# Are Customs Records Consistent Across Countries?

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# Motivation

- In recent decades, many trade researchers have exploited customs records to study:
  - Firm-level trade dynamics
    - market entry and exit
    - market penetration, customer accumulation
  - Patterns of technology diffusion
  - Study international business networks, GVCs
- This work relies heavily on micro patterns in the data
  - Firm-to-firm connections and durations of relationships in international markets
  - Firm-to-firm shipment frequencies, product clasifications, and values.
- But how accurately do the data describe these phenomena?

# This paper

- Our objective: contribute to a small literature assessing the reliability of these micro features of the data
- Compare export records generated by shipments leaving Colombia to the import records generated by the same shipments when they enter the U.S. as imports.
  - Begin with aggregates
  - Go down to HS2 industry
  - Go down to firm to firm
  - Then down to transaction by transaction

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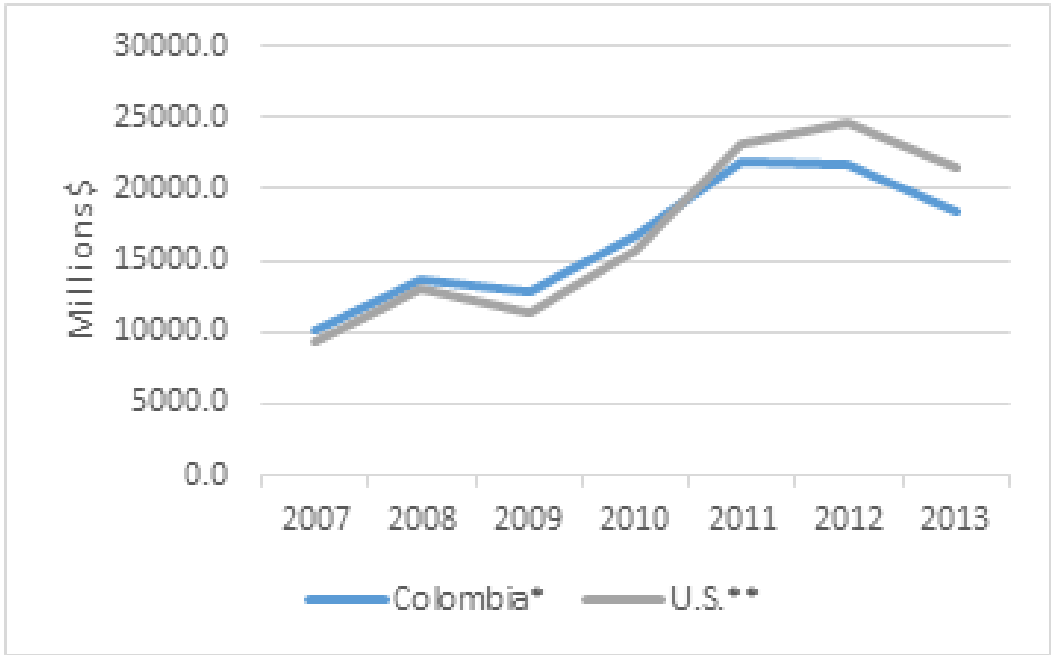
  - Go down to firm to firm
  - Then down to transaction by transaction
- Consider alternative explanations for discrepancies and implications for research.
- Finish with brief discussion of scope for improvements in tracking records.

