Trade within Multinational Boundaries*

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Abstract

We leverage newly linked data from the U.S. Census Bureau and the U.S. Bureau of Economic Analysis to study transactions within U.S. multinational enterprises (MNEs). We reassess two empirical puzzles documented in prior research based on survey data on intrafirm trade: (i) input–output (IO) linkages do not predict the extensive margin of intrafirm trade; and (ii) intrafirm trade is extremely sparse. We show that using administrative data on intrafirm trade allows us to correct for measurement error in survey data and overturn the first puzzle: IO linkages strongly predict trade between U.S. parents and their foreign affiliates. We also provide evidence against the second puzzle: after accounting for two-way trade (to and from U.S. parents) and for the regional nature of MNEs' supply chains, we find that at least 75% of foreign production units trade with their parents. Our findings support traditional theories of firm boundaries, in which vertically linked production units of the same firm should trade with each other.

JEL Codes: F14, F23, D23, L20

Keywords: Multinational enterprises, intrafirm trade, integration, input-output linkages, measurement error, survey data, administrative data.

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1 Introduction

Understanding firms' vertical integration decisions has been a central concern in organizational economics since Coase's (1937) seminal work. Traditional theories of firm boundaries emphasize various benefits of integration, such as reducing transaction and adaptation costs (Williamson, 1971, 1975), mitigating opportunism (Klein et al., 1978), enhancing multi-tasking incentives (Holmström and Milgrom, 1991), aligning control with incentives (Grossman and Hart, 1986; Hart and Moore, 1990), and improving coordination (Hart and Holmström, 2010). These insights have been extended to firms operating across countries (Helpman, 1984; Antràs, 2003; Antrás and Yeaple, 2014). A key implication of these theories is that firms should utilize inputs produced within their boundaries, leading to observable trade flows between vertically linked units of the same firm.

Contrary to this prediction, influential work by Atalay, Hortaçsu and Syverson (2014a) (henceforth AHS) and Ramondo, Rapoport and Ruhl (2016) (henceforth RRR) find little evidence of intrafirm goods trade flows. Both studies rely on intrafirm trade data collected from surveys:[1] AHS use the U.S. Commodity Flow Survey to study trade between different establishments of U.S. firms, while RRR use survey data from the U.S. Bureau of Economic Analysis (BEA) on trade within U.S. multinational enterprises (MNEs). Two broad findings emerge: first, while vertical linkages matter for integration choices, they do affect intrafirm trade—the input–output (IO) coefficient linking the industries of operation of parents and affiliates does not predict whether they trade with each other; second, intrafirm trade is extremely sparse—almost one-half of upstream U.S. establishments do not report making shipments inside their firms, and the median foreign affiliate ships nothing to the rest of the corporation.[2]

These findings challenge prevailing theories of firm boundaries, which posit that ownership should facilitate intrafirm transfers of inputs. In the words of AHS, "if firms do not own upstream and downstream units so the former can provide intermediate materials inputs for the latter, why do they?" Their answer is that ownership enables "the efficient transfer of intangible inputs," a rationale "consistent with small amounts of shipments within vertically structured firms, and even with an absence of internal shipments altogether" (p. 1121).

[1] Administrative data on the universe of intrafirm trade flows is not widely available. For select countries, data from value-added tax (VAT) declarations allow observing transactions within domestic production networks. For example, data on firm-to-firm transactions are available for Belgium (e.g., Bernard et al., 2022), Chile (e.g., Arkolakis et al., 2023), and Turkey (e.g., Demir et al., 2009). However, these data provide information on the value of the transactions, not on what is being traded. Moreover, intrafirm transactions can only be observed if different establishments of the same firm have different VAT identifiers.

[2] Bilir and Morales (2020) also document the sparsity of intra-MNE trade using BEA survey data.

In this paper, we reassess the evidence using newly linked data from the U.S. Bureau of Economic Analysis (BEA) and the U.S. Census Bureau. We measure intra-MNE trade using administrative data from customs records from the U.S. Census Bureau's Longitudinal Firm Trade Transactions Database (LFTTD), which covers the universe of U.S. merchandise trade transactions, including those between multinational parents and their affiliates.[3] We link LFTTD to comprehensive data from the BEA on the production networks of U.S. multinationals.[4] We also utilize the supply and use tables published as part of BEA's Input–Output accounts to measure vertical linkages between industries.

Customs transaction records enable us to correct different types of measurement error that arise when using BEA survey data on goods trade flows between multinational parents and their affiliates. First, some transactions may not be recorded in the BEA's survey (e.g., due to interviewer's or respondent's error or imperfect recall). As a result, researchers may erroneously infer a lack of intra-MNE trade flows. By contrast, LFTTD is based on administrative customs records; we can thus observe *all* transactions between a parent and its foreign affiliates, which allows us to correct false 0's in intra-MNE trade. Second, the BEA's survey reports the *total* value of trade between a parent and its affiliate. In the absence of more detailed information, researchers are forced to allocate all trade flows to the affiliate's main industry. In turn, this generates two empirical challenges. First, researchers may erroneously infer intra-MNE trade flows involving the affiliate's primary industry. Second, researchers may disregard trade flows involving the affiliates' other industries. LFTTD records trade flows at the detailed product level, making it possible to observe the *specific industries* in which a parent trades with its foreign affiliates, allowing us to correct both false 1s (in the affiliate's primary industry) and missing values (in the affiliate's other industries). Finally, the BEA foreign direct investment surveys only collect data on intrafirm trade for affiliates *above a certain size threshold*, meaning that intrafirm trade information for smaller affiliates is missing.[5] There is instead *no reporting threshold* for U.S. traders in LFTTD, thus providing information on transactions between U.S. parents and *all* of their foreign affiliates.

It is well known that measurement error in a binary dependent variable is a form of non-classical measurement error, which leads to biased estimates (e.g., Aigner, 1973; Bollinger, 1996; Meyer and Mittag, 2017). Our results indicate that misclassification in BEA survey

[3] "Administrative data refers to data collected and maintained by federal, state, and local governments, as well as some commercial entities", and is "collected and maintained by agencies or firms are used to administer (or run) programs and provide services to the public" (U.S. Census Bureau, 2025a).

[4] Linking these datasets is made possible by the development of crosswalks between firm identifiers used in the BEA data and the firm identifiers in the Census Bureau's Business Register used in customs records (Kamal, McCloskey and Ouyang, 2022).

[5] The threshold is based on assets, sales, or net income (loss) greater than $25 million.

data on intrafirm trade (false 0s, false 1s, missing values) leads both to attenuation and higher error variance, making it harder to identify the role of IO linkages: after correcting each type of measurement error, the point estimate of the IO linkage measure becomes increasingly larger and more precisely estimated.

By replacing survey data on intra-MNE trade with administrative data, we can thus overturn the first puzzle: IO linkages between multinational parents and their foreign production units (country–industry pairs in their network of foreign affiliates) *do* predict the extensive margin of trade between them. In our baseline specification, a 10 percentage point (pp) increase in the IO linkage increases the probability that the parent imports from (exports to) foreign production units by 29% (21%) relative to the average probability of intra-firm trade in our data.

We also provide evidence against the second puzzle concerning the sparsity of intrafirm trade. We find that a minority of foreign production units export to their U.S. parent. However, sparsity is significantly reduced when accounting for two key features of MNEs' supply chains. First, affiliates may export to or import from their parent, depending on the relative position (upstream/downstream) of their industries along supply chains. When accounting for both directions, we find that more than 50% of foreign production units trade with their U.S. parent.

Second, MNEs tend to organize their production along regional supply chains, described as "Factory North America," "Factory Europe," and "Factory Asia" (Baldwin, 2013). This can arise due to different types of trade frictions, including transport costs, tariffs, communication costs, and rules of origin in free trade agreements (e.g., Baldwin, 2013; Keller and Yeaple, 2013; Conconi et al., 2018).[6] When focusing on production units in North America, we find that around 75% of them trade with their U.S. parents.[7] This should be considered a lower bound on intra-MNE trade in the region, for several reasons, since it does not cover trade flows in all sectors,[8] and excludes affiliate-to-affiliate trade and indirect trade (i.e., third-party firms processing goods traded between U.S. parents and their affiliates). The finding that (at least) 75% of North American affiliates of U.S. multinationals export

[6]For example, Head, Mayer, Melitz and Yang (2025) show that U.S. MNEs in the motor vehicles industry own vertically related plants in many countries around the world. However, they mostly source inputs from their North American subsidiaries for production in North America.

