Global Value Chains: Firm-Level Evidence from the United States*

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Abstract

Using confidential microdata from the U.S. Census Bureau, we measure the extent of international inputs embodied in U.S. exports at the level of the establishment and firm, providing a new way to characterize global value chains (GVCs) in the United States between 2002-2017. A direct link between imported inputs, production, and exports at a granular level provides a natural benchmark against which alternative measures of GVCs—such as those built from combining national-level input-output tables—can be assessed. Such comparisons yield insights on the role of aggregation bias and proportionality assumptions on multi-country supply chain measurement. This new data resource provides a window into the ways U.S. firms are linked to multiple markets through both foreign sourcing and foreign sales. In addition, we quantify the roles of gravity and regional trade agreements on the magnitude and concentration of these multi-country linkages. The analysis provides insights into the factors influencing the flows of global value chains and their resilience.

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1 Introduction

Over the past two decades, there has been a great deal of research documenting the extent of, and trends in, global value chains (GVCs) around the world.[1] Most of this research has employed input-output tables. This is largely because of the increased prevalence of national, bilateral, and global industry-level input-output tables. Such tables have been invaluable in providing a portrait of the growth in GVCs over time.

Yet global value chains, especially those in manufacturing, are inherently about firms – even establishments. It is not an industry that decides to source inputs from abroad, export products to a new market, or establish a factory in one country in order to serve as an export platform to other countries. Moreover, through extensive use of proportionality assumptions, industry and national measures of GVCs constructed from input-output tables are potentially subject to a range of biases, most notably aggregation bias. These biases can distort the overall degree of measured vertical specialization or the true allocation of imported input usage across countries. Indeed, one of the first papers to document global value chains at the firm level, Bems and Kikkawa (2021), shows that for Belgium, the use of input-output tables underestimates the true share of imported inputs embodied in exports.

The purpose of our paper is to develop, document, and analyze measures of GVCs for U.S. manufacturing establishments and firms with detailed micro-level datasets from the U.S. Census Bureau. While there have been numerous case studies of global value chains for particular firms, there have been few papers that calculate firm- or establishment-based GVCs for an entire country, and, there have been none that do this for the United States.

One reason for the paucity of such research is a host of measurement challenges to connect import and export transactions to production activity in the United States. For example, firms may import intermediate inputs for transformation within the U.S. and also import final goods that have been assembled in foreign factories. Yet existing transaction-level trade data for the U.S. does not include information on intended use. Thus, any micro-level GVCs measure must confront the challenge of credibly classifying firms' imports as intermediate inputs or final goods. Moreover, the out-sized role of multi-industry firms in U.S. goods trade implies that we must also be able to credibly ascertain which establishments of a firm, operating across different industries, are the most likely users of an imported input in their production processes. Yet the data does not, by itself, identify which establishments import or export a particular product. Related challenges exist connecting export transactions to

[1] See, for example, Hummels et al. (2001), Koopman et al. (2014), Timmer et al. (2014), Johnson and Noguera (2017), and Antràs and de Gortari (2020).

production activity at the establishment level. In summary, the wide range of firm-level activities requires one to allocate import transactions into intermediate and final goods; the presence of multi-industry firms requires one to move down to the level of establishments to properly conduct that allocation.

We address these well-known measurement challenges to construct establishment-level GVCs for 2002, 2007, 2012, and 2017 by combining three confidential, micro-level datasets maintained by the U.S. Census Bureau. First, the Longitudinal Firm Trade Transactions Database (LFTTD) allows us to observe the universe of goods export and import flows for individual U.S. firms (Kamal and Ouyang, 2020). Second, we rely on the Census of Manufactures (CMF) to obtain detailed information on establishment-by-product-level output and input use (U.S. Census Bureau, 2022b) that forms the basis for national input-output tables. Finally, the Longitudinal Business Database (LBD) enables us to characterize firms' activities across all sectors of the economy (Chow, Fort, Goetz, Goldschlag, Lawrence, Perlman, Stinson and White, 2021), focusing predominantly on manufacturing firms. Pairing these datasets allows one to link the products imported by a firm to the inputs specified as being inputs by the establishment of a firm, allowing the researcher to classify and allocate such imports as inputs to individual establishments. Similarly, linking the products exported by a firm to the products produced by establishments of that firm allows the researcher to assign export products to an individual establishment. The result is a view of production flows through the U.S. economy at a level that was previously impossible. Overall, our methodology identifies about 60 percent of firm imports as imported inputs used in production by establishments, and about 70 percent of firm exports as produced exports by establishments.

We combine an establishment's exports by destination country with the material input use by source country to construct our primary measure of GVCs. This measure captures the imported input content of an establishment's exports. We can construct it at the input product, output product, source country, destination country, and establishment level.

This data reveals a number of new facts about production flows through the U.S. manufacturing sector. We first document our GVC measure for U.S. manufacturing overall; we add up the establishment-level GVC measures and then normalize by total manufacturing exports. Our measure steadily increases between 2002 and 2012 and then slows somewhat in 2017. This contour stands in contrast to a GVC measure constructed analogously to an input-output table-based measure, which exhibits a lower level with essentially no growth from 2007 to 2017, implying a downward aggregation bias that is increasing over the 2002-2017 period. This comparison reveals how aggregation bias can distort the central message on the evolution of international production sharing in U.S. manufacturing in the past two decades – whether it has essentially stopped and even decreased, or not.

We unpack our overall manufacturing GVC measure in several ways. Construction of our measure at the 3-digit NAICS level reveals a great deal of heterogeneity across industries and over time. We also compute our GVC measure by source-destination country pairs. We find, not surprisingly, that the most prominent pairs are those involving the USMCA countries and/or China. For particular 3-digit sectors, the patterns are also consistent with intuition. That said, there is considerable "depth" in our measures with the top source-destination country-pair typically accounting for less than one-half of a percentage point of the overall GVC share of exports.

This novel data allows one to create micro-level estimates of country input cost shares that are independent of estimates using industry-level "proportionality" assumptions that typically form the basis for multi-country input-output measures. The proportionality assumption is employed because national input-output tables do not categorize the source countries of inputs, and because import data do not indicate the sectors for which the imports are used as inputs. Hence, global input-output tables, such as WIOD, typically assign the imported inputs from a country to sectors in proportion to the overall use of the inputs by a sector. We aggregate the industry-by-country cost shares from our data and compare them to those calculated from the WIOD tables. The overall correlation across all manufacturing industries is 0.64, at once indicating a clear positive link, and, at the same time, indicating the distinctiveness of our measure. In particular, we show that for particular industries, such as pharmaceuticals and basic chemicals, the correlation is quite low. We also calculate the correlation of bilateral import-to-U.S., export-from-U.S. (hereafter, import-export) country-pair GVC statistics for a given industry between our Census-based measures and the WIOD measures. The correlation for manufacturing overall is 0.42.

Proportionality, by its nature, generates "smoothing" in GVC measures. For example, under proportionality, as long as total imported inputs by a U.S. sector, and exports from that sector, are positive, the GVC measure will at the sector-level will be positive for all *import-export country-pairs*. However, with our data we show that for several sectors more than 10 percent of import-export country pairs have the GVC measure equal to zero. These evaluations of proportionality should prove useful to all researchers seeking to question whether this assumption has a significant bearing on their empirical results.

We also study the determinants of GVC flows using a gravity framework. Because all of our GVC flows go through the U.S., our gravity concept involves three, not the usual two, countries. This facilitates multiple notions of distance. We examine the role of the combined distance in the flows of the inputs from the source country to the U.S., and from the U.S. to the destination country. We also examine the direct distance from the source country to the destination country. A special case of the direct distance arises with round-trip production – where the source and destination countries are the same. For example, a U.S. establishment imports intermediates from Canada, produces a good, and then exports it back to Canada. Our gravity estimation results reveal the importance of all of the above notions of distance. The most striking result is for an indicator variable for the round-trip case. All else equal, the presence of round-trip production is associated with 3.7 times higher GVC flows than otherwise.

Finally, we study the impact of regional trade agreements (RTA) on GVCs. An extensive literature has studied the impact of RTAs in a gravity context. Johnson and Noguera (2017), in particular, studies the effect of RTAs on GVCs, as captured by their value-added exports (VAX) measure. We extend this research by focusing on the trilateral nature of our linkages. We examine the effects of RTAs involving combinations of the source-U.S.-destination countries. We find that RTAs increase GVC participation. Strikingly, even in the presence of RTAs, the round-trip indicator variable discussed above is still economically and statistically significant. Overall, our results speak to how RTAs affect the importance of the countries involved in U.S. GVC flows.

To summarize, our novel GVC measures constructed from the establishment level for the U.S. manufacturing sector enable us to uncover new patterns in globalization trends, the extent of biases in using industry-level data, the consequences of the proportionality assumption, and, finally, the role of gravity in GVCs, and of RTAs on GVCs.

1.1 Literature Review

Understanding the patterns of international trade through the lens of supply chains that cross country borders multiple times has proven to be essential. From earlier contributions by Yi (2003) and Hummels, Ishii and Yi (2001), to more recent works by Bernard, Jensen, Redding and Schott (2018) and Antràs and de Gortari (2020), both theoretical and empirical literature on GVCs has made enormous progress.[2] Our contribution to this literature involves studying GVC activities at a granular level using U.S. microdata, while earlier works conceptualize or measure GVCs at an aggregate level.