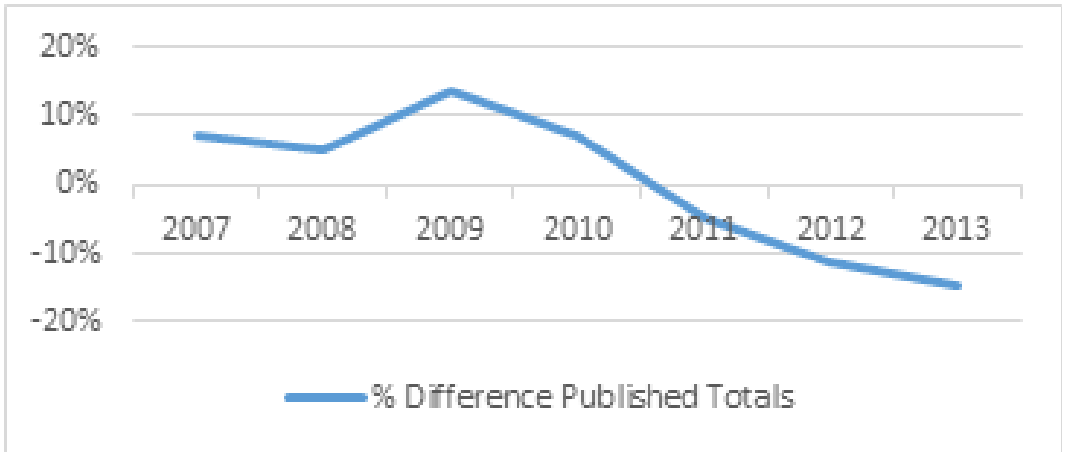
# Related literature

- **Record matching**: massive literature; Christen's (2012) book provides nice overview
- **LFTTD**: Bernard et al. (2009), Barresse et al. (2017), Kamal and Ouyang (2020), Kamal and Monarch (2017)
- **Trade reconciliation studies**: U.S. Census (1996); Orsini and dos Santos (2015); U.S. Census (2012); Fisman and Wei (2004); Mishra et al. (2008); Stoyanov (2012); Ferrantino et al. (2012); 2008 Javorcik and Narciso (2017); Kellenberg and Levinson (2019)
- **Studies using matched customs records** (very incomplete list): Eaton et al. (2008,2014); Blum et al. (2010, 2018); Bernard and Dhingra (2015); Dragusanu (2014); Kamal and Sundaram (2014); Sugita et al. (2019); Dragusanu (2014); Eaton et al (2017); Monarch and Schmidt-Eisenlohr (2017); Bernard et al. (2018a, 2018b); Carballo et al (2018); and Monarch (2019); Helper and Munasib (2021)

# Official aggregates

## Colombian Exports (FOB) to the U.S



# Are discrepancies concentrated in a few industries?

Consider 3 largest HS2 categories, by year


GRAY: ceramic products; ORANGE: apparel not knitted; BLUE: knitted apparel

# A mismatch in transactions or sales per transaction?

- Not uncommon for U.S. importers to split apart transactions for administrative purposes (U.S. Census Bureau experts)
- LFTTD-CO records imply about 8 percent more transactions than the DIAN data.
- But LFTTD-CO also reports 12 percent higher value, so more transactions *and* larger shipment sizes recorded by U.S.
- Not just a matter of shipments generating multiple records in one country but not the other.

# Interpreting the patterns

- Excess of transactions in LFTTD over transactions in DIAN can't just be a record matching problem.
- Is the discrepancy caused by entrepot trade?
  - Country of origin (CO) should differ from shipping country (CS) when entrepot trade occurs.
  - Both databases *should* be based on CO concept, but there's some room for slippage.
    - exporter reports "last known destination"; may not know true destination.
    - importer may not know country of origin.
    - lots of Colombian trade goes through Panama
    - "[T]he majority of trade–80 percent–is shipped indirectly. . ." Ganipati et al. (2021)

