to the correlation found in Feenstra and Jensen (2012) for the year 1997, suggesting that the scope for errors in proportionality has remained somewhat stable over time, at least in the United States.

Table 7: Census-WIOD Correlations by Sector, 2012

| | Correlations of | |
|---|---|---|
| Broad Manufacturing Sector | Input Costs | Bilateral GVC |
| Food, Beverage, and Tobacco | 0.83 | 0.92 |
| Textiles, Apparel, Leather | 0.67 | 0.56 |
| Wood and Wood Products | 0.87 | 0.63 |
| Paper and Paper Products | 0.81 | 0.76 |
| Printing | 0.73 | 0.64 |
| Coke and Petroleum Products | 0.68 | 0.94 |
| Pharmaceutical | 0.30 | 0.26 |
| Chemicals and Chemical Products | 0.62 | 0.81 |
| Rubber and Plastics | 0.67 | 0.49 |
| Non-metallic Mineral Products | 0.86 | 0.66 |
| Basic Metals | 0.94 | 0.69 |
| Fabricated Metal Products | 0.79 | 0.77 |
| Machinery and Equipment | 0.87 | 0.85 |
| Computer, Electronic and Optical | 0.62 | 0.83 |
| Electrical Equipment | 0.75 | 0.69 |
| Motor Vehicles and Trailers | 0.90 | 0.86 |
| Other Transport Equipment | 0.85 | 0.81 |
| Furniture and Other Mfg | 0.58 | 0.48 |
| **Overall Manufacturing** | **0.64** | **0.42** |

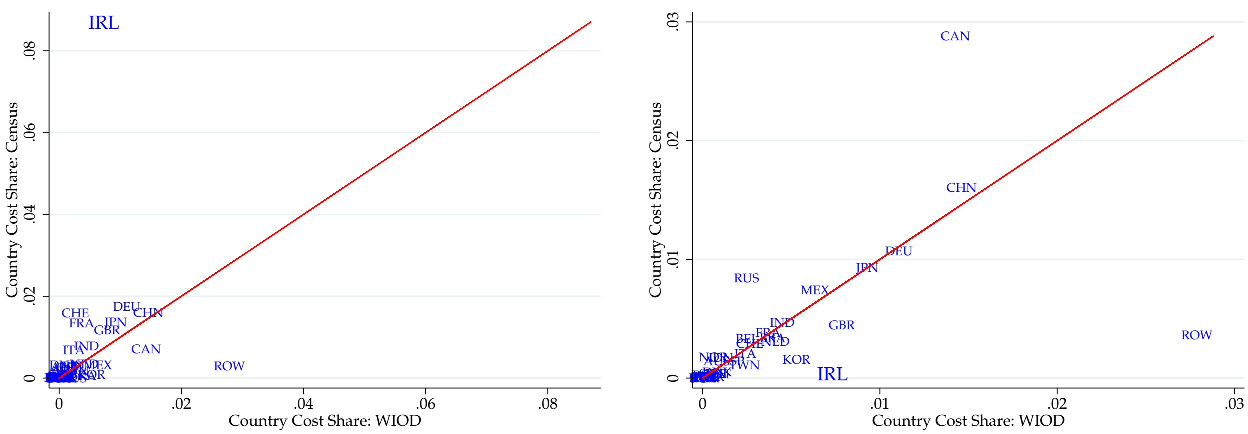
**Notes**: This table displays correlations, by broad sector, between Census-based and WIOD-based measures of: imported input by source country as a share of total cost of materials (column 1); imported input by source country as a share of exports by destination (column 2).
**Source:** Authors' calculations using CMF, LFTTD, and WIOD.

When moving to industry-level GVC statistics involving bilateral pairs of countries engaged in GVCs with the United States, then pairwise proportionality and import proportionality are both at play. Hence either of these could affect the alignment of GVC statistics for particular bilateral pairs of countries within an industry. The second column of Table 7 considers the alignment of the WIOD with Census data on a bilateral basis, calculating the correlation between all *bilateral* import-export country-pair GVC statistics for a given industry (i.e. the GVC measure of imported inputs from Mexico in exports to France in the machinery and equipment industry). For the Census-based measure, we use Equation (5). For the WIOD-based bilateral GVC measures, we use intermediate imports from country $m$ and exports to country $n$ as reported in the WIOD. As shown in the table, these correlations are typically—though not always—lower than the overall cost-share measures. Across all industries, this correlation stands at 0.42 for U.S. manufacturing. As might be expected, the multiple proportionality assumptions generally lowers the accuracy of aggregate-based methods relative to those based on establishment data.

Delving deeper into the potential sources of mis-alignment in column 1 of Table 7, Figure 5 plots the country sources of foreign inputs for Pharmaceuticals (NAICS 3254, Panel A) and Basic Chemicals excluding pharmaceuticals (NAICS 325X, Panel B). What is immediately evident in Panel A of Figure 5 is the role that Ireland plays in the mis-measurement of foreign inputs for the Pharmaceutical sector: the Census-based measure records Ireland occupying nearly 8 percent of material input costs, whereas the WIOD has Ireland's share at less than 1 percent.[29] One can see the opposite pattern in the Basic Chemicals sector—a feature which likely reflects the proportionality assumption pushing too many Irish imports into inputs in basic chemicals rather than into inputs in pharmaceuticals.[30] The outsized role of Ireland in pharmaceuticals trade—as well as for producing measurement headaches in international statistics—has been well-documented (Setser, 2019).[31]

Figure 5: Mis-Alignment Between WIOD and Census Measures of Foreign Input Shares

(a) Pharmaceutical (NAICS 3254) (b) Basic Chemicals (NAICS 325X)




**Notes:** These figures display the foreign cost share of material inputs by source country within broad sectors. The red lines are at the 45 degree line, indicating perfect country-level alignment between sources.
**Source:** Authors' calculations using CMF, LFTTD, and WIOD.

## 5.3 Excess Smoothing in Proportional Measures

Without direct linkage of import sources to export destinations, one source of the misalignment in GVC linkages identified in Table 7 (Column 2) is the smoothing of sources and destinations resulting from pairwise proportionality. To highlight this feature—what we

[29]For more details, see the top ten import-export country pairs for the pharmaceuticals sector in Table A6. Ireland is remarkably the top input source for all top ten bilateral country-pairs.

[30]The relative magnitudes are also sensible, as published data indicate that basic chemicals record nearly eight times as much material input costs as pharmaceuticals.

[31]One might worry particularly about the final vs intermediate goods classification in the pharmaceutical sector, and similarly, how the U.S. territory of Puerto Rico is recorded in the data. On the former point, we manually re-coded any imported product beginning with "30." ("Pharmaceuticals") in the HS schedule to be a final good provided the establishment is in the pharmaceutical sector. On the latter point, we exclude any import transactions in the LFTTD that list Puerto Rico as the district of entry.

describe as "excess smoothing" from pairwise proportionality—we calculate the fraction of bilateral country-pairs (among countries included in the WIOD) that record zero GVC linkages in the Census data. Provided that there are non-zero commodity imports (to U.S.) and exports (from U.S.) within a given sectoral aggregation—a feature which does hold for the 18 manufacturing sectors in WIOD countries—then the proportional-based measure will naturally record strictly positive GVC values across the full cartesian product of country pair links.

Table 8 shows evidence of excess smoothing of GVC linked pairs as evidenced by a significant share of zero bilateral linkages in Census data, though the extent of the excess smoothing varies widely by manufacturing sector. On the whole, there is a greater average share of zeros in the true data among nondurable sectors, though wood and wood products (within durables) records the highest overall share of zeros at 37 percent of all possible pairwise combinations.

Table 8: Fraction of Zero Bilateral GVC Linkages, by Sector, 2012

| NAICS | Percent | NAICS | Percent |
|---|---|---|---|
| *Nondurable Sectors* | | *Durable Sectors* | |
| Food, Beverage, and Tobacco | 14% | Wood and Wood Products | 37% |
| Textiles, Apparel, Leather | 11% | Non-metallic Mineral Products | 13% |
| Paper and Paper Products | 14% | Basic Metals | 6% |
| Printing | 28% | Fabricated Metal Products | 1% |
| Coke and Petroleum Products | 20% | Machinery and Equipment | 0% |
| Pharmaceutical | 4% | Computer, Electronic and Optical | 0% |
| Chemicals and Chemical Products | 2% | Electrical Equipment | 0% |
| Rubber and Plastics | 3% | Motor Vehicles and Trailers | 1.6% |
| | | Other Transport Equipment | 0.2% |
| | | Furniture and Other Mfg | 0.1% |

**Notes**: This table reports the fraction of zero GVC linkages among all possible pairwise combinations ($43^2 = 1,849$) for select sectors.
**Source:** Authors' calculations using CMF and LFTTD.

Naturally, measures of such excess smoothness will increase substantially when additional periphery countries are included in proportional measures, or when the level of industry aggregation decreases. Indeed, one could glimpse this issue by recognizing that the "Rest of World" category tends to record a considerably higher share (on average, nearly 1.5 percentage points) of costs in the WIOD-based measure than in our Census-based measure. Amid very low shares, the possibility of errors relative to zero go up substantially. On the other hand, one might worry about the role of missing inputs in our Census-based measure that are imported *indirectly* through other firms. As explained in Section 2.4 above, our Census-based measures are not able to capture such indirect import content. If firms disproportionately use third-party firms—such as importer-exporters or wholesale firms—to import inputs from such small countries, then our Census-based measure may underestimate the cost share of these small countries. We hope to explore the role of indirect imported inputs in future work.