[7]These findings on trade within U.S. multinationals echo those of (Garg et al., 2023) and (Hong, 2021), who respectively use administrative data for a large state in India and for South Korea to document the importance of trade in physical inputs across different establishments of the same firm.

[8]We only include parents' exports in the same 4-digit NAICS manufacturing sector, which can be linked to each production unit. We thus exclude parents' exports in other manufacturing industries, as well as trade flows in services.

to/import from their parent suggests that U.S. tariffs can be extremely disruptive for U.S. MNEs when applied to regional trading partners.

To the best of our knowledge, the only other paper that employs the newly linked data to construct a complete mapping of U.S. MNE production networks is Antràs et al. (2023). The authors build on the work in Kamal et al. (2022) to combine BEA data on multinational firms with US Census Bureau data on all US establishments and their firm-by-country trade flows. Their finding that MNEs are more likely to trade with countries that are proximate to their affiliates and have a free trade agreement with the country of the affiliates is consistent with the role of regional supply chains also documented in this paper. The ability to combine the strengths of administrative and survey data is made possible by an inter-agency agreement between the U.S. Census Bureau and BEA. These efforts enable the continued development of blended microdata infrastructure that is crucial to inform policy decisions consistent with the 2018 Evidence-Based Policymaking Act (Public Law 115-435, 2018).

This paper is organized as follows. Section 2 describes the data used in our empirical analysis. In Section 3, we show how using transaction-level data on intrafirm goods trade allows us to identify the role of input–output linkages. In Section 4, we show how the sparsity of intra-MNE transactions is significantly reduced when accounting for two-way trade and regional supply chains. Section 5 concludes, discussing the implications of our findings for the theoretical and empirical literatures on firm boundaries and avenues for future research.

2 Data

In our analysis, we combine three datasets to examine the existence of trade flows within MNE production networks and evaluate whether they are predicted by input–output relationships between parents and affiliates: comprehensive data from the BEA on the production network of U.S. multinationals; customs records from the Census Bureau on the universe of U.S. merchandise trade transactions; and input–output tables from the BEA. Linking the microdata on MNE production networks and firm trade transactions is made possible by a joint project between the U.S. Census Bureau and BEA. We describe this effort and each of the datasets in turn below.

2.1 Production Networks of U.S. Multinationals

We utilize data from BEA's confidential and mandatory direct investment surveys to obtain the most comprehensive available information on the industrial structure of U.S. multinationals. These confidential data are widely used in the literature on MNEs, as they provide

detailed information about each parent company and its foreign affiliates (e.g., Yeaple, 2003; Hanson et al., 2005; Bilir and Morales, 2020; Antràs et al., 2023). The data from these surveys form the basis for official statistics on the activities of multinational enterprises that provide the most comprehensive information on the scale of direct investment abroad and impacts on the U.S. economy due to multinational activities (U.S. Bureau of Economic Analysis, 2018b).

We use the 2004 Benchmark Survey of U.S. Direct Investment Abroad (Form BE-10) for our primary analysis (U.S. Bureau of Economic Analysis, 2019c) as in RRR, and focus only on majority-owned affiliates (i.e., ownership share above 50 percent).[9] We use the combination of parent and its main industry along with foreign affiliate-by-industry as the basis for identifying the complete production network of U.S. parent firms (see Appendix A.1 for details). We restrict attention to all parent–affiliate industry pairs in the manufacturing sector.

We further analyze the 2019 Benchmark Survey of U.S. Direct Investment Abroad for the results reported in Section 4 to provide a long-term view of the main results. Appendix Section A.1.1 provides details about the sample construction.

2.2 Intrafirm Trade

We use the Longitudinal Firm Trade Transactions Database (LFTTD), maintained by the U.S. Census Bureau, to separately identify related-party and arm's-length merchandise export and import transactions.

The LFTTD links international shipments to individual firms in the United States (Bernard et al., 2009; Kamal and Ouyang, 2020). The database 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, related-party trade status, and destination and source country, respectively. Related-party trade status is an indicator variable (U.S. Census Bureau, 2025d). For exports, it denotes relationships in which one firm owns a stake of at

[9]In the BEA data, the term "foreign affiliate" refers to a single foreign business enterprise owned by a U.S. parent or a consolidated group of foreign business enterprises owned by the same U.S. parent, located in the same country, and with the same primary 4-digit industry or that are "integral parts of the same business operation." (U.S. Bureau of Economic Analysis, 2004).

least 10% in the other as reported by U.S. exporters in the Electronic Export Information filings (U.S. Census Bureau, 2025b). For imports, it denotes relationships in which one firm owns a stake of at least 5% in the other as reported by U.S. importers in customs entry filings (U.S. Customs and Border Protection, 2025). We identify intrafirm trade transactions using the related-party indicator and aggregate export and import transactions at the parent-destination industry and parent-source industry levels, respectively.

2.3 Census-BEA Crosswalks

Confidential crosswalks that link enterprises reporting on BEA's multinational surveys to firms that engage in international transactions in the LFTTD provide the central foundation for our analysis. Kamal et al. (2022) describe the efforts from a multi-year project between the U.S. Census Bureau and the BEA that has resulted in the construction of confidential crosswalk files that enable a comprehensive identification of multinational firms in the U.S. economy.[10] The crosswalks are developed by linking firm-level surveys on direct investment conducted by BEA and the U.S. Census Bureau's Business Register (BR) spanning the universe of employer businesses using information on business tax identifiers, name, address, industry, and employment. The crosswalks are available beginning in 1997 and updated as new years become available.

2.4 Input-Ouput Linkages

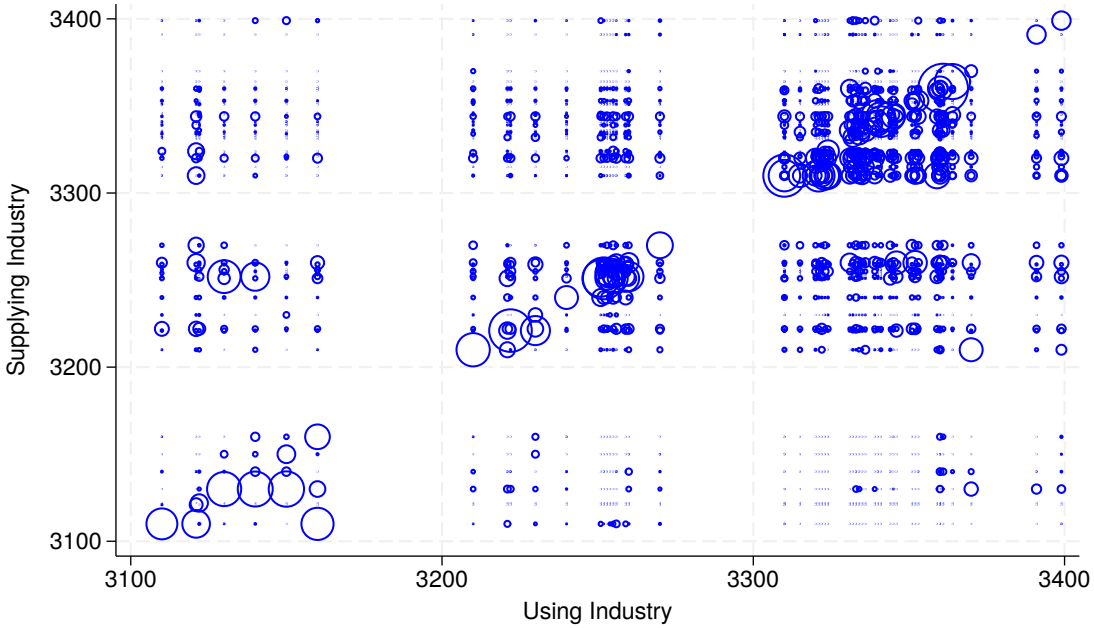
To study vertical linkages between the activities of U.S. parents and their foreign affiliates, we calculate the direct requirement coefficients, IO_{ij}, from the use tables published by BEA as part of the Input-Ouput accounts (U.S. Bureau of Economic Analysis, 2025b). For comparability with prior work, we use the 2002 use table and focus on vertical linkages between manufacturing industries.