# A reflection of Entrepot Trade?

**Figure 4: Monthly Shipments over 2007-2013: LFTTD-CS vs. LFTTD-CO**

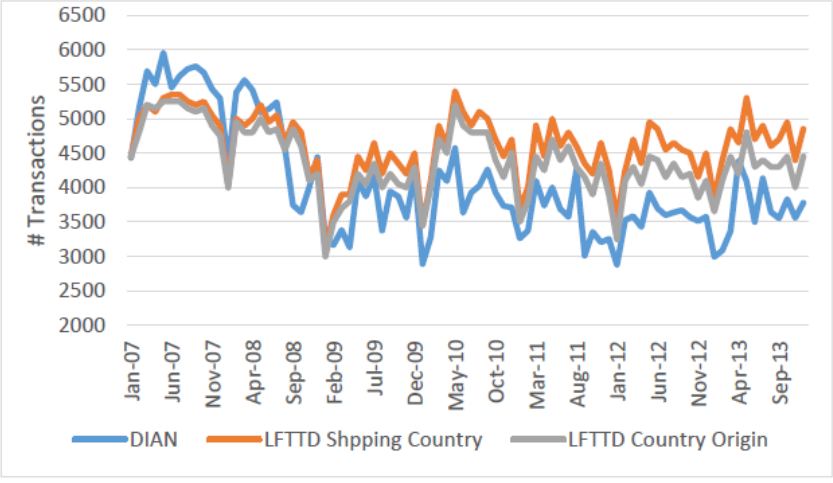
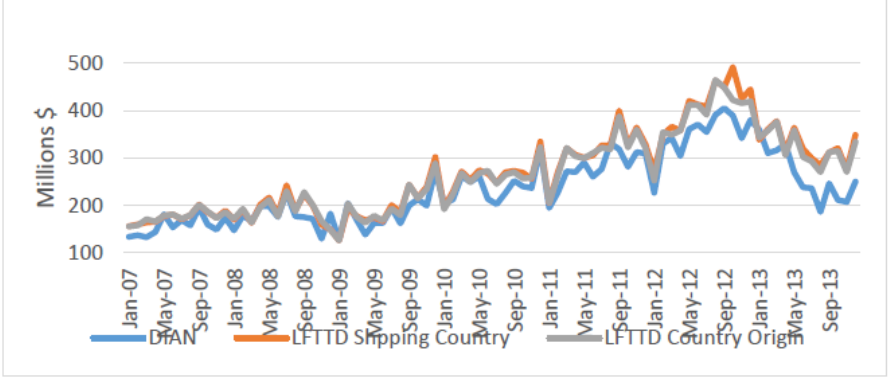



**Figure 5: Monthly F.O.B. value over 2007-2013: LFTTD-CS vs. LFTTD-CO**

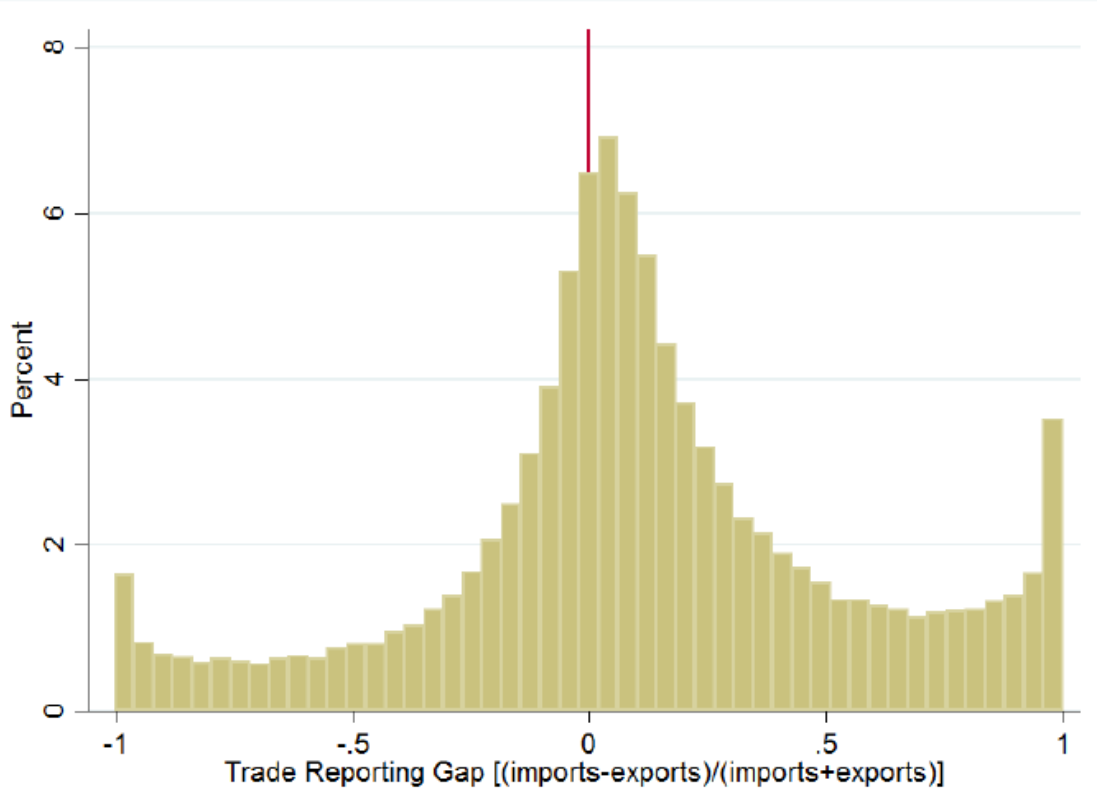



- Entrepot trade *may* be getting more important, still, it doesn't explain growing gap in U.S./Colombia aggregate trade series