There is a small existing literature that focuses on the granular nature of global value

[2] Antrás and Chor (2022) offer a comprehensive overview of this literature.

chains. One of the most well-known issues when measuring global value chains using industry-level data is downward aggregation bias — that is, GVC measures based on industry-level data are likely to underestimate the actual degree of GVC engagement by ignoring potential correlations between import and export activities across firms within industries. Koopman, Wang and Wei (2014) show this in the case of China, and De La Cruz, Koopman, Wang and Wei (2013) do the same for Mexico. Flaaen, Kamal, Lee and Yi (2024) show that the aggregation bias grew between 2002-2017 in the U.S.

Along these lines, the two most closely related papers to our paper are Kee and Tang (2016) and Bems and Kikkawa (2021). Both papers construct GVC measures using firm-level data. The former paper focuses on processing firms and constructs measures of the domestic value-added of exports for China, and the latter paper constructs the imported input content of exports for Belgium. The former paper finds that the domestic value-added embodied in exports in China actually increased post-2000, and studies potential causes of this outcome. The latter paper finds that the import content of exports in Belgium rose over time. Both papers also find evidence of aggregation bias. Building on these recent papers, our paper highlights additional issues associated with using industry-level input-output tables in measuring GVCs. For example, we extend and elaborate on work by Feenstra and Jensen (2012) to empirically assess the import proportionality assumption embedded in most readily available industry-level input-output tables.

The LFTTD data offer great detail on establishments' import and export activities at the transaction level, and thus many papers have studied interesting questions using this database. Building on the construction of LFTTD by Bernard, Jensen and Schott (2009) and Kamal and Ouyang (2020), numerous papers have further connected this database to other microdata from the U.S. Census to explore the relationship between firms' or establishments' trading activities and various other outcomes.—e.g., see Handley, Kamal and Ouyang (2021), Boehm, Flaaen and Pandalai-Nayar (2019), Handley, Kamal and Monarch (2020), and Ding (2023) among others. Our work contributes to this literature by identifying trade transactions directly connected to manufacturing activities using the Census of Manufactures (CM) trailer files. This work extends and refines efforts to allocate exports to establishments in Boehm, Flaaen, Pandalai-Nayar and Schlupp (2021) and integrates that work to import activity. Moreover, as highlighted by Fort (2023), a salient feature of modern manufacturing firms is their involvement in a substantial amount of non-manufacturing activities. This aspect is particularly relevant for measuring GVCs as we must connect firms' import and export activities through the value-added created by their manufacturing activities. To the best of our knowledge, our paper is the first to measure the GVC engagement of U.S. manufacturing establishments directly related to their core manufacturing activities.

Patterns of GVCs can also fit into the standard gravity framework, allowing us to conveniently explore the role of various trade policies in shaping GVCs. Expanding upon earlier works by Noguera (2012), Johnson and Noguera (2017) Laget, Osnago, Rocha and Ruta (2020), and many others, we document the gravity relationship for GVCs centered around U.S. manufacturing firms, using accurate measures of GVCs derived from detailed establishment-level information. This analysis is crucial for evaluating the resilience of GVCs, a topic that has garnered significant attention in recent trade policy discussions.

The rest of the paper is organized as follows. Section 2 details our methodology for constructing establishment-level GVC numbers from U.S. Census administrative data on exports and imports (LFTTD), as well as the Census of Manufactures and their associated trailer files. Section 3 presents several cuts of our GVC measures. The next section presents our gravity and resiliency regression results, and the final section concludes.

2 Measuring Global Value Chains in the United States

Any micro-level approach to measuring global value chains must confront a number of conceptual and practical difficulties that are typically veiled in traditional industry-level input-output analysis. In this section, we describe the core datasets underlying our measures and discuss our methodology for constructing establishment-level measures of GVCs.

2.1 Data Sources

The construction of novel measures of global value chains we highlight in this paper entails combining information from two primary confidential, micro-level datasets maintained by the U.S. Census Bureau. In this section, we describe the key features of each of the data sets that are central to our analysis.

The Longitudinal Firm Trade Transactions Database (LFTTD) links specific international trade transactions to individual firms in the United States (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. The LFTTD is effectively a firm-level dataset, whereas the linking of inputs and outputs in a production chain should ideally take place at the level of an individual establishment.

We rely on the Census of Manufactures (CMF) to obtain detailed information on establishment-level inputs and outputs. 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, 2022b). The CMF is a survey sent to the universe of plants in the manufacturing sector with questions on detailed input usage, product-level shipments, energy usage, inventories, and much more.[3]

2.2 Sample Criteria

Table 1: 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.

Given our focus on the linkages in manufacturing production activity in the United States, our sample includes all establishments in the manufacturing sector as reported on the CMF. We further restrict our sample to firms with non-negligible manufacturing activity in terms of

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

employment and sales, to assist in removing any distortions from large wholesale firms.[4] We report the number of firms and establishments in each year in our analysis sample in Table 1. There are 153,000, 152,000, and 137,000 firms in 2002, 2007, and 2012, respectively; there are 201,000, 198,000, and 179,000 manufacturing establishments in 2002, 2007, and 2012, 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 almost 40% of national employment and over 60% of employment at large (employs over 500 workers) firms in the U.S. economy (Handley, Kamal and Ouyang, 2021).

2.3 Connecting Trade Flows Associated with Production Activity

A careful study of global value chains connecting U.S. manufacturing with the rest of the world has become a difficult task, as firms associated with the transformation of goods have become more complex in their structure and more diversified in their location of activity (see Fort (2023) for more detailed discussion). With respect to the measurement of the trade flows that are associated with manufacturing production activity, the research must confront two principal challenges.

The first challenge arises from recognizing that a modern manufacturing firm in the United States undertakes a variety of activities, a portion of which may be classified outside of manufacturing.[5] Indeed, in extreme form this is captured by the "factoryless" goods-producing firms studied in Bernard and Fort (2015) and Bayard et al. (2015). When the expansion of global supply chains involves some final assembly also occurring outside of the U.S., then not all firm-level imports should be classified as intermediate inputs. When importing final products intended for direct sale downstream, the firm is undertaking wholesale/retail activities, and thus such shipments would not be inputs from the perspective of U.S. production operations. Similarly, a goods-producing firm may undertake some activities as a wholesaler, some activities producing and selling agricultural goods, and some activities

[4] We have not disclosed the specific thresholds but this restriction ensures that we include firms with a reasonable manufacturing footprint in the United States.

[5] A well-known example of this type of firm behavior is in the automotive sector, one that is also quantitatively important. Many automakers produce some models in the United States with a wide variety of imported content, while also importing finished cars to be sold to U.S. consumers.

in manufacturing. When this is the case, it is a challenge to connect exports to the relevant unit of manufacturing output.

The prevalence of multi-industry firms in U.S. manufacturing was highlighted in Ding (2023), and the fact that the bulk of trade value is mediated by large, multi-unit, and multi-industry firms dates back to at least Bernard et al. (2009). We extend these points in Table 2 by reporting the number of six and four-digit industries (based on NAICS) that firms operate in according to their trading status. The typical non-trading firm operates in roughly a single six-digit and single four-digit industry, and this remains stable over the 15 year period of our sample; firms that only export and only import exhibit a very similar average number of six-digit and four-digit industries of operation. However, firms that both export and import have very diverse industrial activities—they operate in roughly 8 six-digit and 5 four-digit industries.

Table 2: Number of Industries by Trader Type and Year

Trader Type	**Year**	**4-digit Industry**	**6-digit Industry**
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
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
Exporter-Importer	2002	5.68	9.54
Exporter-Importer	2007	4.91	8.21
Exporter-Importer	2012	4.74	7.56
Exporter-Importer	2012	4.72	7.42

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

We also note a downward trend in the number of four- and six-digit industries for each trader type. Although it is beyond the scope of this paper to disentangle the reason, we note that the 2002 through 2012 period is characterized by two major shocks that affected

U.S. manufacturing firms. First, China's accession to the World Trade Organization in 2001 has been linked to declines in U.S. manufacturing employment between 2001 and 2007 (Acemoglu, Autor, Dorn, Hanson and Price, 2016; Bloom, Handley, Kurman and Luck, 2019; Pierce and Schott, 2016). Second, the 2008-2009 Great Recession saw a steep decline in international trade relative to gross domestic product described also as a period of the "Great Trade Collapse" (Baldwin, 2009). Handley, Kamal and Ouyang (2021) document the impact of these two major shocks on U.S. good traders and find that U.S. trading firms have been shifting away from goods-producing to services-providing industries between 1992 and 2019 and this pattern is more pronounced for firms that export. By construction, firms that both export and import contribute the most to measures of GVC, and hence these statistics highlight the need to account for heterogeneity in firms' activities across multiple industries.

A second but related challenge comes from the fact that the most detailed trade transaction data available from the LFTTD does not identify the intended use of an import transaction, nor the associated establishment of an import or export transaction. Ignoring the industry-level heterogeneity within a firm imposes an artificial industry definition at the level of a firm, rather than on a production activity that occurs at the level of an establishment. 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. Without further information, it is unclear how the researcher should allocate the multiple inputs to those multiple output products or countries. 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? An establishment-level perspective that splits the firm's production into separate industries would have greater success in connecting inputs and exports to output.

The traditional approaches in the literature for getting around these difficulties each suffer from drawbacks. One approach that relies on the published *industry-level* input-output tables to classify imports at the *firm-level* will suffer from aggregation bias as well as industry misclassification.[6] A second approach is to use product-level concordances to assign imports into intermediate or final good categories. This approach can yield spurious assignment when applied to firm-level data, as an intermediate-good-producing firm may nevertheless also import a similar product to sell to downstream consumers. It would be incorrect to assign this import as an intermediate input to the firm. Thus, the notions

[6]It is important to note that while the published supply and use tables are constructed from plant-level survey evidence—and hence do not have industry misclassification built in—issues arise when applying a firm to a single industry column or row of these published tables.

of imported intermediate and produced exports must be defined at the level of individual establishments that have a unique concept of industry.