The direct requirement coefficient is the value of goods needed from the supplying (upstream) industry i to produce one dollar of output in the using (downstream) industry j. To generate these coefficients, we aggregate BEA's "use" table (i.e., consumption of industry i's commodity by industry j) by 4-digit upstream and downstream industry. After obtaining total output by aggregating the "supply" table (i.e., total value of commodities produced by each industry) by 4-digit industry, we calculate IO_{ij} coefficients by dividing each "use"

[10]Relatedly, Antràs et al. (2023) build on the matching methods developed within the inter-agency project to augment ownership information in the BEA surveys with the U.S. Census Bureau's Company Organization Survey that provided the sole direct source of information on any changes in multi-establishment company organization and industry classification at the establishment level prior to 2023 (U.S. Census Bureau, 2022).

value (defined at the upstream–downstream industry level ij) by the total output of the relevant downstream industry j. Figure 1 illustrates variation in IO_{ij} for all manufacturing industries in 2002.

Figure 1. Input–Output Coefficients in U.S. Manufacturing, 2002



Notes: The figure plots direct requirements coefficients from the 2002 BEA input–output tables, focusing on manufacturing industries. The direct requirement coefficient is the value of goods needed from the supplying (upstream) industry in order to produce one dollar of output in the using (downstream) industry. Bubbles are proportional to the size of the direct requirement coefficient.

3 Intrafirm Trade and input–output Linkages

Previous work based on survey data did not find a robust relationship between IO linkages and the existence of trade between foreign affiliates and their U.S. parents. In this section, we re-examine this relationship leveraging administrative data on intrafirm trade combined with a complete mapping of MNE production networks.

To identify the role of IO linkages in the extensive margin of intra-MNE trade, we estimate the following linear probability model:

$$\mathbb{I}(Imports_{p(j),a(c,i)}) = \beta_0 + \beta_1 IO_{ij} + \delta_c + \delta_i + \delta_p + \epsilon_{p(j),a(c,i)} \tag{1}$$

The dependent variable, $\mathbb{I}(Intrafirm\ Trade_{a(c,i)p(j)})$, is an indicator for whether parent p (operating in industry j) imports from its foreign affiliate a (located in country c and operating

in industry i). IO_{ij} is the direct requirement coefficient of input industry i to output industry j. δ_c, δ_i, δ_p are affiliate-country, affiliate-industry, and parent fixed effects.

We also estimate an analogous specification for parent p's exports to its affiliate a:

$$\mathbb{I}(Exports_{p(j),a(c,i)}) = \beta_0 + \beta_1 IO_{ji} + \delta_c + \delta_i + \delta_p + \epsilon_{p(j),a(c,i)}. \quad (2)$$

3.1 Measurement Error in Survey Data on Intrafirm Trade

We next describe the main challenges that arise when using survey-based intrafirm trade data to estimate equations (1) and (2) and how we can address these challenges by using administrative customs records on intrafirm trade flows.

Consider the hypothetical example illustrated in Table 1, which builds on Table A2 in the Appendix. This shows a multinational parent that has affiliates (related parties) in five countries. Three affiliates (A, B, and C) are large (i.e., have assets, sales, or net income (loss) greater than $25 million), while two ($D$ and E) are small. All affiliates are active in industry 1, which is their primary industry. Some affiliates are also active in other industries (A also operates in industries 2 and 3, B and E in industry 2). The bottom line shows that all affiliates trade with their parent. However, intra-MNE trade does not involve all the industries in which an affiliate is active. For example, affiliate A trades with the parent in industries 1 and 3, but not in industry 2. Similarly, affiliate B trades with the parent in industry 2, but not in industry 1.

Table 1. Hypothetical Example of Trade Between a Parent and Its Affiliates

Large Affiliates						Small Affiliates		
Affiliate A			Affiliate B		Affiliate C	Affiliate D	Affiliate E	
Industry 1	Industry 2	Industry 3	Industry 1	Industry 2	Industry 1	Industry 1	Industry 1	Industry 2
1	0	1	0	1	1	1	0	1

Table 2 illustrates the different types of misclassification that can arise when a researcher has comprehensive information from the BEA about the MNE's production structure, but relies on BEA survey data to populate intra-MNE trade. First, some flows may not be recorded (e.g., due to survey fatigue, imperfect recall, etc.), which can lead to false 0s in intra-MNE trade, as in the case of affiliate C. Second, survey data collects information on the total amount of trade between a parent and each of its affiliates. For this reason, researchers only consider the primary industry i of each affiliate when estimating equations (1) and (2) and allocate all flows to this industry. In some cases, this can lead to false 1s in the dependent variable, as in the case of affiliate B. Further, the focus on the affiliate's primary industry implies missing values for the other industries. For example, researchers would not include observations corresponding to the extensive margin of trade between the

parent and affiliate A in industries 2 and 3. Finally, reporting thresholds in surveys lead to further missing values. For example, intrafirm trade is only recorded between U.S. parents and their large foreign affiliates in the BE-10. Researchers relying on this survey would thus have no information on all small affiliates, in all industries in which they are active, as is the case for affiliate D in industry 1 and affiliate E in industries 1 and 2.

Table 2. Hypothetical Example of Trade Between a Parent and Its Affiliates: Measurement in Survey Data

Large Affiliates						Small Affiliates		
Affiliate A			Affiliate B		Affiliate C	Affiliate D	Affiliate E	
Industry 1	Industry 2	Industry 3	Industry 1	Industry 2	Industry 1	Industry 1	Industry 1	Industry 2
1	0	1	0	1	1	1	0	1
1			1		0			

Using survey data to estimate (1) and (2) thus gives rise to measurement error in the dependent variable, due to misclassification (false 0s and false 1s) or missing data. As discussed in Section A.2 of the Appendix, in the case of a binary dependent variable, this results in non-classical measurement error, which leads to biased estimates and higher error variance.

By using customs records on trade flows between parents and affiliates, we can correct each type of measurement error that arises when using survey data on intrafirm trade. First, we can correct the false 0s in the dependent variable (while still focusing on large affiliates and allocating all flows to the affiliate's primary industry), as shown in Table 3. Second, we can correct the false 1s in the dependent variable (while still focusing on large affiliates and allocating all flows to primary industry), as shown in Table 4. Third, using customs data, we can extend the sample size, including observations associated with affiliates' secondary industries (while still focusing on large affiliates), as shown in Table 5. Finally, using customs data, we can further extend the sample size by including observations associated with smaller affiliates and all associated industries, as shown in Table 6.

Table 3. Hypothetical Example of Trade Between a Parent and Its Affiliates: Correcting False 0s

Large Affiliates						Small Affiliates		
Affiliate A			Affiliate B		Affiliate C	Affiliate D	Affiliate E	
Industry 1	Industry 2	Industry 3	Industry 1	Industry 2	Industry 1	Industry 1	Industry 1	Industry 2
1	0	1	0	1	1	1	0	1
1			1		0			
1			1		1			

Table 4. Hypothetical Example of Trade Between a Parent and Its Affiliates: Correcting False 1s

Large Affiliates						Small Affiliates		
Affiliate A			Affiliate B		Affiliate C	Affiliate D	Affiliate E	
Industry 1	Industry 2	Industry 3	Industry 1	Industry 2	Industry 1	Industry 1	Industry 1	Industry 2
1	0	1	0	1	1	1	0	1
1			1		0			
1			1		1			
1			0		1			

Table 5. Hypothetical Example of Trade Between a Parent and Its Affiliates: Including Affiliates' Secondary industries

Large Affiliates						Small Affiliates		
Affiliate A			Affiliate B		Affiliate C	Affiliate D	Affiliate E	
Industry 1	Industry 2	Industry 3	Industry 1	Industry 2	Industry 1	Industry 1	Industry 1	Industry 2
1	0	1	0	1	1	1	0	1
1			1		0			
1			1		1			
1			0		1			
1	0	1	0	1	1			

Table 6. Hypothetical Example of Trade Between a Parent and Its Affiliates: Including Small Affiliates

Large Affiliates						Small Affiliates		
Affiliate A			Affiliate B		Affiliate C	Affiliate D	Affiliate E	
Industry 1	Industry 2	Industry 3	Industry 1	Industry 2	Industry 1	Industry 1	Industry 1	Industry 2
1	0	1	0	1	1	1	0	1
1			1		0			
1			1		1			
1			0		1			
1	0	1	0	1	1			
1	0	1	0	1	1	1	0	1

3.2 Results

When estimating equations (1) and (2) using administrative data on intrafirm trade, we define the dependent variable at the level of each "foreign production unit," i.e., each country-industry pair (c, i) in which the multinational parent has a foreign affiliate. In the hypothetical example illustrated in Figure 1, the relevant production units are: Mexico, industry 1; Mexico, industry 2; Mexico, industry 3; Canada, industry 1; Canada, industry 2; Germany, industry 1; France, industry 1; China, Industry 1; China, Industry 2.[11,12]

Table 7 reports the results. The number of observations is rounded to comply with

[11] We focus on intra-MNE flows in industry i. When estimating (2), we could also look at p's exports in industry j. However, when a parent has multiple production units in a country (e.g., Mexico, industry 1; Mexico, industry 2; Mexico, industry 3), customs records do not allow us to distinguish parent's related-party exports by the industry of a foreign affiliate.