details

# Are the gaps especially big?

- 4-7 percent for Australia (U.S. Census, 1996)
- 11-17 percent for Brazil (Orsini and dos Santos, 2015)
- 22-48 percent for China (U.S. Census, 2012).
- wide range in 11 year Comtrade panel,126 countries:




source: Kellenberg and Levinson, 2019

# Correlates of discrepancies

- **Tariffs** (Fisman and Wei, 2004; Mishra et al., 2008; Stoyanov, 2012; Ferrantino et al., 2012; Kellenberg and Levinson, 2019)
  - Colombia-U.S. FTA in 2012 may have reduced incentives in U.S. to understate imports.
  - But the gap didn't close after 2012, it grew.
- **Domestic profit taxes** (which create incentives to overstate the value of intermediate inputs)
- **Preferential trade agreements** (which reduce incentives for tariff avoidance when importing from partner countries)
- **Inflation** (which proxies for incentives to avoid capital controls)
- **Corruption and auditing standards** (Javorcik and Narciso, 2017; Kellenberg and Levinson, 2019).

# Now to our focus: micro examination of misreporting

- Do customs records consistently characterize firm-to-firm trading patterns?
  - Who trades with whom?
  - Within particular buyer-seller relationships, how well to shipment records match up?
- Are reporting issues concentrated among particular types of firms?
- Implications for studies that use these data.

# Matching importers and exporters

| | LFFTD (U.S.) | DIAN (Colombia) |
|---|---|---|
| **Importer identifier** | **EIN** → Name, Address (business registry) | Name, Address |
| **Exporter identifier** | **MID** (string based on Name, Address) | **NIT,** Name, Address |

- Longitudinal Firm Trade Transactions Database (**LFTTD**)
  - Employer Identification Number (**EIN**)
  - EIN can be used to retrieve importing firms' and address from Business Register
- Colombia's National Directorate of Customs and Taxes (**DIAN**)
  - includes tax identification number (**NIT**) of exporter
  - includes name and address of importer

# Identifying trading partners

| | LFFTD (U.S.) | DIAN (Colombia) |
|---|---|---|
| **Importer identifier** | **EIN** → Name, Address (business registry) | Name, Address |
| **Exporter identifier** | **MID** (string based on Name, Address) | **NIT,** Name, Address |

- Trading partner matching strategy.
  - we'll use name and address matching to mimimize loss of information.
  - will also briefly examine properties of a psuedo MID constructed from Colombian data
- Once this is done, we'll try to link the individual transactions reported by each pair of trading partners

# Two-stage linking strategy

- **Preliminary data cleaning**
  - Using code that created the LFTTD, clean records to standardize and reduce noise due to recording errors
- **First stage: firm matching** details
  - Block on zip code or state to reduce dimensionality of the pairwise comparison problem.
  - 3 rounds of exact greedy matching on names and addresses;
  - 3 rounds of fuzzy greedy matching on names and addresses
  - outcome: list of importer-exporter pairs, each agent lists the other as a trading partner within a common time window, up to noise
- **Second stage: transaction matching:** details
  - Block on exporter-importer pairs
  - Use transaction info. (HS2, shipment value, date) to link transactions across datasets.
  - outcome: for each pair of trading partners, a list of transactions they have recorded in a roughly consistent way

# Trading partner matching results

| | **LFTTD** | **DIAN** |
|---|---|---|
| No. Colombian exporters identified | 13,500 | 7,281 |
| No. U.S. importers identified | 9,400 | 18,194* |
| Matched no. importing firms | 2,500 | 2,500 |
| Matched firms, total no. transactions | 259,000 (72.9% LFTTD) | 324,707 (95% DIAN) |
| Matched firms, FOB exports ($USM) | 18,430 (84.8% LFTTD) | 19,268 (97.3% DIAN) |