All told, whether excess smoothing presents an issue to the researcher will depend on the specific question being addressed. From a quantitative perspective, the issue naturally applies to a small share of overall GVC activity: The GVC-weighted average of the zero share from Table 8 across all U.S. manufacturing is 3.2 percent.

## 5.4 Biases in Determinants of Bilateral GVC

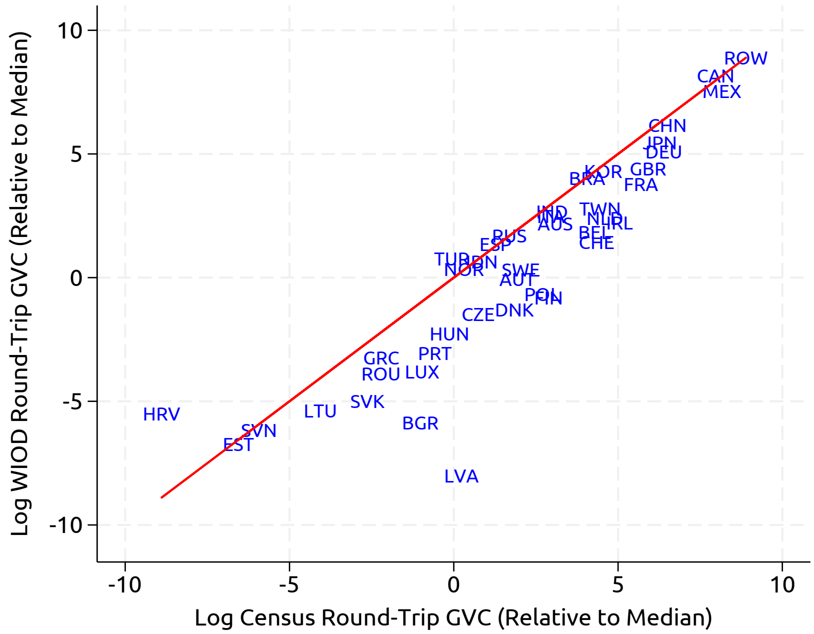
Aggregated data are unable to replicate the patterns we have uncovered in Section 4. We show this by replicating the gravity regressions by constructing the bilateral GVC measure using the WIOD. As is shown in column (7) of Table 4 and column (5) of Table 5, the WIOD-based results do not capture – even in a qualitative sense – the patterns discussed in the previous section.

Figure 6 shows this disconnect directly, focusing on the robust feature of round-trip GVC linkages apparent in our Census-based GVC measures identified above. The figure plots the round-trip GVC values—scaled relative to the median value across all GVC pairs—in our data (x-axis) relative to an equivalent measure in WIOD (y-axis). The figure reveals that nearly all WIOD countries lie below the 45-degree line, indicating significantly higher relative magnitudes of these round-trip GVC flows than would be captured in WIOD. A comparison of columns (6) and (7) of Table 4 is another way of seeing this disconnect.

We conclude this section by examining the layers of measurement where these features may reside, and the role that various proportionality, sample coverage, and aggregation play in their disclosure in publicly available input-output tables.

To initialize this exercise, we replicate column (3) of Table 5 in the first column of Table 9. To begin, some features of our results may be hidden because the country samples underlying many proportionality-based tables do not include sufficient variation; hence column (2) replicates our baseline regression while restricting the set of countries to be identical to that in the WIOD. As is clear, some results here are lost. Unsurprisingly, there now appears to be an insufficient number of RTA partner pairs to exhibit a positive coefficient, and the coefficient on the combined distance metric is no longer significant. Since the EU countries are disproportionately represented in the WIOD, while many smaller countries around the world are missing, neither the RTA nor the distance measure retains its explanatory power when we reduce our sample countries to match those in the WIOD. On the other hand, this sample exhibits only a modestly reduced round-trip effect, implying that the round-trip

Figure 6: Alignment of Round-Trip GVC Values, 2012




**Notes:** This figure plots round-trip GVC pairs (where the import country equals the export country) in Census data (x-axis) vs WIOD (y-axis). Each statistic is scaled relative to the median value across all WIOD-based GVC country pairs, and in logs.
**Source:** Authors' calculations using CMF, LFTTD, and WIOD.

effect we observe does not depend significantly on the set of countries used in the gravity regression.

In the last four columns of Table 9, we explore the role of other differences between the two GVC measures in the gravity relationship by changing the way we measure GVCs, rather than merely restricting the sample. Columns (3) and (4) of Table 9 focus on aggregation bias and pairwise proportionality. Rather than relying on the import-export pairs connected by establishments, we instead aggregate the import and export data at the industry level before constructing GVC measures. In other words, instead of using the sum of the GVC measure defined in equation (5) across $s$ as the dependent variable, we use the following GVC measure:

$$GVC_{mnt}^{agg} = \sum_{s} \left( \frac{\sum_{e \in E_{mst}} \sum_{r} IMP_{emrt}^{I}}{\sum_{e \in E_{st}} GO_{est}} \sum_{e \in E_{nst}} \sum_{p} EXP_{enpt} \right). \tag{7}$$

As we discussed in the previous section, without pairwise proportionality in play, we observe zero GVC flows for a significant number of $(m, n, s, t)$ combinations, since it is possible that $E_{mnst}$ is an empty set. In the WIOD, on the other hand, GVC flows for all $(m, n, s, t)$ combinations are non-zero. With this in mind, we compute Equation (7) for all pair-wise combinations in column (3) and only for the bilateral pairs that exist in the data in column (4).

In both columns (3) and (4), we find much smaller round-trip effects. As shown in

Figure 6, the impact of aggregation bias and the pairwise proportionality assumption reduces the concentration of GVC found in round-trip pairs. More surprising is the impact this assumption has on the distance coefficient – attenuating the negative effects found in the true data, and in the case of extrapolating to all possible pairs of countries (in Column (3)), turning the coefficient positive.[32] With the full set of countries available, the RTA coefficient continues to exhibit a positive and statistically significant sign. The fact that the magnitude is reduced by more than half relative to the establishment-based data is attributable once again to the fact that the relatively more concentrated flows associated with those pairs are smoothed out via proportionality.

Table 9: Gravity Model Comparisons 2002-2017

| | Dependent Variable: Log Bilateral GVC | | | | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Log Distance ($m \rightarrow$US$\rightarrow n$) | -1.36*** | 0.26 | 0.11** | -0.011 | -0.28** | -0.04 |
| | (0.104) | (0.280) | (0.049) | (0.045) | (0.114) | (0.083) |
| Round-trip ($m$=$n$) | 2.21*** | 1.71*** | 0.17*** | 0.21*** | 0.18*** | 0.08*** |
| | (0.112) | (0.119) | (0.0426) | (0.0396) | (0.0282) | (0.015) |
| RTA ($m$, $n$, US) | 0.44*** | -0.13 | 0.16*** | 0.17*** | 0.06 | -0.03 |
| | (0.112) | (0.220) | (0.046) | (0.045) | (0.087) | (0.061) |
| Data | Census | Census | Census | Census | Census | WIOD |
| Basis | Estab | Estab | Agg. | Agg. | Agg. | Agg. |
| Country Sample | All–Data | WIOD-43 | All–Poss. | All–Data | WIOD-43 | WIOD-43 |
| Observations | 117,000 | 7,100 | 139,000 | 117,000 | 7,100 | 7,056 |
| R-Squared | 0.86 | 0.94 | 0.96 | 0.96 | 0.99 | 0.99 |

**Notes**: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Includes Exporter-Year F.E. and Importer-Year F.E.
**Source:** Authors' calculations using CMF, LFTTD, and WIOD.

In column (5), we use the bilateral GVC measures based on the aggregated microdata from columns (3) and (4), and also restrict the set of countries in the sample to match the WIOD. Similar to the comparison between column (1) and column (2), the round-trip effect is only marginally reduced when we restrict our sample from column (4) to column (5), confirming that the sample does not play a significant role in the round-trip effect. And once again the specification loses any significance in the RTA coefficient.

Finally, we run the gravity regression with the WIOD in column (6). In moving from column (5) to column (6), we also introduce the import proportionality that is inherent in assigning imports to input industries in aggregate data. With the addition of this proportionality assumption, the round-trip coefficient is further reduced, albeit much less than from column (2) to column (5), and lose significance for both the distance and RTA coefficients.

[32] This positive impact could be explained by allocating GVC to bilateral country pairs that are relatively remote when in reality these pairs record zero GVC flows.

In summary, we find that the proportionality assumptions necessary to translate aggregate data into multi-country GVC-based measures result in many real-world features of these GVC linkages to be hidden from the researcher.

# 6 A Simple Framework of Global Value Chains

Model frameworks for global value chains (GVCs) have evolved in various forms to reflect the complex structure of GVCs in reality, including roundabout production, multi-stage production with specific inputs, multinational activities, and more. In this paper, we adopt and modify a straightforward framework of firm-level GVCs from the existing literature to reconcile our empirical findings from microdata, while delegating the development of a fully fledged model of GVCs to future research.