[12] We include the diagonal of the IO matrix, i.e., IO_{jj} when estimating (1) and IO_{ii} when estimating (2). Notice that, within a 4-digit NAICS industry, parents and affiliates may trade vertically related products.

Census Bureau disclosure avoidance rules. In all specifications, the coefficient of IO_{ij} or IO_{ji} is positive and significant at the 1% level. Our preferred specifications in columns 2 and 4 include parent fixed effects, which account for any MNE-specific characteristics that may affect intra-firm trade decisions (e.g., industry specialization, size, productivity).[13] The estimates in columns 2 and 4 imply that increasing IO linkages by 10 percentage points raises the probability of intrafirm trade by between 8.2 and 9.5 percentage points, respectively. In turn, this implies a 29% (21%) increase in the probability of intrafirm trade relative to the average probability that foreign affiliates export to (import from) their parents, which is 29.6% (44.7%) (see Table 10).[14]

Table 7. Input–Output Linkages and Intra-MNE Trade Flows Using Linked BEA-Census Data

Dependent Variable	$\mathbb{I}(Imports_{p(j),a(c,i)})$		$\mathbb{I}(Exports_{p(j),a(c,i))}$	
	(1)	(2)	(3)	(4)
IO_{ij}	0.566***	0.819***		
	(0.15)	(0.192)		
IO_{ji}			0.854***	0.950***
			(0.19)	(0.265)
Observations	7,500	7,200	7,500	7,200
Affiliate Country FE	Yes	Yes	Yes	Yes
Affiliate Industry FE	Yes	Yes	No	Yes
Parent Industry FE	No	No	Yes	No
Parent FE	No	Yes	No	Yes
Affiliate Employment	Yes	Yes	Yes	Yes
Parent Employment	Yes	No	Yes	No
Intra-MNE Trade Flows	Census administrative customs records			

Notes: This table displays the results of estimating equations (1) (columns 1 and 2) and (2) (columns 3 and 4). Robust standard errors, clustered by MNE, in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1. Observation counts rounded to comply with Census Bureau disclosure avoidance rules. Source: authors' calculations using BE-10, LFTTD.

The estimates of Table 7 stand in sharp contrast with the corresponding estimates based on BEA survey data only and reproduced in Table 8. Comparing the two tables shows that replacing survey data on intrafirm trade with administrative data reveals that IO linkages

[13]Notice that parent fixed effects absorb parent-industry fixed effects and parent's employment, which are thus not included in columns 2 and 4. Including parent fixed effects increases the size of the coefficients IO_{ij} and IO_{ji}, suggesting that the estimates in columns 1 and 3 likely suffer from omitted variable bias.

[14]Alternatively, a standard deviation increase in IO_{ij} (IO_{ji}) leads to a 6.9% (5.3%) increase in the probability of intrafirm trade.

between multinational parents and their foreign affiliates *do* predict whether they trade with each other.

Table 8. Input–Output Linkages and Intra-MNE Trade Flows Using Only BEA Data

Dependent Variable	$\mathbb{I}(Imports_{p(j),a(c,i)})$		$\mathbb{I}(Exports_{p(j),a(c,i)})$	
	(1)	(2)	(3)	(4)
IO_{ij}	0.008	-0.135		
	(0.215)	(0.227)		
IO_{ji}			0.313	-0.170
			(0.197)	(0.212)
Observations	4,901	4,901	4,901	4,901
Affiliate Country FE	Yes	Yes	Yes	Yes
Affiliate Industry FE	Yes	Yes	Yes	Yes
Parent FE	No	Yes	No	Yes
Affiliate Employment	Yes	Yes	Yes	Yes
Parent Employment	Yes	No	Yes	No
Intra-MNE Trade Flows	BEA survey data			

Notes: This table reproduces the results in Ramondo, Rapoport and Ruhl (2016) based on 2004 BEA data on U.S. MNEs. Columns (1) and (2) display the results in their Table 3, columns (3) and (4), respectively; columns (3) and (4) display the results in their Table 3, columns (7) and (8), respectively. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table 9 illustrates how we can use administrative customs records to correct each type of measurement error that arises when using survey data on intrafirm trade (see discussion in Section 3.1). We focus on parents' imports from their affiliates and always include parent fixed effects, showing how we can arrive at the estimate of 0.819 reported in column 2 of Table 7 after correcting false positives, false negatives, and missing data.

In column 1, we consider U.S. parents' imports from their large foreign affiliates (i.e., those with assets, sales, or net income (loss) greater than $25 million) and restrict the sample of intra-MNE trade in the affiliate's primary industry. In this exercise, we use data on total trade flows between foreign affiliate a and parent p to construct the dependent variable. By doing so, we only correct measurement error associated with false 0s in survey data. The coefficient of IO_{ij} is positive but not statistically significant.[15]

[15]Notice that the number of observations in this column is smaller than in column 1 of Table 8. This is due to the difference in the unit of analysis: RRR rely on BEA survey data on intrafirm trade and thus use the definition of affiliates in survey form BE-10B (see example in Table A1); we rely instead on intrafirm trade data from customs records, and thus consolidate foreign affiliates in the same country (see example in Table A2). In all other columns of Table 9, the number of observations is larger than in RRR, since we can extend the analysis to small affiliates and consider all industries in which affiliates are active.

Table 9. Input–Output Linkages and Intra-MNE Trade Flows Using BEA-Census Linked Data, 2004

Dependent Variable	$\mathbb{I}(Imports_{p(j),a(c,i)})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	large affiliates	all affiliates	large affiliates	all affiliates	large affiliates	all affiliates
Industry	all flows to primary		keep primary only		all industries	
IO_{ij}	0.27	0.363**	0.598**	0.574***	0.847***	0.819***
	(0.228)	(0.177)	(0.255)	(0.195)	(0.22)	(0.192)
Observations	3,900	6,200	3,900	6,200	4,900	7,200
Affiliate Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Affiliate Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Parent FE	Yes	Yes	Yes	Yes	Yes	Yes
Affiliate Employment	Yes	Yes	Yes	Yes	Yes	Yes
Intra-MNE Trade Flows	Census administrative customs records					

Notes: This tables displays the results of estimating equation (1) on different samples. Robust standard errors, clustered by MNE, in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1. Observation counts rounded to comply with Census Bureau disclosure avoidance rules. Source: Authors' calculations using BE-10, LFTTD.

In column 2, we extend the analysis to all foreign affiliates, addressing the problem of missing values that arise due to the BEA reporting threshold. Comparing columns 1 and 2, notice that this leads to a substantial increase in sample size (from 3,900 to 6,200 observations); the coefficient of IO_{ij} increases in size and becomes significant at the 5% level.

In columns 3–4, we reproduce the same structure of columns 1-2, still restricting the analysis to affiliates' primary industry (the number of observations is unchanged). However, we correct additional measurement error in the dependent variable by only coding it as 1 if we observe in the customs data trade flows between a and p involving the affiliate's primary industry. As a result, the coefficient of IO_{ij} increases in both size and significance. For example, in the restricted sample of large affiliates, this changes from 0.27 (not significant) in column 1 to 0.598 (significant at the 5% level) in column 3. Similarly, when including all affiliates, the coefficient of IO_{ij} increases from 0.363 (significant at the 5% level) in column 2 to 0.574 (significant at the 1% level) in column 4.