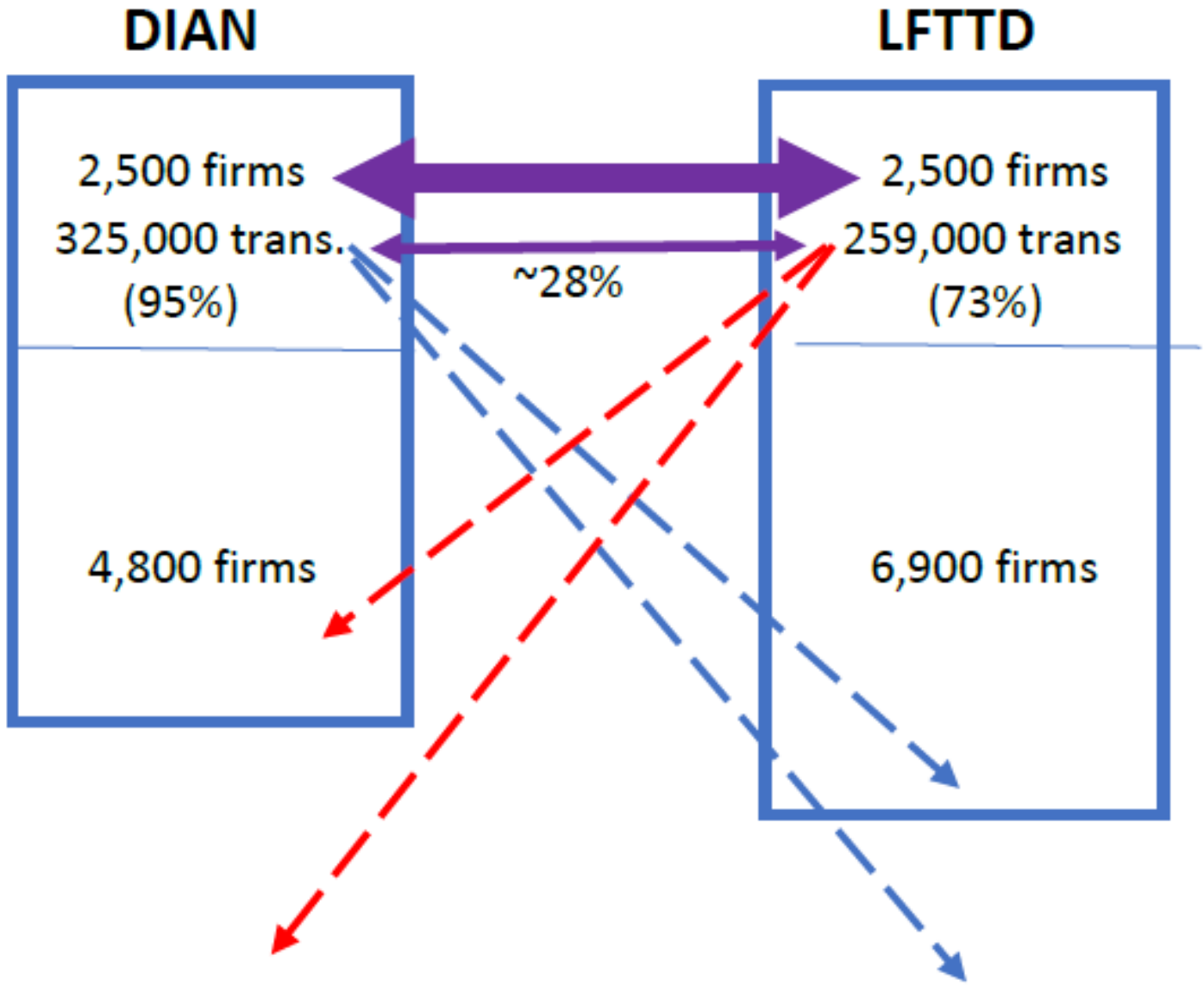
*Based on psuedo MID constructed from importer info. in DIAN.