## 6.1 Model Framework

We build a framework in which firms solve sourcing and selling problems jointly. Firms can source intermediate inputs domestically or internationally and sell their output products in domestic or foreign markets. We assume firms are heterogeneous in productivity. The input market is assumed to be perfectly competitive, while the output market is characterized by monopolistic competition. This framework draws from Bernard, Jensen, Redding and Schott (2018b), combining the firms' sourcing problem of Antrás, Fort and Tintlenot (2017) with the production location choice problem and export problem as in Melitz (2003). We simplify their framework by abstracting from firms' endogenous choice of production location and assuming all firms are single-industry, single-establishment, and single-product firms. Therefore, the notation $f$, which denotes a firm in this section, effectively corresponds to establishment $e$ in the notation used to describe the Census microdata earlier in the paper.

### 6.1.1 Basic Setup

Final goods consumers in country $n$ have the following CES utility:

$$U_n = \left[ \sum_{i \in \Omega_n^N} \sum_{f \in \Omega_{in}^F} (C_{ifn})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where $C_{ifn}$ denotes the country-$n$ consumers' consumption quantity of the product made by firm $f$ in country $i$; $\Omega_{in}^F$ is the set of firms from country $i$ selling products to consumers in country $n$; $\Omega_n^N$ is the set of countries where there is at least one firm that serves the destination market $n$. The term $\sigma$ is a constant elasticity of substitution. Denote the price that consumers in country $n$ pay for the product sold by firm $f$ in country $i$ as $P_{ifn}^F$. With monopolistic competition in the final goods market, market-$n$ consumers' expenditure share for firm $f$'s product is

$$S^F_{ifn} = \frac{(P^F_{ifn})^{1-\sigma}}{\sum_{i' \in \Omega^N_n} \sum_{f' \in \Omega^F_{i'n}} (P^F_{i'f'n})^{1-\sigma}}.$$

Production of final goods is done by combining labor with intermediate inputs. Firm $f$ in country $i$ has the following Cobb-Douglas production technology:

$$Q^F_{if} = \varphi_{if} \left( \frac{L^F_{if}}{\alpha} \right)^{\alpha} \left( \frac{Y^F_{if}}{1-\alpha} \right)^{1-\alpha},$$

where $\varphi_{if}$ is firm $f$'s productivity; $L^F_{if}$ is labor input used in final goods production; $\alpha$ is the labor cost share. We assume that there is a continuum of input varieties on a unit interval and denote $Y^F_{if}$ as the CES aggregate of intermediate inputs—i.e., $Y^F_{if} = \left[ \int_0^1 Y^F_{if}(l)^{\frac{\eta-1}{\eta}} dl \right]^{\frac{\eta}{\eta-1}}$ with $\eta$ being the elasticity of substitution between input varieties.

Sourcing of intermediate inputs follows Antrás, Fort and Tintlenot (2017). We assume that producers of intermediate inputs use only labor as a production input. With the assumption of a perfectly competitive input market, the variable sourcing cost of input variety $l$ from source country $m$ for firm $f$ in country $i$ is given by

$$a_{ifm}(l) = \frac{w_m d^I_{mi}}{z_{ifm}(l)}.$$

$w_m$ is the wage in country $m$ under the assumption that labor is perfectly mobile within a country. $d^I_{mi} \geq 1$ is variable input trade cost from country $m$ to country $i$. Finally, $z_{ifm}(l)$ is an intermediate input productivity that is randomly drawn from a Fréchet distribution $G_m(z) = \exp\left(-T_m z^{-\theta}\right)$. $T_m > 0$ is the scale parameter governing the absolute advantage of country $m$ as the source of intermediate inputs, and $\theta > 0$ is the shape parameter that is inversely related to the dispersion of the distribution.

### 6.1.2 Sourcing and Exporting Decisions

We derive the equilibrium of this model in two steps. First, we derive the intensive margins of sourcing and exporting, conditional on the set of countries from which each firm sources intermediate inputs and to which it sells its final goods. In the second step, we solve for the set of import source countries and export destination countries—$\Omega^{NI}_{if}$ and $\Omega^{NX}_{if}$, respectively—that maximize a firm's profit.

Firms source each intermediate input variety from the lowest-cost supplier among the countries in $\Omega^{NI}_{if}$. Following Eaton and Kortum (2002) and Antrás, Fort and Tintlenot (2017), the equilibrium probability that firm $f$ in country $i$ sources intermediate inputs from country $m \in \Omega_{if}^{NI}$ is

$$\mu_{ifm}(\Omega_{if}^{NI}) = \frac{T_m(w_m d_{mi}^I)^{-\theta}}{\sum_{m' \in \Omega_{if}^{NI}} T_{m'}(w_{m'} d_{m'i}^I)^{-\theta}}.$$

Then, the variable unit cost function for firm $f$ in country $i$ is given by

$$\delta_{if}(\varphi_{if}, \Omega_{if}^{NI}) = \frac{1}{\varphi_{if}} w_i^{\alpha} \left[ \Gamma \left( \frac{\theta + 1 - \eta}{\theta} \right) \right]^{\frac{1-\alpha}{1-\eta}} \left[ \sum_{m' \in \Omega_{if}^{NI}} T_{m'}(w_{m'} d_{m'i}^I)^{-\theta} \right]^{-\frac{1-\alpha}{\theta}}.$$

We assume $\theta + 1 > \eta$ so that the cost function is well-defined. Under monopolistic competition in the final goods market, consumers in country $n$ pay the following price for the product of firm $f$, if the firm exports to country $n$:

$$P_{ifn}^F = \frac{\sigma}{\sigma - 1} d_{in}^X \delta_{if}(\varphi_{if}, \Omega_{if}^{NI}),$$

where $d_{in}^X \geq 1$ is a variable trade cost for final goods from country $i$ to country $n$. For convenience, we refer to $d_{in}^X \geq 1$ as the variable export cost and $d_{mi}^I \geq 1$ as the variable import cost.

In the next step, we derive how firms decide on the extensive margins of sourcing and exporting—i.e., how firms determine which countries to include in $\Omega_{if}^{NI}$ and $\Omega_{if}^{NX}$. In addition to the variable costs of sourcing and exporting, we assume there are also fixed costs associated with these activities, denoted by $F_{ifm}^I$ and $F_{ifn}^X$, respectively. For example, if firm $f$ in country $i$ sources intermediate inputs from country $m$ and exports their product to country $n$, it must pay both $F_{ifm}^I$ and $F_{ifn}^X$. We normalize the fixed cost of production to zero. All fixed costs are assumed to be paid in terms of labor. Firm $f$ chooses the countries to be included in $\Omega_{if}^{NI}$ and $\Omega_{if}^{NX}$ to maximize the following profit:

$$\Pi_{if}^F = \sum_{n \in \Omega_{if}^{NX}} \left( \frac{1}{\sigma} \right) E_{ifn}^F - \sum_{n \in \Omega_{if}^{NX}} w_i F_{ifn}^X - \sum_{m \in \Omega_{if}^{NI}} w_i F_{ifm}^I,$$

where $E_{ifn}^F \equiv S_{ifn}^F w_n L_n$ denotes the total sales of firm $f$ in destination market $n$.

### 6.1.3 GVC Measures

This simple model framework provides a measure of global value chains that we can compare with the measures derived from Census microdata. Using the Cobb-Douglas structure of the production technology, the imports of intermediate inputs from country $m$ are given by $IMP_{ifm}^M = \mu_{ifm}(\Omega_{if}^{NI})(1-\alpha) GO_{if}^M$, where the subscript $M$ denotes variables derived from the model, which have direct data counterparts used earlier in the paper. With this expression, the dollar-value GVC measure for a country-$i$ firm $f$'s imports of intermediate inputs from country $m$ and exports to country $n$ from the model can be written as

$$\begin{aligned} GVC_{ifmn}^{M} &= \frac{IMP_{ifm}^{M}}{GO_{if}^{M}} EXP_{ifn}^{M} \\ &= \mu_{ifm}(\Omega_{if}^{NI})(1-\alpha)E_{ifn}^{F}. \end{aligned} \quad (8)$$

This expression is the model counterpart of the term inside the summation in equation (5). We aggregate this firm-level trilateral GVC measure across firms to compute a measure equivalent to that defined in equation (5), allowing us to use it in the gravity analysis. Country $i$'s aggregate GVC measure for import source country $j$ and export destination country $j$ is defined as follows:

$$GVC_{imn}^{M} = \sum_{f \in F_{imn}} \mu_{ifm}(\Omega_{if}^{NI})(1-\alpha)E_{ifn}^{F}, \quad (9)$$

where we define $F_{imn}$ as $F_{imn} \equiv \{f \mid m \in \Omega_{if}^{NI} \text{ and } n \in \Omega_{if}^{NX}\}$. In other words, $F_{imn}$ is the set of firms located in country $i$ that import intermediate inputs from country $m$ and export their output to country $n$. The only difference between equation (5) and its model counterpart (8) is that $i$ is omitted in equation (5) as we consider only the case of $i = US$.

## 6.2 Numerical Simulations

We can numerically simulate this model framework to see if it can generate the empirical patterns documented with the Census microdata, with a particular focus on the gravity relationship for GVCs. Although the numerical exercise presented in this section is not a full calibration to real-world data, the results highlight the determinants of GVCs and the model features needed to reconcile the strong roundtrip effect observed in the microdata.

### 6.2.1 A New Feature to Reconcile the Round-trip Effect

The model framework we present includes firms' endogenous selection into GVC participation, with the fixed costs of sourcing and exporting playing a key role in their decisions. However, the baseline framework may not capture systematic complementarity between input source countries and export destination countries, because the size of the import (export) fixed cost is independent of the set of export destinations (import source) countries. In other words, the baseline model treats fixed costs of exporting and importing independently, without the potential for commonalities such that sourcing fixed costs are reduced if a firm already exports to a given country.