We propose an alternative approach that exploits the micro-level data that forms the basis of the published input-output accounts, and will allow greater flexibility and detail on individual firm (and establishment) activities. This information is contained in two supplemental data files to the core CMF: the Products Trailer File (CMF-PROD), and the Materials Trailer File (CMF-MAT). The core CMF datasets contain input and output information at the establishment level, however, these supplemental datasets contain detailed information on the *products* produced and *materials* used in the establishment's production process. These files enable us to circumvent the above-described challenges faced when using industry input-output links or product-level concordances to classify imported intermediate inputs.

Our approach does come with its own set of challenges and caveats. While rich in additional detail, the CMF trailer files have historically been under-used by researchers and thus (or, because) they require more extensive cleaning.[7] We describe the cleaning procedures in detail in section 2.4.1. Second, our micro-level data allows us to account for a firm's import and export activity; because we cannot track product flows within the United States—unlike some countries that contain such data through VAT reporting guidelines—we are unable to account for indirect import and export activity through domestic supply linkages.[8] This latter feature has been studied extensively in the context of Belgium by Dhyne, Kikkawa, Mogstad and Tintelnot (2021). Hence, we view our measures as *direct* GVC measures and a lower bound of the true degree of foreign integration in U.S. production activity.

We describe our methodology for connecting imports and exports to individual manufacturing establishments in Section 2.4.

[7]Some notable examples that use the material or product trailer files include Atalay (2014); Bernard, Jensen, Redding and Schott (2010); Ding, Fort, Redding and Schott (2022). However, the research questions in these papers are very different from our application.

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

2.4 Constructing Establishment-Level GVC Measures

2.4.1 Aligning CMF Trailer Files and LFTTD Trade Data

While the CMF product and trailer files are core inputs into the construction of the make and supply/use tables, respectively, by the U.S. Bureau of Economic Analysis, the microdata are seldom used by researchers. These supplementary survey forms to the core Census of Manufacturers ask respondents to identify the products produced and consumed (and their corresponding value) from a series of pre-populated product codes.

The first step with these raw trailer files is to identify and remove administrative 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 a significant share of value coming from 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 total (in terms of value), and cannot be directly linked to product codes in the LFTTD.

After removing aggregate and balancing codes, the next step in cleaning is to concord the NAICS-level product codes from the trailer files to a 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 NAICS product codes and HTS/Schedule B codes to a common NAICS-Baseroot product basis.[9] This is not a straightforward match since many NAICS product codes in the trailer files are not found in the concordance. We apply an iterative matching process. For NAICS 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 of disaggregated (i.e. 7-digit) matches. We iterate up to the 4-digit level until we have matched all NAICS product codes to NAICS-Baseroots.

Once we have imports, exports, material input usage, and production all aligned on a common product classification, we can then proceed to the core measurement challenges: identifying intermediate input imports and allocating those imports to individual estab-

[9]Indeed, the prospect of aligning LFTTD and Material/Product codes all 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.

lishments, and identifying production-associated exports and allocating those exports to individual establishments.

2.4.2 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. Formally, 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:

$$IMP^{MAT}_{efm} = \sum_{p \in \mathcal{M}_{ef}} \frac{mc_{efp}}{\sum_{e,p \in \mathcal{M}_{ef}} mc_{efp}} Imp_{fpm} \tag{1}$$

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.

While this is the most straightforward accounting for intermediate inputs that are directly identified by the establishment, there is a concern that products included in the NESOI category are not accounted for and would therefore lead to a nontrivial downward bias in intermediate imports. To resolve this, 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, thereby residing at the "diagonal" of an input-output table. We show in Table 3 that such instances represent a relatively small share of our material costs, in part due to the available 6-digit level of disaggregation available to us in the CMF-MAT and CMF-PROD microdata. On the whole the overlap is less than 20 percent in any year of our data, and typically closer to 15 percent. As shown in Table 3, if we only had 3-digit level detail of product codes, this overlap would be much more significant. As it stands, these cases should nevertheless be captured as intermediate inputs, given the sequencing of our procedure described above.

Table 3: Overlap Between Input Products and Output Products

	Share of Input Codes Matching Product Codes (by value)			
	2002	**2007**	**2012**	**2017**
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%

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. The 6-digit row is the detail available in the trailer files; the 4 and 3-digit rows calculate how this number would change if less detail was available.
Source: Authors' calculations using the CMF.

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

$$IMP^{I}_{efm} = IMP^{MAT}_{efm} + \sum_{p \notin \{\mathcal{M}_{ef}, \mathcal{P}_{ef}\}} \eta_{ef} Imp_{fpm}. \tag{2}$$

We report the share of firms' imports that we identify as imported inputs in column (1) of Table 4. On average, we allocate about 60% of the average firm's imports to its establishments as intermediate inputs using CMF-MAT and CMF-PROD. This share is similar to Boehm, Flaaen and Pandalai-Nayar (2019) who classify 64% of manufacturing imports as intermediates in 2007. Their methodology used industry-level averages of product lists intended for final use from the CMF-PROD, with the remaining products presumed to be intermediate inputs or capital investment goods.

Of the identified intermediate imports linked to establishments, 60% of that value is allocated based on direct input matching as described in Equation 1, and the remaining are linked indirectly using the CMF-PROD as described in Equation 2. For the representative manufacturing establishment, shown in Table 4, imported inputs represent between 14 and 18 percent of the total cost of materials.

Table 4: Aggregate Manufacturing Statistics

	Intermediate Share of Firm Imports	"Produced" Export Share of Total	Import Cost Share	Exports Share of Shipments
2002	56.9	69.8	14.0	7.7
2007	60.9	70.6	17.6	9.1
2012	62.9	69.8	16.9	10.3
2017	58.5	68.9	18.4	10.4

Notes: Column (1) displays the establishment share of total imports that are identified as intermediate inputs; column (2) displays the share of total firm exports that are identified as being produced by manufacturing establishments; column (3) reports the share of matched imported inputs in cost of materials (CM); and column (4) reports the share of allocated exports in total value of shipments (TVS);
Source: Authors' calculations using CMF and LFTTD.

It is important to highlight that this measure of the intermediate input share of imports is not directly comparable to the two-thirds statistic of the share of intermediates in trade popularized by Johnson and Noguera (2012). The difference lies in whether the emphasis is 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 alignment between these two definitions of input trade, they need not be identical.

2.4.3 Production-Associated Exports

Using a similar approach as in Section 2.4.2, we can 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. 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 plants (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, we must also share out the exports across establishments when multiple establishments of the same firm report producing a given product. Our establishment-level measure of production-associated exports is therefore:

$$EXP_{efn}^{PROD} = \sum_{p \in \mathcal{P}_{ef}} \frac{prod_{efp}}{\sum_{e,p \in \mathcal{P}_f} prod_{efp}} Exp_{fpn}. \tag{3}$$

We report the share of firms' exports that we assign as exports produced by their establishments using Equation 3 in column (1) of Table 4. In the aggregate, we allocate about 70% of the average firm's exports to its establishments as being produced according to the CMF-PROD. For the representative manufacturing establishment, shown in Table 4, produced exports are about 9% of the total value of shipments. 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 this difference may be due to the authors' sole reliance on the 2002 CMF.

We provide additional results on the data construction methodology in the Appendix. In the rest of the paper, we describe new lessons that result from this data, and also describe what researchers might get wrong if they rely solely on industry-level measures to capture global value chain activity.

3 New Measures of U.S. Global Value Chains

The measurement methodology described above yields global value chain measures in the United States that are novel in their detail and scope. In this section, we highlight several new facts that result from these measures.

3.1 Conceptual Issues of GVC Measurement

Our measure of global value chains comes from the vertical specialization (VS) measure highlighted in Hummels, Ishii and Yi (2001) that captures the imported content of exports.[10] In its most detailed form, our measure of GVC is defined in equation (4) for an input product r imported from country m and used by a U.S. establishment e in industry s in its output product p for export to country n in period t as:

$$GVC_{emnrspt} = \frac{IMP^{I}_{emrt}}{GO_{est}} EXP_{enpt}, \tag{4}$$

where IMP^{I}_{emrt} denotes imported inputs measured based on equation (2), and EXP_{enpt} represents produced outputs based on equation (3).[11] We add product dimensions to both imported inputs and produced exports, while omitting the firm subscript f for establishment e from equations (2) and (3). GO_{est} is gross output of establishment e in industry s in period t.

We sum over all country-sector sources of imports, and all country destinations for exports to arrive at an overall establishment-level GVC measure for an establishment e operating in industry s in period t as:

$$GVC_{est} = \frac{\sum_{m,r} IMP^{I}_{emrt}}{GO_{est}} \sum_{n,p} EXP_{enpt}, \tag{5}$$

and similarly across establishments of all sectors to arrive at a total measure for manufacturing as a whole. Finally, we scale our GVC measure (which is in units of dollars) by overall (or sectoral) exports to arrive at a ratio as follows:

$$gvc^{E}_{st} = \frac{\sum_{e \in E_{st}} \left[\frac{\sum_{m,r} IMP^{I}_{emrt}}{GO_{est}} \sum_{n,p} EXP_{enpt} \right]}{\sum_{e \in E_{st}} \sum_{n,p} EXP_{enpt}}, \tag{6}$$

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

Before presenting our GVC and gvc measures, it is worth taking a step back and briefly

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

[11] 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) (Timmer, Dietzenbacher, Los, Stehrer and de Vries, 2015). We use WIOD definitions to enable comparisons to statistics computed using the WIOD.

comparing them to the value-added exports measures developed in Johnson and Noguera (2012), Johnson and Noguera (2017), and Koopman et al. (2014). Value-added exports (hereafter, VAX) capture 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, subject to one caveat, it is equivalent to $1 - gvc$.[12] 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, as well as the exports. This motivates much of our regression analysis in Section 5.