- Matched *firms* account for most trade, but most firms not matched
- Almost twice as many exporters identified by MID than actually appear in DIAN; similar pattern using psuedo-MID on the DIAN data. (See also Kamal and Monarch, 2018)

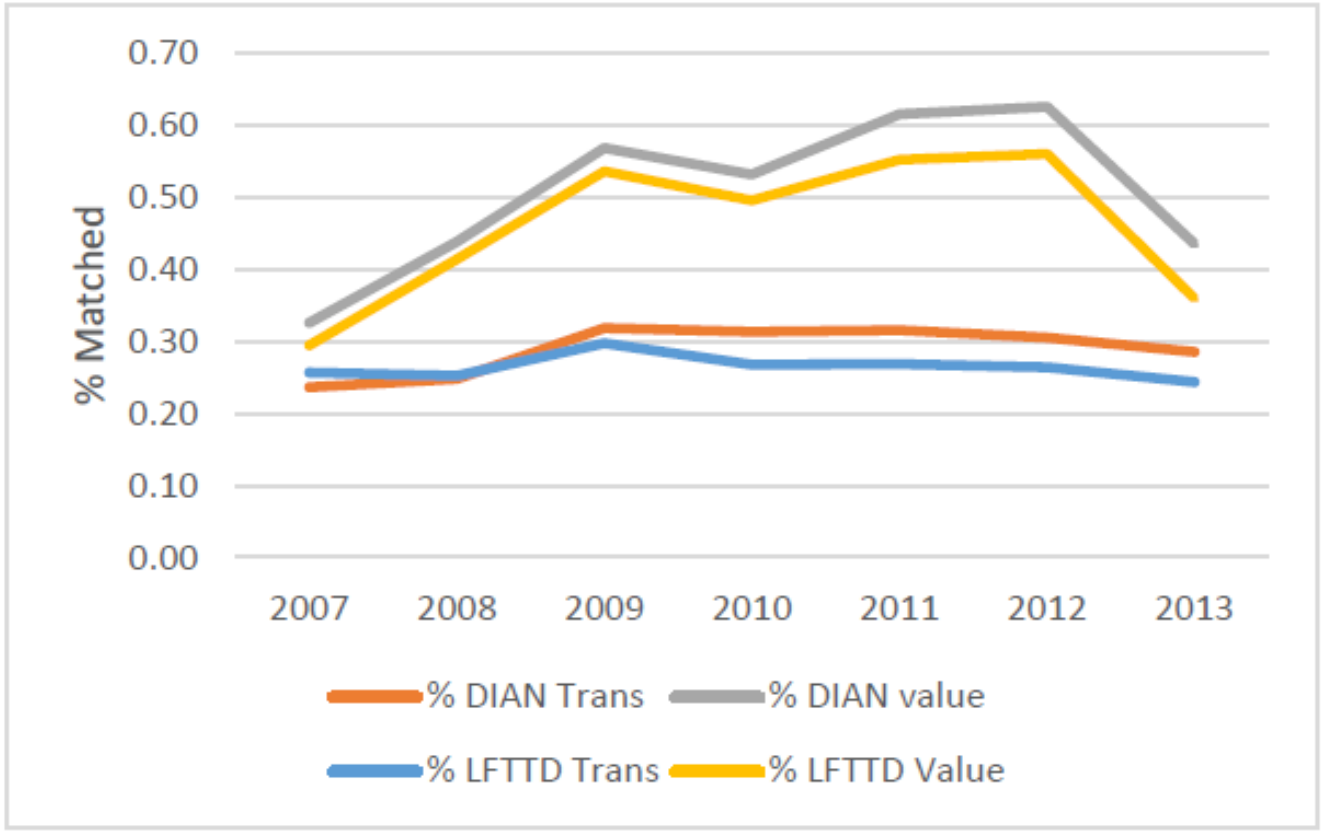
# Transaction matching results

| | **LFTTD** | | **DIAN** | |
|---|---|---|---|---|
| | level | %LFFTD | level | %DIAN |
| # trans. matched | 97,000 | 27.3% | 97,000 | 28.4% |
| FOB value, matched trans. | 10,400 | 48.0% | 10,383 | 52.4% |

- Matched transactions of matched firms account for
  - <30% total transactions,
  - ~50% total value Colombian exports to U.S..