It is straightforward to modify the baseline model with a new intuitive feature that helps reconcile the roundtrip effect. Note that in the model, both export and import fixed costs are firm-specific. We assume that these costs include both common and idiosyncratic components. Specifically, for each firm $f$, we assume that its export and import fixed costs take the following form:

$$\begin{aligned} F^X_{ifn} &= F^X_{in}\varepsilon^X_{ifn}(\Omega^{NI}_{if}) \\ F^I_{ifm} &= F^I_{mi}\varepsilon^I_{ifm}(\Omega^{NX}_{if}), \end{aligned}$$

where $F^X_{in}$ and $F^I_{mi}$ represent the fixed cost components common to all firms. For the common components $F^X_{in}$ and $F^I_{mi}$, we assume no symmetry *within* export or import fixed costs but impose a symmetry *between* export and import fixed costs in the baseline simulation. In other words, $F^X_{in} \neq F^X_{ni}$ and $F^I_{in} \neq F^I_{ni}$, but $F^X_{in} = F^I_{in}$ for any $(i,n)$. Bilateral fixed costs may not be symmetric between countries due to differences in institutions, regulations, etc, but for a given direction of trade flows intermediate inputs and final goods are likely to face a similar degree of fixed costs. We explore the role of this assumption later based on simulations.

The common components of the fixed costs are adjusted for each firm by an idiosyncratic factor $\varepsilon^X_{ifn}(\Omega^{NI}_{if}) > 0$ for exporting and $\varepsilon^I_{ifm}(\Omega^{NX}_{if}) > 0$ for importing. The adjustment to the fixed exporting cost for firm $f$ and export destination $n$ depends on whether country $n$ is included in the set $\Omega^{NI}_{if}$. Similarly, the fixed importing cost for firm $f$ and import source country $m$ is adjusted based on whether $m$ is included in $\Omega^{NX}_{if}$. In the numerical simulation, we implement this adjustment by lowering both export and import fixed costs if a firm exports to and imports from the same country. Specifically, we set the two idiosyncratic factors $\varepsilon^X_{ifn}(\Omega^{NI}_{if})$ and $\varepsilon^I_{ifm}(\Omega^{NX}_{if})$ as follows.

$$\begin{aligned} \varepsilon^X_{ifn}(\Omega^{NI}_{if}) &\equiv \bar{\varepsilon}^X_{ifn} \times \left(1 - \xi_f \mathbf{1}(n \in \Omega^{NI}_{if})\right) \\ \varepsilon^I_{ifm}(\Omega^{NX}_{if}) &\equiv \bar{\varepsilon}^I_{ifm} \times \left(1 - \xi_f \mathbf{1}(m \in \Omega^{NX}_{if})\right) \end{aligned}$$

In the expressions above, $\bar{\varepsilon}^X_{ifn} > 0$ and $\bar{\varepsilon}^I_{ifm} > 0$ are firm-country-specific draws that are exogenously fixed. Based on the same logic applied to the common components of fixed costs, we assume that for each firm $f$, $\bar{\varepsilon}$ is asymmetric between countries within export or import but symmetric between export and import. $\xi_f$ is a firm-specific roundtrip adjustment factor which reduces a firm's export and import fixed costs for the country that is included in both the set of sourcing countries and that of export destinations of the firm. We randomly draw $\xi_f$ for each firm from a uniform distribution on $[0,1]$. Systematically lower fixed costs for round-trip sourcing and exporting capture a firm's potential cost savings due to overlapping market-specific knowledge between input and output markets, as well as better coordination in production processes when importing inputs from and exporting outputs to the same country.[33]

### 6.2.2 Parameter Values

We construct a hypothetical economy under which we simulate the model to assess the behavior of the model numerically. The simulation is done for a partial equilibrium model for given country-level wages. We assume that there are 15 countries, each of which is populated by 1,000 firms. Firms are heterogeneous in their productivities. We randomly draw each firm's productivity from a Pareto distribution with the shape parameter equal to 4 and the lower bound 1. We simplify the country-level comparative advantage structure by assuming that all countries have identical wages ($w_i$), labor endowment ($L_i$), and average productivity ($T_i$), except for country 1, which has double the values for each.[34] The value-added share is set at 1/3 for all countries. In the remainder of this section, we will report simulation results for GVC flows with country 1 at the center of the chain, similar to how our GVC measure is constructed from the data, with the U.S. at the center. Lastly, the elasticity of substitution in the CES utility function and the shape parameter $\theta$ in the Fréchet distribution for intermediate input productivity are both set to be 4.

To generate bilateral trade frictions, we first randomly draw variable export costs $d_{in}^X$ for each country pair $(i, n)$ such that $i \neq n$ from a uniform distribution on $[1, 1.5]$ under the restriction of $0 \leq \mid d_{in}^X - d_{ni}^X \mid \leq 0.03$ in order to implement the symmetric nature of variable trade costs. We adopt a simpler symmetry between variable export costs and variable import costs by assuming $d_{in}^X = d_{in}^I$—i.e., variable trade costs are identical for trade flows from country $i$ to country $n$ regardless of whether they are intermediate inputs or final goods. The assumption regarding the symmetry of fixed costs is as previously described.

While variable trade costs include many country-specific trade barriers, most notably distance, we can also explore the role of regional trade agreements in influencing these costs. We randomly sample 30% of country pairs as having regional trade agreements with each other, independent of the initial assignment of variable trade costs. If a country pair is selected to have an RTA, we eliminate both export and import variable costs by setting $d$ equal to one for that pair.

[33] Motivated by the strong positive correlation between export and import intensities at the firm level, Blaum (2024) implements the idea of lowering fixed costs for firms that both export and import, while assuming fixed costs are not specific to any partner country. We extend this idea by reducing fixed costs for firms that export to and import *from the same country*, similar to Albornoz and García-Lembergman (2023), but also allowing for fixed cost adjustments in both directions between exporting and importing.

[34] Although we do not attempt a full calibration of the model, this assumption regarding the relative size and productivity of a country is intended to mimic our empirical results by making country 1 similar to a hypothetical U.S.

### 6.2.3 Gravity with Simulated Data

After simulating the model using the parameter values described above, we obtain firm-level simulated GVC flows, as derived in equation (8). For $i = 1$, we aggregate this measure across firms to arrive at the bilateral GVC measure in equation (9), with country 1 at the center of the supply chain. The log of this bilateral GVC measure serves as the dependent variable in the simulated gravity exercise, which is specified similarly to its empirical counterpart in equation (6). We follow the specification that includes the roundtrip indicator, the log of combined distance, and an RTA dummy for the case where all three countries have an RTA with one another, as reported in Table 9, using it as the benchmark. The distance measure in (6) is replaced by the values of $d$'s drawn for the simulation, before they get lowered based on the country pair's RTA status. For roundtrip pairs, we assign a small random value between zero and 0.01 to replace their direct distance before taking the log, mimicking the treatment of internal distance in the CEPII data. RTA indicators are constructed based on whether two countries are randomly selected to have an RTA. Source and country fixed effects are included in all regressions.

We simulate our model under four scenarios. Scenario 1 uses the parameter values described in Section 6.2.2, including non-degenerate draws of $\xi_f$ to account for the adjustment of fixed costs related to roundtrip behavior. In scenario 2, we assume no adjustment of fixed costs for roundtrip behavior by setting $\xi_f = 0$ for all $f$. Scenario 3 keeps $\xi_f = 0$ as in the second scenario and further restricts the model by assuming that fixed export and import costs have no idiosyncratic components—i.e., $\bar{\varepsilon}^X_{ifn} = \bar{\varepsilon}^I_{ifm} = 1$ for all countries and firms. In other words, the third scenario assumes that all firms in a country share the same fixed cost schedule. Lastly, scenario 4 retains all the restrictions imposed in the third scenario and further assumes that export fixed costs and import fixed costs are not symmetric—i.e., $F^X_{in} \neq F^I_{in}$.

We present the gravity estimation results using simulated data in Table 10. For each scenario, we report the results corresponding to the specifications in Table 9.[35] We find a positive and significant roundtrip effect in scenario 1, where fixed costs are adjusted for roundtrip flows. The combined distance has a strongly negative effect on GVC flows, and GVC flows are larger when all three countries have an RTA with one another. In Scenario 2, where the roundtrip adjustment of fixed costs is removed, the roundtrip effect is reduced to only one-third of its impact in Scenario 1. Further removing firm heterogeneity in fixed costs from Scenario 2 does not significantly change the magnitude of the roundtrip effect, as shown in the results from Scenario 3. When we also remove the symmetry between export and import fixed costs in Scenario 4, the roundtrip effect is no longer significant. We also

[35] Since we do not calibrate this model framework to the actual data, the magnitude of the coefficients cannot be directly compared to those in Table 9. We interpret the results from this simulated gravity exercise qualitatively and leave the full calibration of the model to future research.

examine whether the significantly larger roundtrip effect observed in Scenario 1, compared to other scenarios, is attributable to the specific set of randomly drawn parameter values. A Monte Carlo exercise with 100 repetitions of the simulation yields an average roundtrip coefficient of 0.1906 for Scenario 1, with a standard deviation of 0.0149. This confirms that the larger roundtrip effect in Scenario 1, relative to other scenarios, is a robust finding.