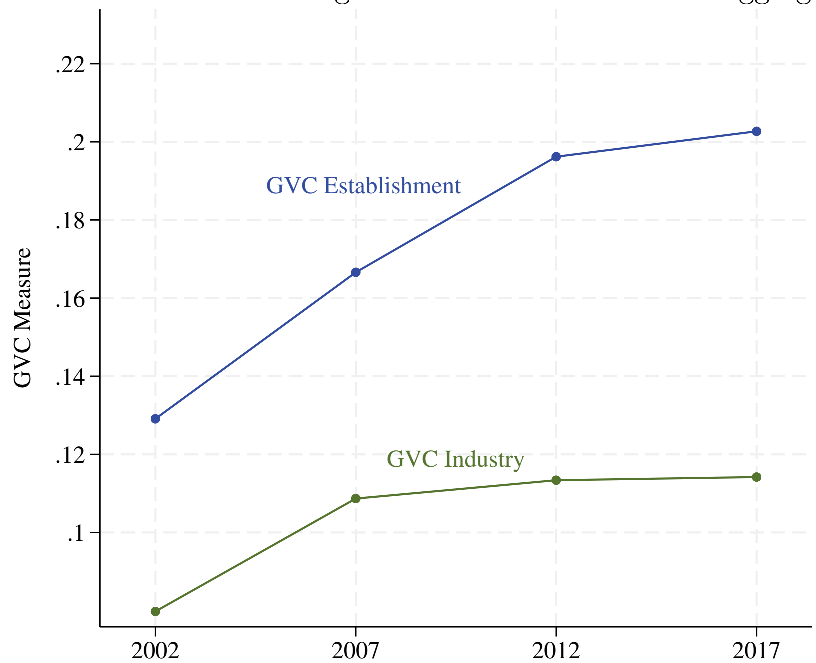
3.2 Aggregate GVC Activity within U.S. Manufacturing

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 1. There are steady gains in the spread of 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 relative to the trend in previous years.

Our measure stands in contrast to what would be calculated solely from aggregate industry-level estimates of imports, output, and shipments. As first shown by Bems and Kikkawa (2021) using Belgian data, such aggregate estimates of GVC activity are subject to important aggregation bias that can distort central features of what we think we know about trends in the fragmentation of global production. To isolate such aggregation bias, we calculate the aggregate-based measures from our own data (essentially ignoring the establishment-level mappings between imports and exports) as in:

[12] Subject to the caveat, $1 - gvc$ would capture the domestic value-added embodied in exports as a share of total exports. The caveat is that 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, $1 - gvc$ will underestimate the VAX share. This is relevant if goods are produced in more than two stages.

Figure 1: GVC in Manufacturing: Establishment-based vs. Aggregate



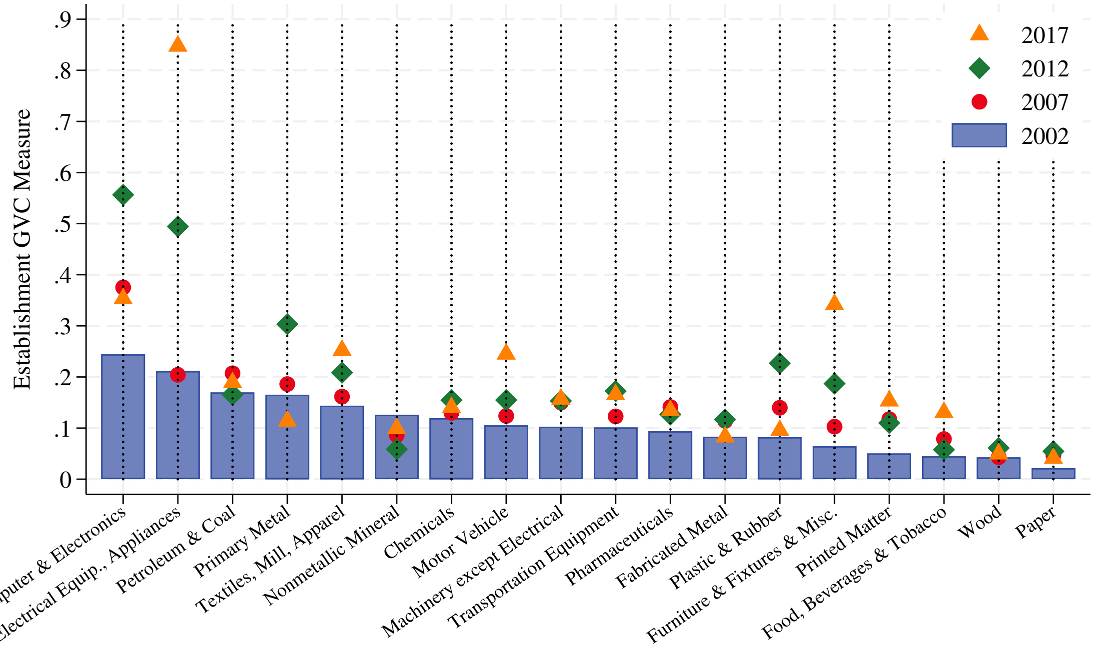
Notes: This figure plots GVC measures for the manufacturing sector as a whole.
Source: Author's calculations using CMF and LFTTD.

$$gvc^I_{st} = \frac{\left(\sum\limits_{e\in E_{st}} \sum_{n,p} EXP_{enpt}\right)\left(\frac{\sum\limits_{e\in E_{st}} \sum_{m,r} IMP^I_{emrt}}{\sum\limits_{e\in E_{st}} GO_{est}}\right)}{\sum\limits_{e\in E_{st}} \sum_{n,p} EXP_{enpt}}. \tag{7}$$

The green line in Figure 1 plots the 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 access to the micro-level data, but also the trends. As shown in the green line, the aggregate-based measure slowed considerably in 2012, and then remains flat in 2017. We provide extensive discussion of the components and further interpretation of this aggregation bias in related work (see Flaaen, Kamal, Lee and Yi (2024)).

We plot the industry-level GVC values from equation (6) in Figure 2, where the bars signify values from 2002, the red dots values for 2007, the green diamonds for 2012, and the orange triangles for 2017. These industry-level results largely align with expectations, both in terms of relative levels as well as relative growth patterns. 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 experi-

Figure 2: 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: Author's calculations using CMF and LFTTD.

encing little or negative growth in foreign linkages are non-metallic minerals, petroleum and coal, and wood products.

3.3 The Import Source Content of U.S. Exports

By expanding our GVC measure back to the level of import source country by export destination country, we reveal another novel component of our data: where are the embedded import source countries of U.S. exports, by export destination? This is an intuitive and concrete measure of how countries are connected through global value chains, and one that does not rely on proportionality assumptions or aggregation bias but is based on actual establishment-level input and output measures.

We first define a bilateral GVC measure for import source country m and export destination country n for a manufacturing industry s in year t as follows:

$$GVC_{mnst} = \sum_{e \in E_{mnst}} \left(\frac{\sum_r IMP^I_{emrt}}{GO_{est}} \sum_p EXP_{enpt} \right), \tag{8}$$

where E_{mnst} is the set of establishments in industry s that import inputs from country m

and export their products to country n in year t. In other words, 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), we divide equation (8) by $\sum_{e \in E_{mnst}} \sum_{n,p} EXP_{enpt}$.

Table 5 provides 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-industries. A striking feature of Table 5 is how Canada and Mexico occupy all of the Top 9 destination slots for the input-output country pairs.[13] We see evidence of what Johnson and Moxnes (2023) refer to as "round-trip" behavior—where a firm/establishment simultaneously imports from and exports to the same country—for both Canada and Mexico. We explore this feature of our data in much greater detail further below. While North America is also a prominent input source in U.S. global value chains, other countries such as China, Japan, Singapore, and Germany occupy top bilateral positions as source countries.

Table 5: Top GVC Country Pairs, Overall Manufacturing 2012

Source Country	**Destination Country**	**GVC Share**
Mexico	Canada	0.45%
China	Canada	0.39%
Mexico	Mexico	0.37%
Canada	Canada	0.31%
Canada	Mexico	0.23%
Japan	Canada	0.17%
China	Mexico	0.13%
Singapore	Canada	0.10%
Germany	Canada	0.10%

Notes: This table displays the top 9 import and export country pairs for the overall U.S. manufacturing sector (one country pair in the top ten is withheld given Census disclosure rules). The "GVC Share" shows the GVC measure of the country pair from equation (8) as a share of overall manufacturing exports.

Specific sectors within manufacturing reveal a much richer portrait of the countries that are connected through global value chains in the United States. The top ten country-pair links for a few select sectors are shown in Table 6. For example, in the Pharmaceuticals sector, Ireland is remarkably the top input source for all top ten bilateral country-pairs,

[13]One country-pair in the list of top ten for manufacturing as a whole is redacted due to Census disclosure rules.

with their input imports linked to exports to a wide range of countries from Asia to Europe to South America. We will discuss this pattern further in the following section.