DIAN
LFTTD
2,500 firms
325,000 trans.
(95%)
~28%
2,500 firms
259,000 trans
(73%)
4,800 firms
6,900 firms

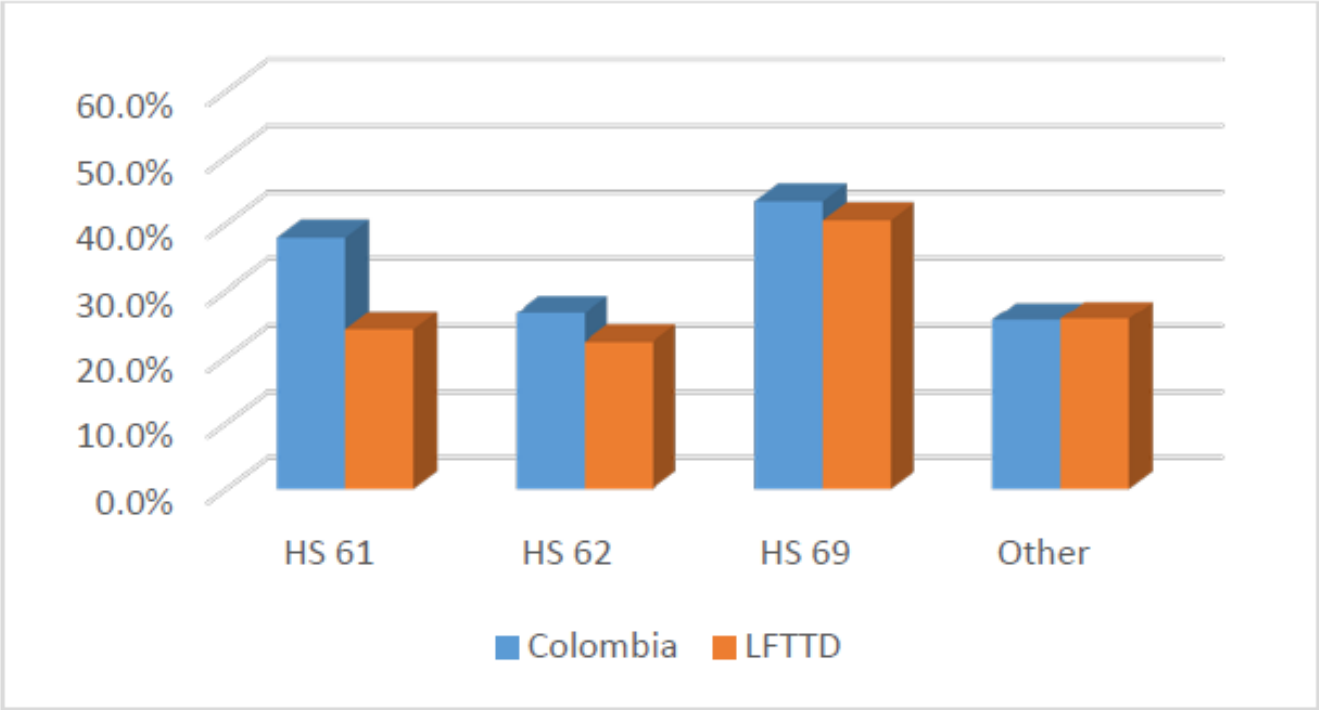
# % Transactions, % FOB value matched over time




The Great Trade Collapse appears to knock out smaller exporters, which are less likely to match.