Table 10: Gravity Estimation with Simulated Data

| Variable | Dependent Variable: Log Simulated Bilateral GVC<br>Scenario 1 | <br>Scenario 2 | <br>Scenario 3 | <br>Scenario 4 |
|---|---|---|---|---|
| Round-trip ($m$=$n$) | 0.19*** | 0.06*** | 0.05** | 0.03 |
| | (0.011) | (0.021) | (0.022) | (0.021) |
| Log Distance ($m$ →US→ $n$) | -0.51* | -0.91* | -0.76 | -1.35*** |
| | (0.262) | (0.512) | (0.524) | (0.503) |
| RTA ($m$, $n$, US) | 0.05** | 0.10** | 0.10** | 0.08* |
| | (0.022) | (0.043) | (0.044) | (0.042) |
| Exporter F.E. | yes | yes | yes | yes |
| Importer F.E. | yes | yes | yes | yes |
| Observations | 196 | 196 | 196 | 196 |
| R-squared | 0.99 | 0.99 | 0.99 | 0.99 |
| Symmetric Sourcing and Export Fixed Costs | yes | yes | yes | no |
| Idiosyncratic Fixed Costs | yes | yes | no | no |
| Round-trip Adjustment | yes | no | no | no |

**Notes**: "Symmetric Sourcing and Export Fixed Costs" means that sourcing and export fixed costs for a particular country pair are identical. "Idiosyncratic fixed costs" indicates whether fixed export and import costs have firm-specific components."Round-trip adjustment" indicates whether fixed export and import costs are lowered for the country that appears in both the set of import sources and that of export destinations. Each scenario is described in the text in detail. The number of observations is equal to the square of the number of partner countries for country 1. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
**Source**: Model simulated data.

In summary, we find that introducing complementarity between import sources and export destinations is crucial for capturing the roundtrip effect observed in the gravity relationship documented by the microdata. Omitting this feature results in a gravity relationship that is inconsistent with the data. While symmetric export and import fixed costs do generate a roundtrip effect, we show that endogenous fixed costs for exporting and sourcing significantly amplify this effect by introducing systematic complementarity between input sources and output destinations. Such complementarity may arise from spillovers of a firm's idiosyncratic knowledge about a particular foreign market. The development and quantification of a fully developed model will be addressed in future research.

# 7 Conclusion

An extensive body of work documenting the characteristics of and trends in GVCs in the past two decades has been driven, in large part, by development of multi-country, multi-sector input-output tables. Yet, global value chains are inherently about firms and how they organize production, including sourcing inputs from abroad and exporting products to a new market, across their establishments. Input-output tables by construction rely on industry-level output, exports, and imports that aggregates out export and import intensities at the establishment-level and rely on import proportionality assumption that ignores heterogeneity in input sourcing within sectors. Further, pairwise proportionality leads to positive GVC measures for all import-export country pairs even if true linkages do not exist. This paper measures GVCs for the U.S. manufacturing sector from establishment-level GVCs and thus minimizes biases due to aggregation and import and pairwise proportionality assumptions.

We develop novel linkages between origin country-specific imported inputs embodied in an establishment's destination-specific manufactured exports. We show that in the absence of establishment-level linked data, U.S. GVCs would be under-estimated and their growth trends substantially muted. Further, bilateral GVCs measured using input-output tables do not feature a round-trip effect or strong role of RTAs in facilitating trade flows within U.S. GVCs and thus misses an important source of complementarity between input and output markets.

The establishment-level linkages between imports and material use and between exports and output provide a complete picture of U.S. manufacturer's direct involvement in global value chains. However, a salient feature of modern manufacturing firms is their involvement in a substantial amount of non-manufacturing activities (Ding, Fort, Redding and Schott, 2022; Ding, 2023; Fort, 2023). Moreover, our methodology misses the indirect connections of U.S. establishments to global value chains through connections to other U.S. firms. This suggests that out current methodology, while comprehensively measuring direct foreign input sourcing by U.S. manufacturing plants, could be excluding other dimensions of how U.S. establishments contribute to global value chains. We leave extending the micro data linkage methodology to encompass such features for future research.

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# A Data Appendix

## A.1 Constructing Establishment-Level GVC Measures

### A.1.1 Sample Criteria

Given our focus on linking firms' trade flows to their production activities, our sample includes all establishments in the manufacturing sector. Detailed information on products produced/shipped and materials consumed contained in the CMF product and material trailer files, respectively, are collected from establishments that receive a long form. About 60% of establishments, typically accounting for over 97% of value of shipments in the manufacturing sector, are sent a report form; and about 70% of these establishments receive a long form and the rest receive a short form (U.S. Census Bureau, 2002, 2007b, 2012, 2017).

The long forms contain a pre-populated list of (i) primary and secondary products and miscellaneous services specific to a group of related industries; and (ii) list of materials generally used in the production process specific to an industry. From the list of products, establishments are asked to identify the products, value of each product (and quantity of the product for select cases) shipped during the survey year. From the list of materials consumed, establishments are asked to identify those consumed and the associated cost (and quantity consumed for select cases) during the survey year. The short form requests summary products and materials data but not detailed categories which "would increase the value of the "not specified by kind" categories" (U.S. Census Bureau, 2007a).[36]

Table A1: Number of Firms and Establishments by Trader Type and Year

| Trader Type | Year | Firms | Establishments |
|---|---|---|---|
| Non-Trader | 2002 | 118,000 | 126,000 |
| Non-Trader | 2007 | 98,000 | 103,000 |
| Non-Trader | 2012 | 86,000 | 91,000 |
| Non-Trader | 2017 | 88,500 | 93,000 |
| Exporter-Only | 2002 | 11,000 | 14,000 |
| Exporter-Only | 2007 | 24,000 | 29,000 |
| Exporter-Only | 2012 | 21,000 | 25,000 |
| Exporter-Only | 2017 | 20,500 | 25,500 |
| Importer-Only | 2002 | 13,000 | 18,000 |
| Importer-Only | 2007 | 10,000 | 11,000 |
| Importer-Only | 2012 | 10,000 | 12,000 |
| Importer-Only | 2017 | 9,500 | 12,500 |
| Exporter-Importer | 2002 | 11,000 | 43,000 |
| Exporter-Importer | 2007 | 20,000 | 55,000 |
| Exporter-Importer | 2012 | 20,000 | 51,000 |
| Exporter-Importer | 2017 | 17,500 | 48,500 |

**Notes**: This table displays the number of firms and establishments in the sample by type of trader and year. Counts are rounded to comply with Census Bureau disclosure avoidance rules.
**Source**: Authors' calculations using CMF and LFTTD.

[36] This implies that imported inputs would be allocated using the indirect methodology discussed below.

About 40% of manufacturing establishments, that are small single-establishment firms, are not required to file a census report and instead basic information (e.g., receipts, payroll, location) on these firms are populated using administrative records. However, there is no information available on detailed product and materials for these establishments and we drop these administrative records.[37]

We report the number of firms and establishments in each year in our analysis sample in Table A1. There are 153,000, 152,000, 137,000, and 135,500 firms in 2002, 2007, 2012, and 2017 respectively; there are 201,000, 198,000, 179,000, and 179,500 manufacturing establishments in 2002, 2007, 2012, and 2017, respectively. Not surprisingly, non-traders account for the largest share of firms and establishments since trading is a high-fixed-cost activity. The number of exporter-only, importer-only, and exporter-importer firms are very similar at over 10,000 each. However, exporter-importer firms have more than double the number of establishments than the other two types of traders. This is consistent with the fact that exporter-importer firms tend to be larger, accounting for about half of economy-wide employment and over 60% of employment at large (employs over 500 workers) firms in the U.S. economy (Handley, Kamal and Ouyang, 2021).

### A.1.2 Aligning CMF Trailer Files and LFTTD Trade Data

For reporting establishments in the CMF-PROD and CMF-MAT, we perform two main cleaning steps. First, we identify and remove aggregator codes from the set of product codes associated with each establishment. Such codes may serve as aggregates of usable product codes (77100000), or serve as "balancer" codes to ensure that the sum of product-level shipments and materials matches the total value specified elsewhere in the survey.

A feature of the CMF-MAT trailer files is that a non-trivial share of value is associated with miscellaneous codes indicating products not specified in the pre-populated survey form. These "not elsewhere specified or indicated" (NESOI) codes typically account for 20-30 percent of the industry total (in terms of value), and cannot be directly linked to product codes in the LFTTD. Table A2 reports the share of costs and shipments reported to be "not elsewhere specified" as part of either the CMF-MAT (Panel A) and CMF-PROD (Panel B), respectively. This share is quite low in the CMF-PROD.

Second, after removing aggregate and balancing codes, we concord the Census product codes from the trailer files to a NAICS-level code that can be matched to the HTS and Schedule B codes found in import and export data, respectively. We utilize the concordances in Pierce and Schott (2012) that match both Census product codes and HTS/Schedule B codes to a common NAICS-Baseroot product basis.[38] This is not a straightforward match since many Census product codes in the trailer files are not found in the concordance. We apply an iterative matching process. For Census product codes that do not match to a NAICS-Baseroot code at the most disaggregated level (i.e. if no match at the 7-digit level), we attempt to match at the next level of aggregation (i.e. 6-digit level) and impute a matching 7-digit-level and associated NAICS-Baseroot based upon the existing set

[37]Dropping administrative records in the CMF is a common practice in empirical research e.g., Bernard, Jensen and Schott (2006); Kehrig and Vincent (2021); White, Reiter and Petrin (2018); Hsieh and Klenow (2009).

[38]Indeed, the prospect of aligning LFTTD and material/product codes at the product level for manufacturing firms was one of the primary use cases outlined by Pierce and Schott (2012) in their description of this concordance.