The patterns for the other sectors shown 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, NAFTA (now 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 FDI, and, specifically, export-platform FDI, can influence patterns of global value chains (see Tintelnot (2016) and Antrás, Fadeev, Fort and Tintelnot (2022)).

The sector "Other Transport Equipment" (NAICS 3364OT, a WIOD aggregate) includes aerospace products, railroad rolling stock, ship and boat building, and miscellaneous transport such as motorcycles and military transport. The patterns here 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 for other transport equipment, 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.

4 Strengths and Weaknesses of Import Proportionality

Lacking direct measures of supply chain flows across countries, the most common approach used in the literature is to use aggregate measures of trade that are connected through harmonized country-level input-output tables. The result of these extraordinary measurement efforts is multi-country input-output tables, of which the most well-known example is the World Input-Output Database (WIOD) that is maintained by a consortium of 12 research

Table 6: Top GVC Country Pairs, Selected Manufacturing Sectors 2012

NAICS	**Source Country**	**Destination Country**	**GVC Share**
		Pharmaceuticals	
3254	Ireland	Italy	0.72%
3254	Ireland	Japan	0.41%
3254	Ireland	Belgium	0.40%
3254	Ireland	South Korea	0.33%
3254	Ireland	France	0.32%
3254	Ireland	Ireland	0.28%
3254	Ireland	Canada	0.26%
3254	Ireland	Brazil	0.16%
3254	Ireland	Mexico	0.14%
		Machinery and Equipment	
333	Mexico	Canada	0.21%
333	Canada	Canada	0.19%
333	Germany	Canada	0.17%
333	Japan	Canada	0.15%
333	China	Canada	0.12%
333	Mexico	Mexico	0.12%
333	United Kingdom	Canada	0.11%
333	Mexico	Australia	0.11%
333	Mexico	Germany	0.11%
333	Canada	Australia	0.10%
		Motor Vehicles and Trailer	
3361MV	Mexico	Canada	1.31%
3361MV	Mexico	Mexico	1.27%
3361MV	Canada	Canada	0.83%
3361MV	Japan	Canada	0.74%
3361MV	Germany	Mexico	0.38%
3361MV	Canada	Mexico	0.37%
3361MV	Japan	Mexico	0.24%
3361MV	Germany	Canada	0.24%
3361MV	Germany	Germany	0.19%
3361MV	South Korea	Canada	0.18%
		Other Transport Equipment	
3364OT	France	France	0.24%
3364OT	Japan	Japan	0.24%
3364OT	Japan	United Arab Emirates	0.21%
3364OT	Japan	China	0.21%
3364OT	Japan	France	0.17%
3364OT	Canada	France	0.15%
3364OT	United Kingdom	France	0.15%
3364OT	France	Brazil	0.14%
3364OT	United Kingdom	United Arab Emirates	0.12%
3364OT	France	Japan	0.12%

Notes: This table displays the top 10 bilateral country pairs for the select sectors of the U.S. manufacturing sector. The "GVC Share" shows the GVC measure of the country pair (from equation 6) as a share of sectoral manufacturing exports.

institutes headed by the University of Gronigen (see Timmer, Dietzenbacher, Los, Stehrer and de Vries (2015) and Timmer, Los, Stehrer and de Vries (2016) for a summary of their methods). The most current version (November 2016 Release) of the WIOD spans 44 countries, 56 sectors (18 in manufacturing, according to NAICS definitions), and ranges from 2000-2014.

Such an industry-by-country-based construction of global value chains utilizes the well-known proportionality assumption, where an individual countries' imports are allocated as inputs across industries in the same proportion as their overall imports. This assumption reflects the nature of input-output tables, which calculate the overall inputs a particular industry uses rather than distinguishing by where those inputs originate. Lacking further information, statistics like those in WIOD take the overall country shares and apply the relative input costs across industries.

While other research has pointed out the potential for flaws in the proportionality assumption in specific cases (e.g. de Gortari (2020), Antrás and Chor (2022)), we are unaware of any systematic evaluation of the performance of the proportionality assumption for a given country. The reason surely comes from the difficulty of constructing the sort of comprehensive structure of inputs and outputs by source and destination country that is only made possible by the availability of the set of Census data products that we utilize in this paper.

4.1 A Simple Comparison between Census-based and WIOD-based GVC Measures

To compare the Census data with what would be generated using the WIOD, we use the November 2016 release and isolate the imports of inputs into the United States. We convert the NACE 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. Finally, we calculate the foreign cost share – both in the aggregate and separately by source country – for each of the 18 manufacturing sectors in the data. We collapse the Census Bureau data to match the 43 countries and a Rest of World (RoW) aggregate and at the same level of NAICS classification.

A summary of the alignment of the country import cost share measures between the WIOD and our Census-based data is described in the first column of Table 7, based on simple correlations.[14] For manufacturing as a whole, the correlation is 0.64 – a strong positive

[14]The measure is specifically $IC_{st} = \frac{\sum_{e \in E_{st}} IMP^{I}_{est}}{\sum mc_{est}}$, which we replicate in the WIOD.

Table 7: Census-WIOD Correlations by Sector, 2012

	Correlations of	
NAICS Labels (3-digit manufacturing)	Input Costs	Bilateral Pair GVC Values
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**

Source: Author's calculations using the WIOD, CMF, LFTTD.
Notes: Column (1) displays the correlation between country input cost shares, (Country Source Imported Inputs/Cost of Materials), using Census and WIOD data by sector. Column (2) displays the correlation between bilateral country-pair GVC measures by industry using Census and WIOD data.

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 proportionality assumption. The industry-level detail of Table 7 describes the heterogeneity in this alignment, though all industries show a correlation well above zero. High correlations above 0.9 are in sectors such as basic metals (NAICS 331) and Motor Vehicles and Trailers (portions of NAICS 336), whereas the correlation falls to around 0.3 for pharmaceuticals (NAICS 3254).

The second column of Table 7 takes a step back to consider the alignment of the WIOD with Census data on a bilateral basis. That is, the second column calculates 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) using the WIOD and Census-based measures. For the Census-based measure, we use equation (8). 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.

Delving deeper into the potential sources of mis-alignment in column 1 of Table 7, Figure 3 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 3 is the role that Ireland plays in the mis-measurement of foreign inputs for the Pharmaceutical sector: the Census Bureau microdata records Ireland occupying nearly 8 percent of material input costs, whereas the WIOD has Ireland's share at less than 1 percent. 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.[15] The outsized role of Ireland in pharmaceuticals trade—as well as for producing measurement headaches in international statistics—has been well-documented (Setser, 2019).[16]

Other sectors paint a broadly positive view of the alignment between the Census and WIOD-based measures. Figure 4 produces an analogous illustration for two industries that align relatively well: Machinery and Equipment (NAICS 333) and Non-metallic Minerals (NAICS 327). While the major source countries of imported inputs do not line up perfectly along the 45-degree in the chart, there is broad agreement as to the relative magnitudes, as well as relative rank, across input sources.

4.2 Excess Smoothing in Proportional Measures

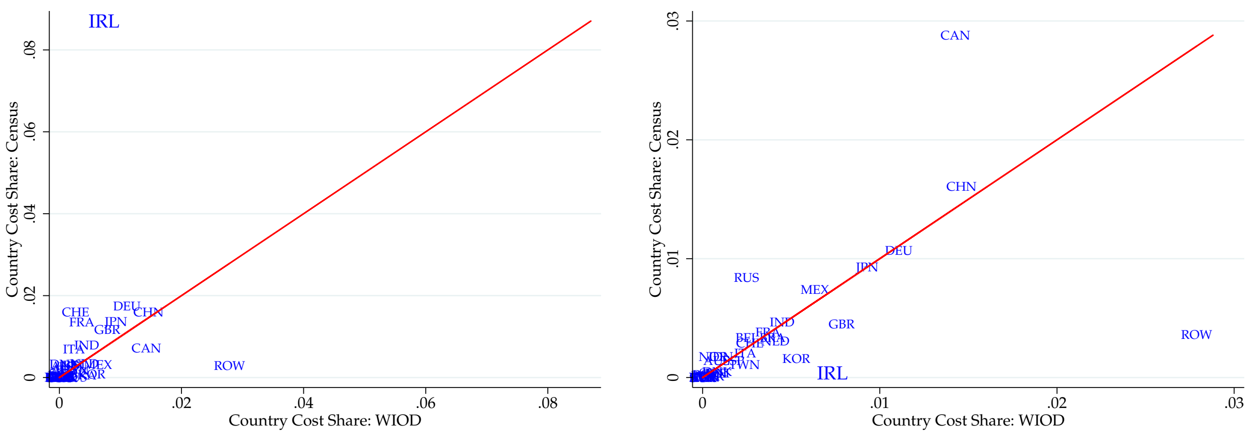
Without direct linkage of import sources to export destinations, one source of the misalignment in GVC linkages identified in Table 7 (Column 2), is the smooth distribution of import

[15] The relative magnitudes also make sense, as published data indicate that basic chemicals record nearly 8 times as much material input costs as pharmaceuticals.

[16] 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.