In columns 5–6, we address the problem of missing values in BEA survey data associated with trade flows involving affiliates' secondary industries. For this purpose, we extend the sample to all industries in which foreign affiliates are active and use customs data to correctly allocate trade flows to each industry. Notice that this leads to an increase in sample size. For example, the number of observations increases from 3,900 in column 3 to 4,900 in the corresponding specification of column 5. Crucially, the coefficient IO_{ij} is now significant at the 1% level in all specifications and becomes larger (e.g., it increases from 0.598 in column 3 to 0.847 in the corresponding specification in column 5).

The results of Table 9 suggest that different types of misclassification in survey data on intrafirm trade (false 0s, false 1s, missing values) lead to bias in the estimates and increase error variance, making it harder to identify the effect of IO linkages on the probability of trade between parents and affiliates. The strong and significant estimates that we obtain once we correct for measurement error indicate that intra-MNE trade is shaped by production linkages.

4 The Sparsity of Intrafirm Trade

As discussed in the Introduction, a second puzzle arises in earlier studies based on survey data on intrafirm trade: transactions between vertically related units of the same firm are very sparse. Using the U.S. Commodity Flow Survey, AHS find that almost one-half of upstream establishments in the United States do not report making shipments inside their firms. Based on BEA survey data on intrafirm trade, RRR report that the median foreign affiliate of a U.S. multinational does not trade with the rest of the corporation.

In this section, we use rich data from LFTTD to show that intrafirm trade is indeed sparse, but only if one does not account for two-way trade and the existence of distance-related trade frictions. We consider all "foreign integrated units" of a multinational, i.e., all country-industry pairs in which parent p's affiliates are active.

Table 10 reports the share of integrated units that trade with their parents in 2004 (the same year as the study of RRR) and 2019 (the most recent available benchmark year for which we can construct these statistics). When we consider only one direction of flows (p's related-party imports from country c in industry i), we find that intrafirm trade is indeed sparse: less than 30% (40%) of units ship anything to their parents in 2004 (2019).

We next show that sparsity is greatly reduced when we account for two characteristics of MNEs' supply chains. First, parents may also export to their foreign affiliates (e.g., a U.S. multinational may export car parts to a foreign affiliate involved in car assembly). When we consider trade flows in the opposite direction (p's related-party exports from country c in industry i) we find that around 45% (48%) of foreign integrated units imported from their parent in 2004 (2019). When allowing for two-way trade, the share of units trading with their parent increases to around 53% (57%) in 2004 (2019).

Table 10. Foreign Production Units Trading With Their U.S. Parent

Direction of Trade	Share in 2004	Share in 2019	Affiliate Location
Parent's imports	29.6%	36.4%	All countries
Parent's exports	44.7%	48.1%	All countries
Parent's imports or exports	53.3%	56.6%	All countries
Parent's imports or exports	73.7%	73.3%	North America

Notes: The table reports the share of foreign integrated units (country-industry pairs of the foreign affiliates of a multinational) trading with their U.S. parents in 2004 and in 2019. Source: authors' calculations using BE-10, LFTTD.

Second, due to trade frictions related to distance (e.g., transport costs, tariffs, rules of origin in regional trade agreements), MNEs organize their production along regional supply chains (e.g., "Factory North America," "Factory Europe,", "Factory Asia"). When focusing on two-directional trade between U.S. parents and their foreign affiliates in North America, we find that almost 75% of affiliate–industry pairs trade with their U.S. parent. This share is remarkably stable over the fifteen-year period 2004–2019.[16]

[16]The prevalence of intrafirm trade within the North American production chain is consistent with the interconnectedness of the North American automobile supply chain. For example, pistons (critical components of combustion engines used to convert fuel into energy to power the wheels) cross the border six times within the three countries through final assembly of a vehicle (Wall Street Journal, 2025a).

The estimates reported in Table 10 should be considered a lower bound on intra-MNE trade, given that (i) we only consider parents' exports the industry of the foreign integrated units; (ii) we do not observe affiliate-to-affiliate trade, indirect trade (i.e., independent firms processing goods traded between U.S. parents and their affiliates), and intra-MNE trade in intangible inputs.

5 Conclusions

We conclude by discussing the implications of our findings for the theoretical and empirical literatures on firm boundaries and important avenues for future research.

Traditional theories of vertical integration highlight different trade-offs driving a firm's choice to produce an input within its boundaries or source it from the market. While these theories emphasize different benefits of integration (e.g., reductions in transactions costs, alignment of control and incentives, improved multi-tasking incentives, or improved coordination), all imply that we should observe trade between vertically related units of the same firm. Prior influential studies relying on survey-based information on intrafirm goods trade for the United States did not find empirical support for this theoretical prediction.

In our analysis, based on newly linked data from the U.S. Census Bureau and the BEA, we replace survey-based data on intrafirm goods trade with administrative data from customs transactions. We find that input–output linkages between parents and their foreign production units do predict transactions between them; and, after accounting for two-way trade between parents and foreign production units and for geographical frictions between them, intrafirm flows in tangible inputs are very common.

Our findings provide empirical support for traditional theories of firm boundaries, such as transaction cost models and property rights models. They suggest that a key reason why firms own upstream and downstream units is that the former can provide materials inputs for the latter. This is, of course, not to say that other motives may not be at work. In particular, ownership may also mediate transfers of intangible inputs, as posited by AHS and RRR. However, only such transfers are not needed to rationalize ingration choices.

An interesting avenue for future research is to extend the analysis to intangible inputs. Recent decades have witnessed the "servitization" of manufacturing: in many countries, there is a trend toward more production, use, and sale of services by manufacturing firms and services account for the majority of GDP and employment globally (e.g., Buera and Kaboski, 2012; Ding et al., 2022; Kamal and Kroff, 2023). Standard theories of firm boundaries apply to both tangible and intangible inputs. We would thus expect intrafirm trade in intangible

inputs to also depend on IO linkages between different units of a firm. Studying intrafirm trade in intangibles is, however, more empirically challenging, for three main reasons.

First, an analysis of the determinants of intrafirm flows in services trade would need to rely on survey data, given that there are no customs collections for services trade transactions (United Nations Statistics Division, 2010). Most U.S. statistics on trade in services are based on data collected by the BEA through its survey programs (U.S. Bureau of Economic Analysis, 2018a).[17] As shown in this paper, reliance on survey data to measure intrafirm trade can pose key measurement challenges that make it harder to identify the role of input–output linkages. Second, services trade data are collected at the level of broad industries (intellectual property, telecommunications, computer, and information services, and other business services such as professional and management consulting, research and development services, and technical services), which is much coarser than the HS system used for trade in goods. Finally, profit-shifting motives may worsen misreporting errors, particularly in intellectual property and other business services (Jenniges et al., 2018).

Our finding that (at least) three-quarters of North American foreign production units export to or import from their U.S. parent could be rationalized using a model of multinational multi-stage production with trade costs à la Head et al. (2025).[18] However, more work is needed to understand how trade frictions shape the production structure of firms. For example, Atalay et al. (2014b) show that U.S. firms systematically engage in more intrafirm shipments over longer distances, implying that internal transactions confer a "distance premium." Their findings suggest that intrafirm shipments are motivated by cost savings from avoiding external transaction frictions. Examining the role of regional supply chains in shaping the distance premium through reductions in transaction costs is especially salient for firms operating in the highly integrated North American market. As described by Ford Motor Company CEO Jim Farley, higher trade barriers across North American borders would "blow a hole" in the U.S. auto industry, given the high reliance of American automakers on parts and equipment made in their plants located in Canada and Mexico (Wall Street Journal, 2025b). The prevalence of trade within multinational production networks, especially in "Factory North America," underscores the importance of understanding how increases in regional trade barriers could result in outsized disruptions in production networks.

[17] Confidential crosswalks have also been developed between the Census Bureau's BR and BEA's international services trade surveys: select business services and intellectual property (Kamal and Ouyang, 2022); insurance (Kamal and Ouyang, 2023b); financial services (Kamal and Ouyang, 2023a). These crosswalks are available to qualified researchers in the Federal Research Statistical Data Centers.