Table A2: Value of "All Other" Products as Share of Costs/Shipments

| | *Share of Costs/Shipments* |
|---|---|
| *Panel A: Material Trailer File* | |
| 2002 | 30.9% |
| 2007 | 28.1% |
| 2012 | 21.6% |
| 2017 | 33.3% |
| *Panel B: Product Trailer File* | |
| 2002 | 0.4% |
| 2007 | 0.3% |
| 2012 | 0.3% |
| 2017 | 0.5% |

**Notes**: This table displays the value of manufactured products classified as "Not Elsewhere Specified or Indicated" (NESOI) as a share of total cost of materials (Panel A) or total value of shipments (Panel B).
**Source**: Authors' calculations using Economic Census publications (U.S. Census Bureau, 2024a).

of disaggregated (i.e. 7-digit) matches. We iterate up to the 4-digit level until we have matched all Census product codes to NAICS-Baseroots.[39]

Finally, once imports, exports, material input usage, and production are all aligned on a common product classification (6-digit NAICS-Baseroot), we proceed to the core measurement challenges: identifying intermediate input imports and allocating those imports to individual establishments, and identifying exports that are manufactured by the establishment (production-associated exports) and allocating those exports to individual establishments.

### A.1.3 Establishment-level Intermediate Imports

For an establishment $e$ of firm $f$, we calculate a set of products identified as intermediate inputs based on the set of products specified as being used as inputs by the establishment in the CMF-MAT. The set of intermediate products $\mathcal{M}_{ef}$ of establishment $e$ of firm $f$ is defined such that $p \in \mathcal{M}_{ef}$ if $mc_{efp} > 0$, where $mc_{efp}$ is the material cost of product $p$ used by establishment $e$ of firm $f$ as identified in the CMF-MAT.

Applying this set of products to import data is complicated by the fact that the LFTTD exists at the firm level, and thus there is the possibility for input products to match to more than one establishment. Formally, we can describe this possibility using the following notation: $\exists$ a product $p$ and establishments $e$ and $k$ such that $p \in \mathcal{M}_{ef}$ and $p \in \mathcal{M}_{kf}$. In these cases, we allocate imports based on the relative material costs as defined in the CMF-MAT. Hence, the first step in our construction of an establishment-level measure of intermediate input imports from country $m$ can be summarized as:

$$IMP^{MAT}_{efm} = \sum_{p \in \mathcal{M}_{ef}} \frac{mc_{efp}}{\sum_{e,p \in \mathcal{M}_{ef}} mc_{efp}} Imp_{fpm} \tag{A1}$$

[39]Beginning in 2017, product information was collected and published on a North American Product Classification System or NAPCS basis in the Economic Census (U.S. Census Bureau, 2003). We utilize concordances between 2017 NAPCS and 2012 Census product codes (U.S. Census Bureau, 2022b). Census material codes remain unchanged over the sample period.

which takes firm level imports $Imp_{fpm}$ of firm $f$ of product $p$ from country $m$ and allocates them to establishments, as intermediate inputs provided $p \in \mathcal{M}_{ef}$ and using the shares of material costs of product $p$ across all establishments of the firm $f$.

Since a non-trivial share of material inputs are reported under the NESOI category, imported inputs that are not directly matched to the materials reported by establishments may belong in this category. To account for this possibility, we proceed in two steps. First, we utilize the CMF-PROD and identify what are likely the set of produced (or, final goods) products for establishment $e$ following Boehm, Flaaen and Pandalai-Nayar (2019). Formally, for an establishment $e$ of firm $f$, we define the set of output products to be $p \in \mathcal{P}_{ef}$ if $prod_{efp} > 0$ where $prod_{efp}$ is the shipment value of product $p$ by establishment $e$ of firm $f$ as identified in the CM-PROD.

In the second step, we exclude products identified in the CMF-PROD from the list of imported products that are not explicitly identified as inputs of establishment $e$. The remaining set of imported products are most likely to be included in the NESOI category reported by the establishment in the CMF-MAT, and thereby classified as intermediate inputs.

One potential concern with our approach is the possibility that an establishment reports a particular product as both an input in production *and* an element of output, hence, residing at the "diagonal" of an input-output table. We show in Panel A of Table A3 that such instances represent a relatively small share of our material costs, due in part to the availability of establishment-level product data at the 6-digit level of disaggregation in the CMF-MAT and CMF-PROD. At the establishment-level, the overlap is less than 20 percent in any sample year, and typically closer to 15 percent as shown in Panel A, Table A3. However, if only 3-digit level detail of product codes were available, the overlap would be double or more. Nevertheless, while these "diagonal" cases would be captured as intermediate inputs under our current methodology, further research is warranted to better understand an establishment's production function when inputs and outputs match so precisely.[40]

The overlap identified in Panel A, Table A3 is lower than similar statistics in Antràs, Fadeev, Fort and Tintelnot (2024, Appendix Table A.8.). While a direct comparison is difficult because of numerous differences in sample construction, basis of calculation, etc., we highlight the important role of aggregation when using these trailer files. Panel B replicates the calculations of Panel A of Table A3, by aggregating the data to the level of the firm. Here we see *much* higher rates of overlap, more in line with what is shown in Antràs, Fadeev, Fort and Tintelnot (2024) which also uses a firm-level basis for their calculations.

Once this residual set of imported products is constructed, we allocate these imported products across establishments within the firm. In the absence of any other information, we use the NESOI product code value for establishment $e$ as a share of total NESOI values of the firm, denoted as $\eta_{ef}$. Hence, our final estimate of intermediate imports for a given product $r$ of establishment $e$ of firm $f$ from country $m$ is given by:

$$IMP^{I}_{efm} = IMP^{MAT}_{efm} + \sum_{p \notin \{\mathcal{M}_{ef}, \mathcal{P}_{ef}\}} \eta_{ef} Imp_{fpm}. \tag{A2}$$

Of the identified intermediate imports linked to establishments, 60% of the value is

[40]For example, an innovative approach is developed in Cox (2023). She creates detailed (HS6) steel-specific input-output tables using exclusion requests filed by U.S. importers in response to the 2018 U.S. steel tariffs. However, this level of detail is not available for all products.

Table A3: Overlap Between Input Products and Output Products

| | Share of Input Codes Matching Matching Product Codes (by value) | | | |
|---|---|---|---|---|
| | **2002** | **2007** | **2012** | **2017** |
| | *Panel A: Establishment-level Match* | | | |
| 6-digit | 14.5% | 16.0% | 14.5% | 19.4% |
| 4-digit | 25.8% | 28.7% | 29.6% | 29.0% |
| 3-digit | 44.5% | 46.8% | 45.0% | 44.2% |
| | *Panel B: Firm-level Match* | | | |
| 6-digit | 34.0% | 33.5% | 28.7% | 33.6% |
| 4-digit | 48.8% | 47.6% | 46.9% | 44.1% |
| 3-digit | 60.9% | 59.2% | 58.5% | 52.5% |

**Notes**: This table calculates the overall fraction of the value of input costs in which the input product code matches to a produced product code of the same establishment or firm. The 6-digit row is the detail available in the trailer files; the 4 and 3-digit rows re-calculates this statistic under more aggregated industry classifications.
**Source**: Authors' calculations using CMF and LFTTD.

allocated based on direct input matching as described in Equation A1, and the remaining are linked indirectly using the CMF-PROD as described in Equation A2. These statistics are shown in column (1), Table A4 across the sample years.

Table A4: Share of Imported Inputs Identified via Indirect Method

| | *Share of Total* |
|---|---|
| 2002 | 43.5% |
| 2007 | 42.3% |
| 2012 | 42.4% |
| 2017 | 56.8% |

**Notes**: This table displays the share of imports identified as inputs using the indirect method described in Equation A2.
**Source**: Authors' calculations using CMF and LFTTD.

It is important to highlight that the intermediate input share of imports in Table 3 is not directly comparable to the statistic in Johnson and Noguera (2012): "[t]rade in intermediate inputs accounts for as much as two thirds of international trade." The difference is between the emphasis on the establishment or the product. The output products produced by an establishment may be used downstream in further production—and thereby be classified as in input on a product-level basis—but that product should be considered a final product from the perspective of the establishment. Thus, while there should be some degree of alignment between these two definitions of input trade, they need not be identical.

### A.1.4 Production-Associated Exports

Using a similar approach as in Section A.1.3, we connect the production of a manufacturing establishment to its exports. The underlying challenge here is determining whether a firm engages in exports of a particular product that it did not produce in the United States. Exports of goods where the firm exports more than it produces is referred to as "carry-along trade" in the trade literature (Bernard, Blanchard, Beveren and Vandenbussche, 2018a). Examples of this could be re-exports or otherwise utilizing the wholesale/distribution services of the firm to export products made outside of its U.S. manufacturing establishments (such as agricultural or mining products), or by another firm entirely.

We construct a set of products identified as being produced by the establishment in the CMF-PROD: a product $p$ is in the set $\mathcal{P}_{ef}$, i.e., $p \in \mathcal{P}_{ef}$, if $prod_{efp} > 0$. Once again, the challenge is how to properly account for exports where multiple establishments of the same firm record the same product as being produced. Thus, in addition to specifying the establishment-specific list of products produced by the establishment, the exports need to be allocated across establishments when multiple establishments of the same firm report producing a given product. Our establishment-level measure of production-associated exports is therefore:

$$EXP^{PROD}_{efn} = \sum_{p \in \mathcal{P}_{ef}} \frac{prod_{efp}}{\sum_{e,p \in \mathcal{P}_f} prod_{efp}} Exp_{fpn}. \tag{A3}$$

# B Appendix: Additional Results

## B.1 The Import Source Content of U.S. Exports: Overall Patterns

This section documents core patterns in the embedded import source countries of U.S. exports by export destination. This measures how countries are connected through the United States based on actual establishment-level input and output measures that does not rely on proportionality assumptions or aggregation bias.