Figure 3: Mis-Alignment Between WIOD and Census Measures of Foreign Input Shares

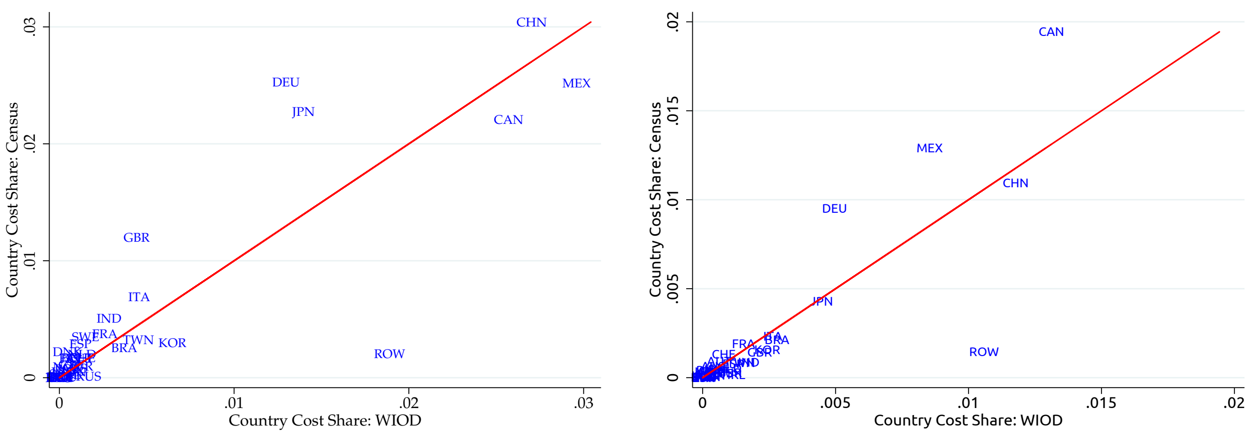
(a) Pharmaceutical (NAICS 3254) (b) Basic Chemicals (NAICS 325X)



Sources: Author's calculations using WIOD and Census data sources as described in the text.
Notes: These figures display the foreign cost share of material inputs by country for two sectors. The red lines are at the 45 degree line, indicating perfect country-level alignment between sources.

Figure 4: Alignment Between WIOD and Census Measures of Foreign Input Shares

(a) Machinery and Equipment (NAICS 333) (b) Non-metallic Minerals (NAICS 327)



Sources: Author's calculations using WIOD and Census data sources as described in the text.
Notes: These figures display the foreign cost share of material inputs by country for two sectors. The red lines are at the 45-degree line, indicating perfect country-level alignment between sources.

sources across all export destinations. To highlight one example of what we identify as "excess smoothing" in proportionality-based measures, we calculate the fraction of bilateral country-pairs (among WIOD countries) 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 greater share of zero bilateral linakges in Census data than in WIOD, 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%

Source: Author's calculations using the CMF and LFTTD.
Notes: This table reports the fraction of zero GVC linkages in a particular sector among all possible pairwise combinations ($43^2 = 1,849$).

Naturally, measures of such excess smoothness will increase substantially when additional periphery countries are included in proportional measures. 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 2.3 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 Determinants of GVC Patterns

This section analyzes the integrated flows of imports, domestic production, and foreign exports in a more systematic manner. 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 level of actual 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 can help to shed light on the trends in aggregate patterns of global value chains in the U.S. shown in Figure 1.

For this analysis, we once again aggregate our data to the level of bilateral pairs of countries by aggregating the bilateral GVC measure defined in equation (8) across U.S. manufacturing sectors. We then merge in information on country attributes (distance, trade agreements, etc.) from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). Because this 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) care must be taken to merge multiple features to a given observation in the data.

5.1 Gravity in Global Value Chains

A natural starting point is the well-known gravity framework, which typically relates bilateral gross trade flows to bilateral determinants that include proxies for trade costs such as distance. Even when aggregated to the country-level, our data exists at the trilateral level (bilateral pairs sandwiching the United States), and thereby exhibits additional and unique factors to explore that are specific to how global value chains connect production in a three-country setting.

Most obviously, the proxy measures of trade frictions captured by bilateral distance requires different measures and interpretations in the context of GVCs. In our context, the traditional measure of distance between two non-U.S. countries does not capture any direct trade flow; here, the analogue 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.[17] 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). Returning to our example, are the 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 (i.e. Germany, rather than the U.S.)?

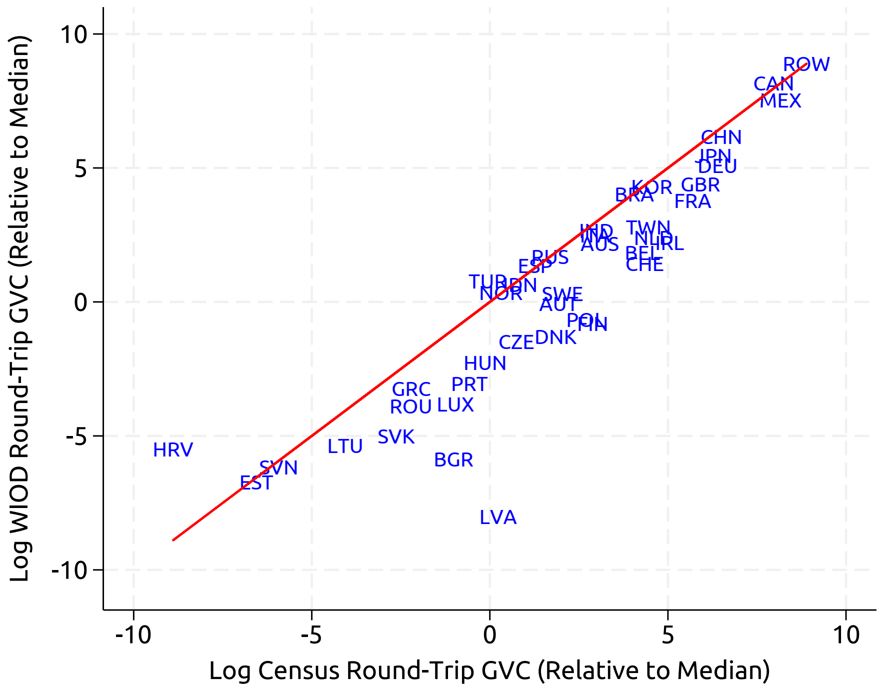
A special case of the direct distance arises when $d_{m,m} = 0$. This illustrates another non-traditional factor affecting GVC flows — the prominence of "round-trip" production, in which a U.S. establishment imports an input from a given country and subsequently exports output to the same country. In 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. When both distance measures and the round-trip indicator are controlled for, 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.

A first glance at this feature of GVC activity indicates it is not well accounted for by an industry-level perspective. In Figure 5 we plot the round-trip GVC values—scaled relative to the median value across all GVC pairs in WIOD—in our data relative to an equivalent measure in WIOD. The figure reveals that nearly all WIOD countries lie below the 45-degree

[17]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.

line, indicating significantly higher relative magnitudes of these round-trip GVC flows than would be captured in WIOD. Section 5 explores this feature of the data in greater detail.

Figure 5: Alignment of Round-Trip GVC Values, 2012



Sources: Author's calculations using WIOD and Census data sources as described in the text.
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.

To explore these ideas, we estimate a novel form of the gravity model connecting these bilateral pairs of production flows through the United States according to equation (9) below:

$$log(GVC_{mnt}) = \alpha + \delta_{m,t} + \eta_{n,t} + \beta \mathbb{I}(m = n) + \gamma d_{m,US,n} + \lambda d_{m,n} + \varepsilon_{mnt}, \tag{9}$$

where the dependent variable is $log(GVC_{mnt}) \equiv \log(\sum_s GVC_{mnst})$. All specifications also include exporter-year fixed effects ($\eta_{n,t}$) and importer-year fixed effects ($\delta_{m,t}$). 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). As in Noguera (2012), we compare the results with our GVC measure to those with the gross value of trade in Appendix B. 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 4.

We report the gravity results in the first four columns of Table 9, where we begin with

Table 9: Gravity Model of GVC, 2002-2017

	Dependent Variable: Log Bilateral GVC						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Round-trip (m=n)	2.33***			1.32***	2.20***	2.23***	2.21***
	(0.112)			(0.119)	(0.112)	(0.111)	(0.112)
Log Distance (m →US→ n)		-1.64***		-0.414***	-1.38***	-1.39***	-1.36***
		(0.106)		(0.118)	(0.105)	(0.104)	(0.104)
Log Distance (m to n)			-0.26***	-0.175***			
			(0.009)	(0.011)			
RTA (m & n)					0.044**		
					(0.020)		
RTA (m & US, n & US)						0.198***	
						(0.059)	
RTA (m, n, US)							0.438***
							(0.112)
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	117,000
R-squared	0.861	0.861	0.861	0.861	0.861	0.861	0.861

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

some bivariate regressions of the key variables of interest.[18] The coefficient on the round-trip indicator is large and highly significant, and coefficients on each of the two distance variables take the expected negative sign, with the direct trade cost proxy (combined distance) exhibiting a far greater magnitude. Column (4) contains results when all of these variables are included together. The coefficient on the round-trip indicator is attenuated somewhat, but remains large and highly significant. Indeed, the fact that the m to n distance measure is comparatively very low for the round-trip country pairs (reflecting the within-country distance methodology of CEPII), it follows that some of the effect attributed specifically to a round-trip effect would fall instead on this distance measure. Of equal interest is how the coefficients on both distance measures are significantly negative, with the combined distance measure having roughly double the magnitude of the direct ($m \to n$) distance.