[18] In their model, MNEs in the electric vehicle industry choose in which countries to locate battery and assembly plants. This model can give rise to regional concentration in intra-MNE trade, e.g., batteries produced in plants in North America (Asia) are used by assembly plants in North America (Asia).

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A Appendix

A.1 Construction of the Sample

This section describes the construction of the sample used in our main analysis and classification rules to determine firms' output and input sectors.

A.1.1 U.S. Parents and Their Foreign Affiliates

We restrict attention to U.S. parents whose primary activity is manufacturing (see discussion below for how we assign parents a predominant industry). Multinationals have complex ownership structures where a U.S. affiliate of a foreign multinational may own other U.S. affiliates and thus report on both the BE-10 and BE-15 (U.S. Bureau of Economic Analysis, 2025a)—i.e., they appear as both U.S. parents *and* U.S affiliates of foreign parents. Our sample excludes multinational firms that are foreign-owned. To identify these firms, we search for Census firm identifiers that are on both BE-10 and BE-15 data files (applying Census–BEA crosswalks), as well as using an algorithm developed in Kamal et al. (2022). This ensures that our sample consists exclusively of U.S. multinational parents (not U.S. affiliates of foreign parents) and their foreign affiliates.

We also exclude foreign affiliates of U.S. parents that are unlikely to be involved in production. Specifically, we exclude foreign affiliates that:

1. Engage in distribution-only activities.[19]

2. Operate in tax havens—Bermuda, Cayman Islands, Hong Kong, and Singapore (Dharmapala and Hines, 2009).[20]

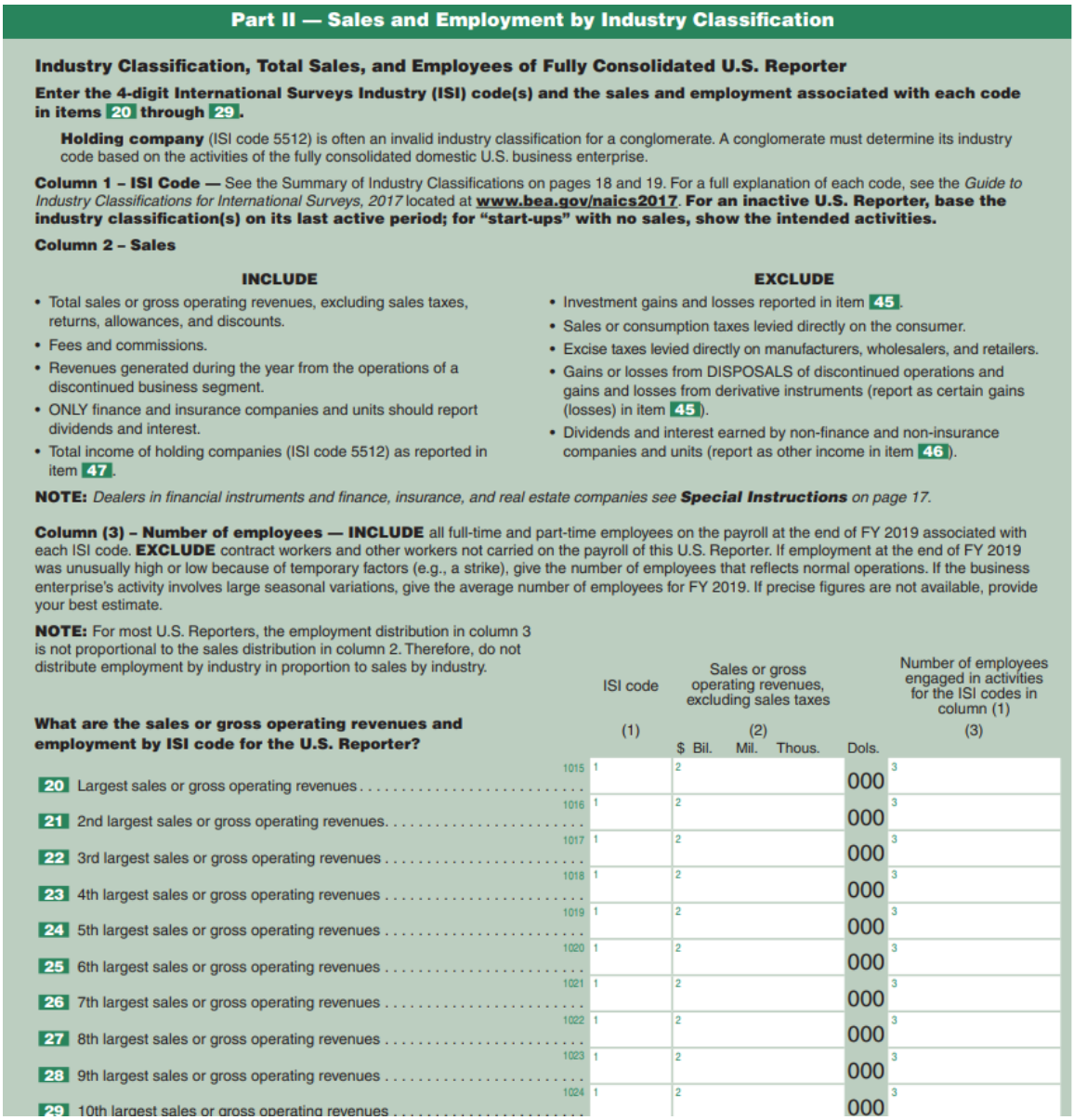
The benchmark survey collects employment and sales information of the U.S. parent for the (up to) ten industries with the highest sales (see Figure A1). For our analysis, we assign each U.S. parent, p, a main industry j based on its U.S. operations. We use sales reported in the BE-10 and assign the main industry as the one with predominant sales. For this assignment, we apply an iterative method rather than simply choosing the single industry with the most sales.[21]

[19]These foreign affiliates are identified based on responses to Question 28 "Major activity of foreign affiliate" in Form 10B and if the response is: "seller of goods the foreign affiliate does not produce" (U.S. Bureau of Economic Analysis, 2004).

[20]We keep tax havens that have a population of $\geq$ 1 million, which include Ireland, Switzerland, and Benelux (i.e., Belgium, Netherlands, and Luxembourg).

[21]For example, suppose a firm has establishments across three manufacturing 4-digit NAICS with sales of \$10 million in each and one services 4-digit NAICS with sales of \$20 million. Under a simple ranking

Figure A1. U.S. Parent Industry Information, Form 10-A



Part II — Sales and Employment by Industry Classification

Industry Classification, Total Sales, and Employees of Fully Consolidated U.S. Reporter

Enter the 4-digit International Surveys Industry (ISI) code(s) and the sales and employment associated with each code in items 20 through 29.

Holding company (ISI code 5512) is often an invalid industry classification for a conglomerate. A conglomerate must determine its industry code based on the activities of the fully consolidated domestic U.S. business enterprise.

Column 1 – ISI Code — See the Summary of Industry Classifications on pages 18 and 19. For a full explanation of each code, see the *Guide to Industry Classifications for International Surveys, 2017* located at **www.bea.gov/naics2017**. **For an inactive U.S. Reporter, base the industry classification(s) on its last active period; for "start-ups" with no sales, show the intended activities.**

Column 2 – Sales

INCLUDE

- Total sales or gross operating revenues, excluding sales taxes, returns, allowances, and discounts.
- Fees and commissions.
- Revenues generated during the year from the operations of a discontinued business segment.
- ONLY finance and insurance companies and units should report dividends and interest.
- Total income of holding companies (ISI code 5512) as reported in item 47.

EXCLUDE

- Investment gains and losses reported in item 45.
- Sales or consumption taxes levied directly on the consumer.
- Excise taxes levied directly on manufacturers, wholesalers, and retailers.
- Gains or losses from DISPOSALS of discontinued operations and gains and losses from derivative instruments (report as certain gains (losses) in item 45).
- Dividends and interest earned by non-finance and non-insurance companies and units (report as other income in item 46).

NOTE: *Dealers in financial instruments and finance, insurance, and real estate companies see* ***Special Instructions*** *on page 17.*

Column (3) – Number of employees — INCLUDE all full-time and part-time employees on the payroll at the end of FY 2019 associated with each ISI code. **EXCLUDE** contract workers and other workers not carried on the payroll of this U.S. Reporter. If employment at the end of FY 2019 was unusually high or low because of temporary factors (e.g., a strike), give the number of employees that reflects normal operations. If the business enterprise's activity involves large seasonal variations, give the average number of employees for FY 2019. If precise figures are not available, provide your best estimate.