We first modify Equation (5) to notate bilateral GVC measures by sector as follows:

$$GVC_{mnst} = \sum_{e \in E_{mnst}} \left( \frac{\sum_r IMP^I_{emrt}}{GO_{est}} \sum_p EXP_{enpt} \right), \tag{A4}$$

where $E_{mnst}$ is the set of establishments in industry $s$ that import inputs from country $m$ and export products to country $n$ in year $t$. Thus, we first compute bilateral GVC measures for each establishment and then aggregate them across all establishments in industry $s$ participating in a particular supply chain of $(m, n)$. To compute the GVC share for each $(m, n, s, t)$, Equation (5) is divided by $\sum_{e \in E_{mnst}} \sum_{n,p} EXP_{enpt}$.

Table A5 shows the top country pairs of linked import source and export destinations based on the sum of the bilateral GVC share measure across all manufacturing sub-sectors. A striking feature in Table A5 is how Canada and Mexico occupy all of the top destinations for the input-output country pairs. We see evidence of "round-trip" behavior in the aggregate for both Canada and Mexico. While North America is a prominent input source in U.S. global value chains, countries such as China, Japan, Singapore, and Germany also occupy top bilateral positions as source countries.

Specific sectors within manufacturing reveal a richer portrait of the countries that are connected through global value chains in the United States. The top ten country-pair links

Table A5: Top GVC Country Pairs in the Manufacturing Sector, 2012

| | | GVC Share in Exports | |
|---|---|---|---|
| **Source** | **Destination** | **Total** | **By Destination** |
| Mexico | Canada | 0.39% | 1.98% |
| China | Canada | 0.34% | 1.72% |
| Mexico | Mexico | 0.32% | 2.23% |
| Canada | Canada | 0.27% | 1.36% |
| Canada | Mexico | 0.20% | 1.37% |
| Japan | Canada | 0.14% | 0.73% |
| China | Mexico | 0.12% | 0.79% |
| Singapore | Canada | 0.09% | 0.44% |
| Germany | Canada | 0.08% | 0.43% |

**Notes**: The first two columns in this table displays the top import and export country pairs, by bilateral GVC (measured in Equation (5), for the overall U.S. manufacturing sector. The last two columns display bilateral GVC as a share of overall manufacturing exports ("Total") and as a share of manufacturing exports by the destination ("By Destination"), respectively.
**Source**: Authors' calculations using CMF, LFTTD, and USA Trade Online (U.S. Census Bureau, 2024b).

for a select few sectors are shown in Table A6. For example, in the Pharmaceuticals sector, Ireland is remarkably the top input source for all top ten bilateral country-pairs, with imported inputs from Ireland linked to exports to a wide range of countries in Asia, Europe, and South America.

The patterns for the three other sectors also illustrate well-known features of industry linkages. For machinery and equipment, the top bilateral country pairs reflect U.S. exports to Canada that rely on some well-known manufacturing centers (Mexico, Germany, Japan, and Canada itself). Other top bilateral pairs link exports in the machinery and equipment sector to Australia via inputs from Canada and Mexico.

For motor vehicles and parts, USMCA countries naturally play a dominant role, with Mexico-Canada, Mexico-Mexico, and Canada-Canada occupying the top three positions. The impact of non-US automakers is evident as well, as inputs from Japan, Germany, and South Korea are connected to exports to Canada through U.S. operations. These are further direct evidence of how foreign direct investment (FDI), and, specifically, export-platform FDI, can influence patterns of global value chains (see Tintelnot (2016) and Antrás, Fadeev, Fort and Tintelnot (2022)).

For "Other Transport Equipment", the patterns also align with expectations, with a few surprises along the way. Two round-trip bilateral pairs—France-to-France and Japan-to-Japan—occupy the top two ranks, with links between imports sources from Japan, Canada, and the United Kingdom with exports to France also in the top ten. More surprising are imported inputs from Japan and the United Kingdom with the United Arab Emirates being prominent country-pair links. More generally, a striking feature of bilateral GVC links in other transport equipment is how distant the value chains are: nine of the top ten bilateral pairs would need to cross two oceans as part of the value chain moving from the source country, to the United States, and then to the destination country.

Table A6: Top GVC Country Pairs in Selected Manufacturing Sectors, 2012

| Source | Destination | GVC Share in Exports Total | By Destination |
|---|---|---|---|
| | **Pharmaceuticals** | | |
| Ireland | Italy | 0.69% | 11.04% |
| Ireland | Japan | 0.39% | 4.61% |
| Ireland | Belgium | 0.38% | 4.96% |
| Ireland | South Korea | 0.31% | 16.07% |
| Ireland | France | 0.30% | 5.05% |
| Ireland | Ireland | 0.27% | 9.74% |
| Ireland | Canada | 0.25% | 2.69% |
| Ireland | Brazil | 0.15% | 5.69% |
| Ireland | Mexico | 0.13% | 3.89% |
| | **Machinery and Equipment** | | |
| Mexico | Canada | 0.19% | 0.91% |
| Canada | Canada | 0.17% | 0.82% |
| Germany | Canada | 0.15% | 0.75% |
| Japan | Canada | 0.14% | 0.68% |
| China | Canada | 0.11% | 0.54% |
| Mexico | Mexico | 0.11% | 1.00% |
| United Kingdom | Canada | 0.10% | 0.48% |
| Mexico | Australia | 0.10% | 1.72% |
| Mexico | Germany | 0.10% | 3.17% |
| Canada | Australia | 0.09% | 1.56% |
| | **Motor Vehicles and Trailer** | | |
| Mexico | Canada | 1.18% | 2.73% |
| Mexico | Mexico | 1.15% | 5.95% |
| Canada | Canada | 0.75% | 1.73% |
| Japan | Canada | 0.67% | 1.54% |
| Germany | Mexico | 0.34% | 1.78% |
| Canada | Mexico | 0.34% | 1.74% |
| Japan | Mexico | 0.22% | 1.13% |
| Germany | Canada | 0.22% | 0.50% |
| Germany | Germany | 0.17% | 3.09% |
| South Korea | Canada | 0.16% | 0.37% |
| | **Other Transport Equipment** | | |
| France | France | 0.23% | 3.29% |
| Japan | Japan | 0.22% | 2.88% |
| Japan | United Arab Emirates | 0.19% | 2.90% |
| Japan | China | 0.19% | 2.68% |
| Japan | France | 0.16% | 2.28% |
| Canada | France | 0.14% | 2.04% |
| United Kingdom | France | 0.14% | 2.00% |
| France | Brazil | 0.13% | 2.27% |
| United Kingdom | United Arab Emirates | 0.11% | 1.70% |
| France | Japan | 0.11% | 1.46% |

**Notes**: The first two columns in this table displays the top import and export country pairs, by bilateral GVC (measured in Equation (5), for select industries in the U.S. manufacturing sector. The last two columns display bilateral GVC as a share of overall industry exports ("Total") and as a share of industry exports by the destination ("By Destination"), respectively.
**Source**: Authors' calculations using CMF, LFTTD, and USA Trade Online (U.S. Census Bureau, 2024b).

## B.2 Regional Trade Agreements and Additional Gravity Results

Table A7: Regional Trade Agreement Country Pairs (2017)

**Panel A: RTAs with the United States (2017)**

*All bilateral pairs of the below form RTAs each with the U.S.*

| | |
|---|---|
| Australia | Israel |
| Bahrain | Jordan |
| Canada | Mexico |
| Chile | Morocco |
| Colombia | Nicaragua |
| Costa Rica | Oman |
| Dominican Republic | Panama |
| El Salvador | Peru |
| Guatemala | Singapore |
| Honduras | South Korea |