These results reveal several novel features of international supply chains connecting to the U.S. manufacturing sector. The negative relationship on the combined distance measure suggests that trade frictions operate along the multi-country supply chain, with the degree of production spanning three countries being attenuated as the cumulative frictions

[18]The results in Table 9 are pooled across all years in our sample (every five years from 2002 to 2017); in Appendix Table B5, we provide estimates pertaining to each year.

of the production chain accumulate. This finding is consistent with intuition and would easily feature in most models of global production chains. The other findings from Table 9 are less intuitive and suggest important complementarities between input and output markets that are less easily accounted for by existing theory. The negative coefficient on the direct ($m \rightarrow n$) distance after accounting for combined distance implies proximity between input and output markets supports global value chain formation. The large coefficient on the round-trip indicator is the extreme example of this complementarity, highlighting the importance of back-and-forth production sharing by establishments within a given country. This complementarity between input and output markets is an under-explored topic that we return to in greater detail below.

5.2 The Impact of Regional Trade Agreements on Value Chains

The last few decades has seen a proliferation of regional trade agreements (RTAs) while production chains increasingly cross multiple borders before final consumption. 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 the gross flows of trade in a gravity model context has a long history, as documented extensively in Larch and Yotov (2024). The estimates of a bilateral RTA indicator generally range from 0.1 to 0.3 though Larch and Yotov (2024) highlight important heterogeneity across covariate structures, time horizons, and the like. The impact of regional trade agreements is also a focus of work by Noguera (2012) and Johnson and Noguera (2017) that narrows in on measures of trade in value-added. Here, Johnson and Noguera (2017) find a *negative* relationship between RTAs and their VAX (the domestic value-added embodied in a country's exports) suggesting that RTAs facilitate increased production sharing broadly stated. Our data provides the opportunity to extend this finding beyond a relationship between RTAs and *overall* production sharing of a country's exports, and to specific trilateral supply chain linkages at an establishment basis.

Hence, we construct several indicator variables for whether regional trade agreements are in place between various combinations of the countries involved. 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 then whether all three countries (m, n, and the U.S.) are all under an RTA.[19] We add these variables to the existing gravity regression variables shown in equation (9), and present the results in columns (5) - (7) of Table 9.

We display results in columns (5) - (7) of Table 9, where we continue to include the round-trip indicator and combined distance as controls.[20] 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.[21] But the coefficient increases substantially once we focus instead on those importers and exporters (separately) have an RTA with the United States (column 6), and even further when the RTA includes all three countries (column 7).[22]

Once again the impact of trade agreements on GVC flows may have changed over time; an inspection of the yearly estimates of these results helps to shed light on these changes.

5.3 What Aggregate Input-Output Tables May Miss

The data highlighted in this paper provides new insights into the patterns and determinants of global supply chain linkages. We conclude by examining the layers of measurement where these features may reside, and the role that proportionality, sample coverage, and aggregation play in their disclosure in publicly available input-output tables.

Column (1) of Table 10 replicates analysis from column (7) 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 this 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

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

[20] 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 & n) coefficient.

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

[22] See Appendix Table A4 for a listing of all the countries included in these RTAs.

a modestly reduced round-trip effect, implying that the round-trip effect we observe does not depend significantly on the set of countries used in the gravity regression.

As discussed extensively above, the difference between the GVC measure based on microdata and that based on aggregate input-output tables is not solely due to sample criteria. In the last four columns of Table 10, 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 10 focus on the role of aggregation. 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 (8) across s as the dependent variable, we use the following GVC measure, which is subject to aggregation bias by design:

$$GVC_{mnt}^{agg} = \sum_{s} \left(\frac{\sum_{e \in E_{mnst}} \sum_{r} IMP_{emrt}^{I}}{\sum_{e \in E_{mnst}} GO_{est}} \sum_{e \in E_{mnst}} \sum_{p} EXP_{enpt} \right). \tag{10}$$

As we discussed in the previous section, without 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 (10) 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 discussed in Flaaen, Kamal, Lee and Yi (2024), a positive correlation between exports and imports at the establishment level leads to a downward bias in GVC measurement when using aggregate data. The significant reduction of the round-trip effect in the aggregated microdata implies that this bias is pronounced relatively more in round-trip trading behavior. Introducing aggregation bias to the GVC measures also diminishes the strong explanatory power of distance and RTAs found in microdata.

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. Finally, we run the gravity regression with the WIOD in column (6). By construction, the GVC measure computed with the WIOD is subject to aggregation bias. Additionally, compared to columns (3)-(5), where we hypothetically introduced aggregation bias with our microdata, the WIOD table is also subject to the proportionality assumption. With both aggregation bias and the proportionality assumption in play, we find a very small round-trip effect and lose significance for both the distance and RTA coefficients.

Table 10: Gravity Model Comparisons 2012

	Dependent Variable: Log Bilateral GVC					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Log Distance (m →US→ n)	-1.36***	0.26	0.11**	-0.011	-0.28**	-0.02
	(0.104)	(0.280)	(0.049)	(0.045)	(0.114)	(0.045)
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)	(0.008)
RTA (m, n, US)	0.44***	-0.13	0.16***	0.17***	0.06	-0.02
	(0.112)	(0.220)	(0.046)	(0.045)	(0.087)	(0.034)
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	7,100
R-Squared	0.86	0.94	0.96	0.96	0.99	0.99

Source: Author's calculations using the WIOD, CMF and LFTTD.
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.

6 Conclusion

The proliferation of supply chains crossing international boundaries has long fascinated economists and troubled policymakers, but accurate measurement of these connections at a granular level had continued to be outside the reach of empirical trade economists. In this paper, we build, for the first time, establishment-level estimates of global value chains connecting import, production, and export activity. Such a micro-level perspective is important to ensure that the imports and exports are each connected to production activity, which is most directly observable at the level of an individual plant. This paper has offered a window into the many important lessons such unique data can have for ongoing research on global value chains.

Going forward, research with U.S. establishment-level GVCs can proceed in two directions – econometric analysis of the role of U.S. GVCs in propagating recent global shocks, such as the U.S.-China tariff war, the pandemic, and the Russia invasion of Ukraine, as well as policy analysis of the welfare consequences of such shocks. Along these lines, Utar et al. (2023) study the effects of the U.S.-China tariff war on Mexican GVC firms and find that these firms expanded, as a result. Marrying this work with work on the effects in the U.S. would be worthwhile.

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A Data Appendix

This section contains additional statistics pertaining to the methodology for identifying intermediate input imports in the Census data. Table A1 reports the share of imports (by firms with at least one manufacturing establishment, in our sample) that we identify as intermediates for the relevant establishment, and also the average import share of overall costs, by year. Table A2 reports the share of costs and shipments reported to be "not elsewhere specified" as part of either the Census of Material Trailer File, or the Census of Products Trailer File. The 2017 data are not available for this statistic. Finally, Table A3 reports the share of intermediate input imports that we identify by way of the NESOI method outlined in equation (2).

Table A1: Additional Statistics on Intermediate Input Imports

	Intermediate Share of Firm Imports	Import Cost Share
2002	56.9	14.0
2007	60.9	17.6
2012	62.9	16.9
2017	58.5	18.4

Source: Author's calculations from CM and LFTTD as described in text.

Table A2: Not Elsewhere Specified (NESOI) Products, as Share of Costs/Shipments

	Share of Costs/Shipments
Material Trailer File	
2002	29.5%
2007	28.1%
2012	21.6%
2017	
Product Trailer File	
2002	N/A
2007	0.3%
2012	0.3%
2017	

Source: Author's calculations using Economic Census, U.S. Census Bureau.

Table A3: Fraction of Imports Identified via Indirect NESOI Method

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

Source: Author's calculations from CM and LFTTD as described in text.

Table A4: 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.

B Appendix: Additional Results

Table B5: 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 to US to 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: This table ...

B.1 The Role of Industry Definition in GVC Measures

In addition to exploring the role of aggregation bias we also highlight the role of industry mis-classification that arises due to choice of the source data for identifying industry. While it is well-known that large, and hence presumably multi-industry, firms play an out-sized role in mediating U.S. goods trade, documenting the industrial breadth of trading firms has not been previously explored for the United States.

The source of industry information in Equations 6 and **??** do not suffer from mis-classification bias since it is determined at the level of the establishment which is the most disaggregated economic unit. However, establishments may not be the primary economic unit in all statistical collections. For example, statistical collections in many countries only collect input and output information at the level of the firm's main industry such as Belgium (Bems and Kikkawa, 2021). If firms are only required to report a primary industry, we would miss heterogeneity in firms' activities across sectors when using a concept of primary industry to measure GVC.