NOTE: For most U.S. Reporters, the employment distribution in column 3 is not proportional to the sales distribution in column 2. Therefore, do not distribute employment by industry in proportion to sales by industry.

What are the sales or gross operating revenues and employment by ISI code for the U.S. Reporter?

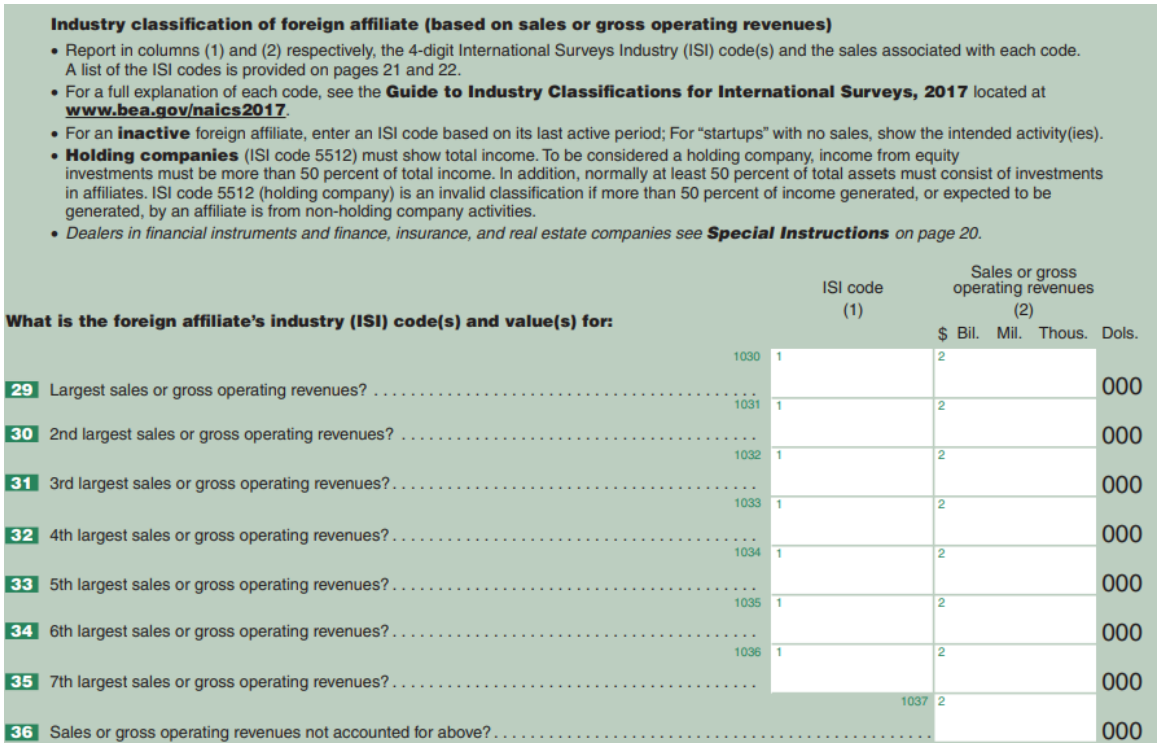
	ISI code (1)	Sales or gross operating revenues, excluding sales taxes (2) $ Bil. Mil. Thous. Dols.	Number of employees engaged in activities for the ISI codes in column (1) (3)
20 Largest sales or gross operating revenues	1015	000	
21 2nd largest sales or gross operating revenues	1016	000	
22 3rd largest sales or gross operating revenues	1017	000	
23 4th largest sales or gross operating revenues	1018	000	
24 5th largest sales or gross operating revenues	1019	000	
25 6th largest sales or gross operating revenues	1020	000	
26 7th largest sales or gross operating revenues	1021	000	
27 8th largest sales or gross operating revenues	1022	000	
28 9th largest sales or gross operating revenues	1023	000	
29 10th largest sales or gross operating revenues	1024	000	

Notes: This figure displays an excerpt from Form BE-10A indicating the industry information reported by the U.S. parent. See U.S. Bureau of Economic Analysis (2019a) for the full form.

methodology, the firm's main industry would be in services since that industry has the highest total sales ($20 million). Under the iterative method, we first identify a predominant sector (i.e., 2-digit industry), which would be manufacturing since total manufacturing sales are $30 million. Next, we consider the 3-digit industry with the highest sales *within* the predominant 2-digit industry. And finally, we assign the main 4-digit industry as the one with the highest sales within the predominant 3-digit industry.

To construct the production network of U.S. multinationals, we use information from the BE-10B Form on the (up to seven) industries in which foreign affiliates have the highest sales (see Figure A2).[22]

Figure A2. Foreign Affiliate Industry Information, Form 10-B



Industry classification of foreign affiliate (based on sales or gross operating revenues)

- Report in columns (1) and (2) respectively, the 4-digit International Surveys Industry (ISI) code(s) and the sales associated with each code. A list of the ISI codes is provided on pages 21 and 22.
- For a full explanation of each code, see the **Guide to Industry Classifications for International Surveys, 2017** located at **www.bea.gov/naics2017**.
- For an **inactive** foreign affiliate, enter an ISI code based on its last active period; For "startups" with no sales, show the intended activity(ies).
- **Holding companies** (ISI code 5512) must show total income. To be considered a holding company, income from equity investments must be more than 50 percent of total income. In addition, normally at least 50 percent of total assets must consist of investments in affiliates. ISI code 5512 (holding company) is an invalid classification if more than 50 percent of income generated, or expected to be generated, by an affiliate is from non-holding company activities.
- *Dealers in financial instruments and finance, insurance, and real estate companies see* ***Special Instructions*** *on page 20.*

What is the foreign affiliate's industry (ISI) code(s) and value(s) for:	ISI code (1)	Sales or gross operating revenues (2) $ Bil. Mil. Thous.	Dols.
29 Largest sales or gross operating revenues?	1030 1	2	000
30 2nd largest sales or gross operating revenues?	1031 1	2	000
31 3rd largest sales or gross operating revenues?	1032 1	2	000
32 4th largest sales or gross operating revenues?	1033 1	2	000
33 5th largest sales or gross operating revenues?	1034 1	2	000
34 6th largest sales or gross operating revenues?	1035 1	2	000
35 7th largest sales or gross operating revenues?	1036 1	2	000
36 Sales or gross operating revenues not accounted for above?	1037	2	000

Notes: This figure displays an excerpt from Form BE-10B indicating the industry information reported by the U.S. parent for its foreign affiliates located in a given country. See U.S. Bureau of Economic Analysis (2019b) for the full form.

We consider all combinations of parent (with corresponding main industry) and its affiliate–industry pairs as the most comprehensive mapping of individual MNE production networks. Our sample includes all observed combinations (in the manufacturing sector) of parent industry (j) reported in BE-10A (primary industry only) and affiliate industry (i) reported in BE-10B (maximum of seven per affiliate).[23]

[22]The information is collected on a consolidated basis within a country and primary industry *or* within a country and "business operation" (if multiple enterprises are "intergral parts" of that same function)—see BE-10 instruction booklet Section 1.B.2.d.1 (U.S. Bureau of Economic Analysis, 2004).

[23]In 2004, the three possible forms for a given affiliate were BE-10B(LF), BE-10B(SF), and BE-10B Mini. Currently (and by the time of the 2019 survey), the same corresponding forms are now called BE-10B, BE-10C, and BE-10D, respectively.

Table A1 illustrates the information that can be extracted from the BE-10 forms. In this hypothetical stylized example, a U.S. parent p has 7 foreign affiliates: two (a_1 and a_2) in Mexico, two in Canada two (a_3 and a_4), one in Germany (a_5), one in France (a_6), and one in China (a_7). All affiliates are active in industry 1, which is their primary industry. Some affiliates are also active in other industries (a_1, a_4, and a_7 also operate in industries 2, a_2 also operates in industry 3). Some affiliates (a_1 to a_5) are large (i.e., exceed the size threshold above which the BEA collects information on intra-MNE trade), others (a_6 and a_7) are small.