**Panel B: Country-pairs where all three (including U.S.) are under an RTA (2017)**

| | | | |
|---|---|---|---|
| AUS-CHL | COL-SLV | ISR-CAN | OMN-SGP |
| AUS-KOR | CRI-CAN | ISR-MEX | PAN-CAN |
| AUS-SGP | CRI-CHL | JOR-BHR | PAN-CHL |
| BHR-JOR | CRI-DOM | JOR-CAN | PAN-CRI |
| BHR-MAR | CRI-GTM | JOR-MAR | PAN-HND |
| BHR-OMN | CRI-HND | JOR-OMN | PAN-MEX |
| BHR-SGP | CRI-MEX | JOR-SGP | PAN-PER |
| CAN-CHL | CRI-NIC | KOR-AUS | PAN-SGP |
| CAN-COL | CRI-PAN | KOR-CAN | PAN-SLV |
| CAN-CRI | CRI-PER | KOR-CHL | PER-CAN |
| CAN-HND | CRI-SGP | KOR-PER | PER-CHL |
| CAN-ISR | CRI-SLV | KOR-SGP | PER-COL |
| CAN-JOR | DOM-CRI | MAR-BHR | PER-CRI |
| CAN-KOR | DOM-GTM | MAR-JOR | PER-HND |
| CAN-MEX | DOM-HND | MAR-OMN | PER-KOR |
| CAN-PAN | DOM-NIC | MEX-CAN | PER-MEX |
| CAN-PER | DOM-SLV | MEX-CHL | PER-PAN |
| CHL-AUS | GTM-CHL | MEX-COL | PER-SGP |
| CHL-CAN | GTM-COL | MEX-CRI | SGP-AUS |
| CHL-COL | GTM-CRI | MEX-GTM | SGP-BHR |
| CHL-CRI | GTM-DOM | MEX-HND | SGP-CHL |
| CHL-GTM | GTM-HND | MEX-ISR | SGP-CRI |
| CHL-HND | GTM-MEX | MEX-NIC | SGP-JOR |
| CHL-KOR | GTM-NIC | MEX-PAN | SGP-KOR |
| CHL-MEX | GTM-SLV | MEX-PER | SGP-OMN |
| CHL-NIC | HND-CAN | MEX-SLV | SGP-PAN |
| CHL-PAN | HND-CHL | NIC-CHL | SGP-PER |
| CHL-PER | HND-COL | NIC-CRI | SLV-CHL |
| CHL-SGP | HND-CRI | NIC-DOM | SLV-COL |
| CHL-SLV | HND-DOM | NIC-GTM | SLV-CRI |
| COL-CAN | HND-GTM | NIC-HND | SLV-DOM |
| COL-CHL | HND-MEX | NIC-MEX | SLV-GTM |
| COL-GTM | HND-NIC | NIC-SLV | SLV-MEX |
| COL-HND | HND-PAN | OMN-BHR | SLV-HND |
| COL-MEX | HND-PER | OMN-JOR | SLV-NIC |
| COL-PER | HND-SLV | OMN-MAR | SLV-PAN |

**Notes**: This table identifies sample criteria that satisfy the RTA ($m$ & US, $n$ & US) indicator (Panel A) and RTA ($m$, $n$, US) indicator (Panel B) as described in the text.

Table A8: Gravity Model of GVC, Annual Estimates 2002-2017

| | Dependent Variable: Log Bilateral GVC | | | |
|---|---|---|---|---|
| | 2002 | 2007 | 2012 | 2017 |
| Variable | (1) | (2) | (3) | (4) |
| Round-trip ($m$=$n$) | 1.45*** | 1.48*** | 1.49*** | 1.139*** |
| | (0.266) | (0.228) | (0.227) | (0.244) |
| Log Distance ($m \rightarrow$US$\rightarrow n$) | 0.316 | -1.401*** | -0.371 | -0.516** |
| | (0.254) | (0.247) | (0.237) | (0.212) |
| Log Distance ($m$ to $n$) | -0.206*** | -0.147*** | -0.178*** | -0.174*** |
| | (0.0220) | (0.0217) | (0.0210) | (0.0194) |
| Exporter F.E. | yes | yes | yes | yes |
| Importer F.E. | yes | yes | yes | yes |
| Observations | 26,000 | 29,500 | 29,000 | 32,000 |

**Notes**: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
**Source:** Authors' calculations using the CMF, LFTTD, and WIOD.

## B.3 The Role of Industry Definition in GVC Measures

In addition to exploring the role of aggregation bias in GVC measurement we also highlight the role of industry mis-classification that arises due to choice of the source data for identifying industry. Large firms play an out-sized role in mediating goods trade (e.g., Freund and Pierola (2015)). These traders also tend to operate across multiple sectors (e.g., Handley et al. (2021)). However, establishments may not be the primary economic unit in all statistical collections that would correctly capture the heterogeneity in firms' activities across sectors. For example, statistical collections in many countries only collect input and output information at the level of the firm's main industry (e.g., Belgium studied by Bems and Kikkawa (2021)). If firms are only required to report a primary industry, it could bias GVC measures.

To explore the extent and direction of bias in GVC measurement due to industry misclassification, we start with the establishment level information and define $s$ as the primary sector of the firm. A primary sector is defined as the sector accounting for the highest share of the firms' payroll.[41] We construct an analog of $gvc_t^I$ except that we use the definition of sector based on firms' primary industries as follows:

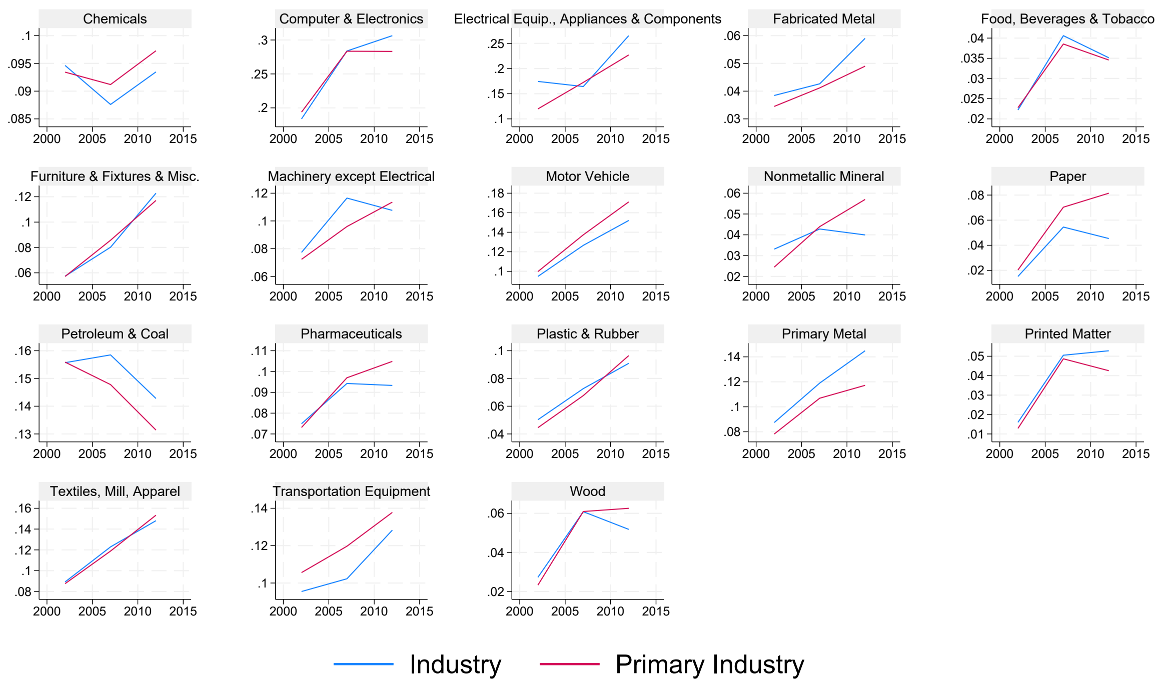
$$gvc^{I\star}{}_t = \frac{\left[\sum_{f,e,s^\star} EXP_{fes^\star t} \frac{\sum_{f,e,s^\star} IMP^I_{fes^\star t}}{\sum_{f,e,s} GO_{fes^\star t}}\right]}{\sum_{f,e,s^\star} EXP_{fes^\star t}}. \tag{A5}$$

*A priori*, the direction of the measurement bias introduced by using the primary industry of the firm is not obvious and is an empirical question. At the national level, we find that $gvc^{I\star}{}_t$ is 10% in 2002 and 13% in 2007 and 2012, aligning very closely with $gvc_t^I$.

However, the aggregate statistics mask variation in both levels and trends within subsectors as displayed in Figure A1 where $gvc^{I\star}{}_{st}$ is in red and $gvc_{st}^I$ is in blue. GVC measures for Food, Furniture, Plastic and Rubber, Motor Vehicle, and Textiles are less sensitive to the choice of industry definition in both level and trend. While both measures track closely in levels over 2002 and 2007 for Computer and Electronics, Fabricated Metal, Machinery, Non-metallic Mineral, Paper, Pharmaceuticals, Primary Metal, Printed Matter, and Wood, they diverge in 2012. For the other three sub-sectors (Chemicals, Electrical Equipment, Petroleum and Coal, Transportation Equipment), broadly, the two measures track in terms of trend but differ in level.

[41] We create payroll shares by each 6-digit industry of the firm.

Figure A1: Comparison of $gvc_t^I$ and ${gvc^{I\star}}_t$, 2002, 2007, 2012




**Notes:** This figure plots GVC for 3-digit manufacturing sectors. "Industry" defined in Equation 3 and "Primary Industry" defined in Equation A5.
**Source:** Authors' calculations using CMF and LFTTD.

## B.4 The Role of Establishment versus Firm Aggregation in GVC Measures

If a firm is the most disaggregated economic unit in a statistical collection, even when industry is reported on the basis of its establishments' activities, GVC measures constructed from firm-industry data may suffer from aggregation bias. To explore the extent of aggregation bias due to ignoring establishment level heterogeneity, but not suffering from industry mis-classification, we aggregate across all establishments in a given sub-sector $s$ for firm $f$ to create a firm-industry based measure of sectoral GVC as follows:

$$gvc_{st}^{F} = \frac{1}{\sum_{f,e} EXP_{fest}} \sum_{f} \left[ \sum_{e} EXP_{fest} \frac{\sum_{e} IMP_{fest}^{I}}{\sum_{e} GO_{fest}} \right]. \tag{A6}$$

We find that the average absolute difference between $gvc_{st}^{E}$ and $gvc_{st}^{F}$ across sectors is very small (0.005) and the correlation is very high (0.97).[42] This suggests that industry mis-classification is a more important source of bias than availability of firm-industry information only in GVC measurement.

[42]The results are available upon request.