To mimic this scenario 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.[23] We then create a firm-primary industry, $s^\star$, based measure of sectoral GVC as follows:

$$gvc^F_{s^*t} = \frac{1}{\sum_{f\in F_{s^*}} EXP_{ft}} \left[\sum_{f\in F_{s^*}} EXP_{ft} \frac{\sum_{f\in F_{s^*}} IMP^I_{ft}}{\sum_{f\in F_{s^*}} GO_{ft}} \right]. \tag{B1}$$

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

We also construct a national GVC measure based on firm-primary industry for all manufacturing by summing across sectors s such that,

$$gvc^{F\star}{}_t = \frac{1}{\sum_{f,s^\star} EXP_{fs^\star t}} \sum_{s^\star} \sum_{f} \left[EXP_{fs^\star t} \frac{\sum_{fs^\star} IMP^I_{fs^\star t}}{\sum_{fs^\star} GO_{fs^\star t}} \right]. \tag{B2}$$

Lastly, we construct an analog of gvc^I_t except that we use the definition of sector based on firms' primary industries as follows:

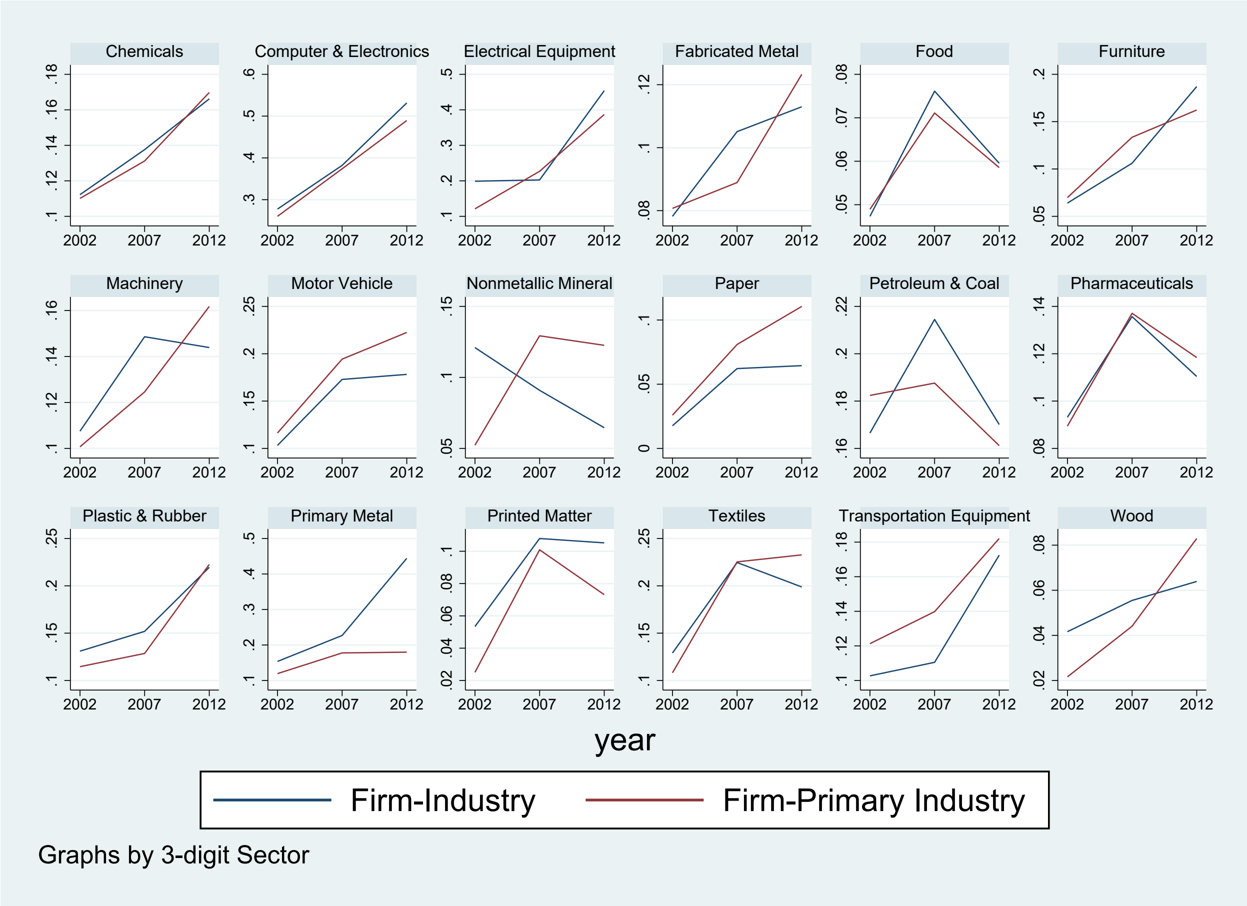
$$gvc^{I\star}{}_t = \frac{\left[\sum_{f,e,s^\star} EXP_{fes^\star t} \frac{\sum_{f,e,s^\star} IMP^I_{fes^\star t}}{\sum_{f,e,s} GO_{fes^\star t}}\right]}{\sum_{f,e,s^\star} EXP_{fes^\star t}}. \tag{B3}$$

A priori, the direction of the measurement bias introduced by using the primary industry of the firm is not obvious. We explore this empirically. We find that at the national level, $gvc^{I\star}{}_t$ is 10% in 2002 and 13% in 2007 and 2012 which lines up closely with gvc^I_t; $gvc^{F\star}{}_t$ is 13% in 2002 and 18% in 2007 and 20% in 2012 which is a little higher compared to gvc^F_t.

We then compare GVC measures derived from firm-industry level data, gvc^F_{st}, and firm-primary industry level data, $gvc^F_{s^\star t}$, in Figure B1. There are several differences between these measures that vary by sector. The average difference between these two sets of statistics is small, 0.008, however, this masks large variation across sectors. gvc^F_{st} is higher than $gvc^F_{s^\star t}$ in half or more of the sectors in a year.[24] In Furniture, Motor Vehicle, Paper, and Transportation Equipment, gvc^F_{st} is lower than $gvc^F_{s^\star t}$. However, they exhibit similar trends except in Non-metallic Mineral where gvc^F_{st} trends downwards and $gvc^F_{s^\star t}$ trends upwards.

[24] In 2012, 11 of the 18 sectors have higher $gvc^F_{s^\star t}$.

Figure B1: Comparison of $gvc_s^F t$ and $gvc_{s^\star t}^F$, 2002, 2007, 2012

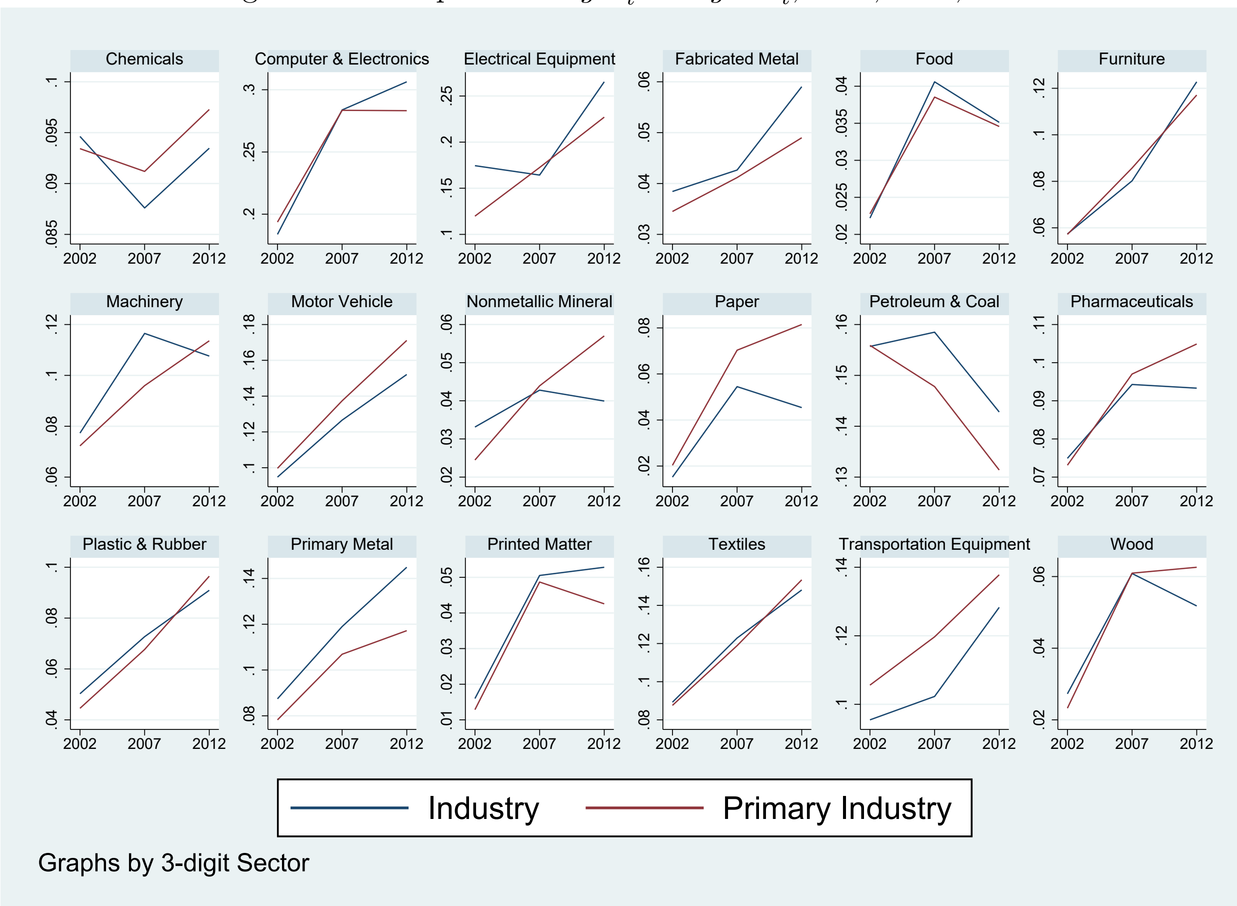


Notes: This figure plots GVC for 3-digit manufacturing sectors. “Firm-Industry” defined in Equation **??** and “Firm-Primary Industry” defined in Equation B2.

Source: Author’s calculations using CMF and LFTTD.

We also compare GVC measures calculated using industry aggregates in Figure B2. “Industry” denotes gvc_{st}^F where s is derived using the six-digit NAICS of an establishment; “Primary Industry” denotes $gvc_{s^\star t}^F$ where s is derived using the six-digit NAICS of a firm that accounts for the largest share of the firm’s payroll. We find that using a primary industry classification results in higher levels of GVC in certain industries, notably in Fabricated Metal, Motor Vehicle, Paper, Pharmaceuticals, and Transportation Equipment.

Figure B2: 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 6 and "Primary Industry" defined in Equation B2.

Source: Author's calculations using CMF and LFTTD.