Table A1. Hypothetical Example

Parent	Affiliate	Country	Industries	Large
p	a_1	Mexico	1,2	1
p	a_2	Mexico	1,3	1
p	a_3	Canada	1	1
p	a_4	Canada	1,2	1
p	a_5	Germany	1	1
p	a_6	France	1	0
p	a_7	China	1,2	0

Notes: This table illustrates the hypothetical network structure of a U.S. MNE based on Form BE-10B.

A.2 Mapping MNE Production Networks in Customs Records

We use the LFTTD dataset to trace trade flows within U.S. MNEs. Customs data allow us to identify all trade flows between parent p and its "related parties" in a foreign country, which includes any affiliate in that country. We thus redefine foreign affiliates at the related-party level. Going back to the hypothetical example of Table A1, affiliates a_1 and a_2 in Mexico are consolidated into affiliate A and affiliates a_3 and a_4 in Canada are consolidated into affiliate B, as illustrated by Table A2.

Table A2. Hypothetical Example

Parent	Affiliate	Country	Industries	Large
p	A (a_1 and a_2)	Mexico	1,2,3	1
p	B (a_3 and a_4)	Canada	1,2	1
p	C (a_5)	Germany	1	1
p	D (a_6)	France	1	0
p	E (a_7)	China	1,2	0

Notes: This table illustrates the hypothetical network structure of a U.S. MNE based on Form BE-10B and LFTTD.

A.2.1 Industry Concordances

Our analysis requires the application of multiple concordances since different industry classifications are used to collect information in BEA's multinational surveys, BEA's use and supply tables, and Census's customs merchandise trade data. The BE-10 survey collects information using the international surveys industry (ISI) classification (U.S. Bureau of Economic Analysis, 2022), which is approximately equivalent to a 4-digit North American Industry Classification System (NAICS). BEA's use and supply tables compile information using a different set of industry codes (also related to NAICS), which we refer to as IO industry codes. Finally, the customs merchandise trade data is collected (and included in LFTTD) using 10-digit Harmonized System (HS) product codes.

In order to assign a direct requirement coefficient to all possible industry pairs between a U.S. parent and its foreign affiliate, we concord the ISI to IO industry codes. First, we concord ISI to NAICS codes using concordances published by BEA (U.S. Bureau of Economic Analysis, 2022).[24] Then we utilize a concordance between NAICS and IO industry codes (Appendix A, U.S. Bureau of Economic Analysis, 2007).[25]

In order to assign industry information to LFTTD merchandise trade transactions in constructing extensive margin trade flows between parents and affiliates, we must also concord 10-digit HS product codes to IO industry codes. We first concord the 10-digit HS codes to 6-digit NAICS using concordances between 10-digit HS and 6-digit NAICS codes published by the Census Bureau (U.S. Census Bureau, 2025c).[26] We can then link to IO codes using BEA's IO and NAICS concordance (U.S. Bureau of Economic Analysis, 2007). The

[24]The majority of ISI industries are equivalent to 4-digit NAICS industries.

[25]A spreadsheet version of this concordance can be found under "Supplemental Data and Additional Information" on BEA's Input–Output Accounts webpage (`https://www.bea.gov/data/industries/input-output-accounts-data`).

[26]For our main analysis, which uses 2004 trade flows, we rely on the 2005 concordance because this is the earliest available concordance.

final analysis sample is at the *parent–affiliate industry* level where parent and affiliate firms are associated with IO industries at the 4-digit level.[27]

A.2 Measurement Error in Survey Data

As discussed in Section 3, survey data on intra-MNE trade suffer both from measurement error and missing data. In this section, we discuss how these problems affect the estimates when they apply to a binary dependent variable, as is the case for Equations (1) and (2).

Data often correspond only imperfectly to the theoretical constructs presented in the model (Greene, 2003). The difference between the true value of a variable and its observed value—can significantly impact statistical analyses. Its implications vary based on the type of measurement error, the variable involved, and the statistical method applied.

Missing data can at times be "as an extreme form of measurement error" (Blackwell, Honaker and King, 2017). Missing data can be intentional or unintentional. Intentional missing data occurs when data are deliberately excluded by the data collector, such as through sampling decisions, matrix sampling, questionnaire routing, or censored survival times. On the other hand, unintentional missing data results from unforeseen circumstances beyond the data collector's control, such as skipped survey items, data transmission errors, participant dropout, or refusal to participate. When the data is missing at random and does not significantly affect the estimation process unless efficiency is a concern, it is considered ignorable (Griliches, 1986). A second type occurs when the missing data is systematically related to the phenomenon being studied, in which case ignoring the issue can lead to inconsistencies in the estimators.[28]

Misclassification of a binary dependent variable is a type of non-classical measurement error (not additive and correlated with true value). In a linear probability model like the one estimated by RRR and in equations (1) and (2), this leads to biased estimates rather than simply adding noise as in the case of classical measurement error (Aigner 1973; Bollinger 1996; Meyer and Mittag 2017).[29] Bollinger (2008), Hausman et al. (1998) and Meyer and

[27]For our 2019 analysis, when we use the 2017 concordance, the name of the IO level on the concordance file is "U.Summary".

[28]Rubin (1976) classifies missing data into three categories. Under *Missing Completely at Random* (MCAR), the probability of missingness is independent of both observed and unobserved data. In this case, missing data does not introduce bias into estimators, but only reduces the effective sample size and increases variance (reducing efficiency). When the data is *Missing at Random* (MAR), the probability of missingness depends only on observed data and not the missing (unobserved) values. In this case, maximum likelihood or multiple imputations can provide consistent and asymptotically unbiased estimates if the model is correctly specified. *Missing Not at Random* (MNAR) occurs when the probability of missing data is systematically related to unobserved data, which can lead to biased estimates; see also Graham (2009).

[29]See Chen et al. 2011 for an overview of the literature on measurement error in nonlinear models. Papers examining surveys have found high misclassification in binary variables, e.g., Bound et al. (2001).

Mittag (2017) present general cases of a linear probability model with heterogeneous misclassification.

As an illustration, consider the following linear probability model:

$$y = x'\delta + \varepsilon, \tag{A1}$$

where the misclassification varies with x.

If $y = 1$, the probability of misclassification is:

$$P(y^* = 0 \mid y = 1, x) = \alpha(x) = \alpha_0 + \alpha_1 x. \tag{A2}$$

If $y = 0$, the probability of misclassification is:

$$P(y^* = 1 \mid y = 0, x) = \beta(x) = \beta_0 + \beta_1 x. \tag{A3}$$

where $\alpha(x)$ and $\beta(x)$ capture heterogeneous misclassification that varies with x; $\alpha_1 \neq 0$ and $\beta_1 \neq 0$ introduce correlation between x and the misclassification probabilities.

Using the law of iterated expectations, the conditional expectation of y^* given x is:

$$E[y^* \mid x] = (1 - \alpha(x))P(y = 1 \mid x) + \beta(x)P(y = 0 \mid x). \tag{A4}$$

Substituting $P(y = 1 \mid x) = x'\delta$ and $P(y = 0 \mid x) = 1 - x'\delta$, and expanding the terms, we obtain:

$$E[y^* \mid x] = \beta_0 + \beta_1 x + (1 - \alpha_0 - \beta_0 - \alpha_1 x - \beta_1 x)x'\delta. \tag{A5}$$

If we estimate an OLS regression of y^* on x:

$$y^* = \gamma_0 + x'\gamma_1 + \eta, \tag{A6}$$

the estimated coefficient γ_1 is:

$$\gamma_1 = (1 - \alpha_0 - \beta_0 - \alpha_1 E[x] - \beta_1 E[x])\delta. \tag{A7}$$

Note that *heterogeneous misclassification* leads to different bias directions: If $\alpha_1 > 0$, the probability of misclassifying $y = 1$ as $y^* = 0$ increases with x, biasing the coefficient downward; if $\beta_1 > 0$, the probability of misclassifying $y = 0$ as $y^* = 1$ also increases with x, biasing the coefficient upward. The net effect depends on the relative sizes of α_1 and β_1. If the misclassification is symmetric ($\alpha_1 = \beta_1$), the bias can still be non-zero (vanishing only in knife-edge cases, Meyer and Mittag 2017). The expectation of x among misclassified observations affects the bias direction, and the bias is amplified as the misclassification increases.