# % Transactions matched, by industry

3 leading sectors

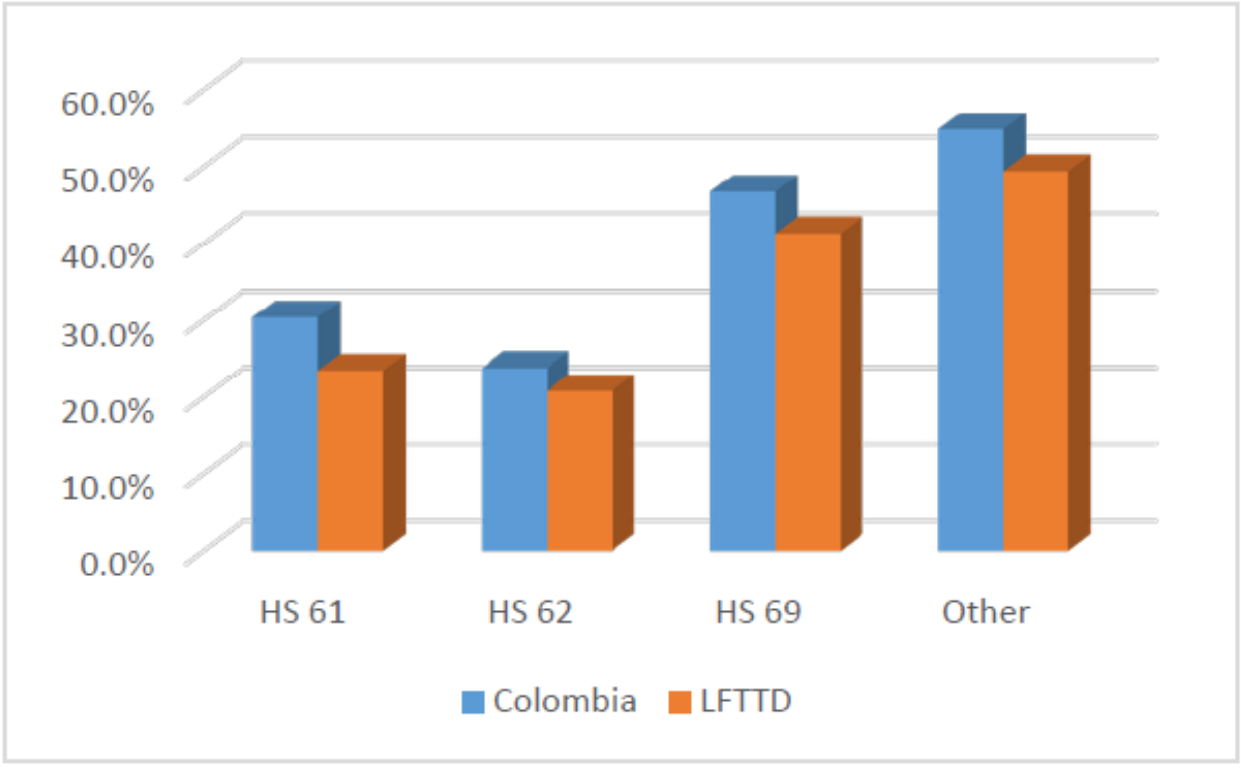



HS 61: Articles of apparel and clothing accessories, knitted or crocheted.
HS 62: Articles of apparel and clothing accessories, not knitted or crocheted.
HS 69: Ceramic products.

- Industries with relatively high turnover, small firms, appear to match less frequently

# % FOB value matched at transaction level

3 leading sectors



# Related party versus Arm's Length (LFTTD only)

| | **Related party** | | **Arm's Length** | |
|---|---|---|---|---|
| | level | %LFFTD | level | %LFTTD |
| # Trans. bet. matched firms | 81,000 | 82.2% | 178,000 | 66.9% |
| # Trans. matched | 30,500 | 30.2% | 67,700 | 25.2% |
| FOB value, matched firms | 2,930 | 80.9% | 15,500 | 83.8% |
| FOB value, matched trans. | 1,257 | 34.7% | 9,165 | 49.5% |

- Related party firms are more likely to match, but their transactions are less likely to match.
- Shades of Bernard et al. (2006) on transfer pricing?

# Match rates by shipment value

| | LFFTD | | DIAN | |
|---|---|---|---|---|
| quintile | trans. | value | trans. | value |
| 1 | 24% | 25% | 25% | 25% |
| 2 | 28% | 28% | 29% | 29% |
| 3 | 26% | 26% | 27% | 27% |
| 4 | 26% | 26% | 30% | 30% |
| 5 | 29% | 51% | 32% | 56% |

- Better match rates in largest quintile, especially in value terms.

# Wholesale/Retail vs Other Importers (LFTTD only)

| | **Non W/R trade** | | **W/R trade** | |
|---|---|---|---|---|
| | level | %Non W/R | level | %W/R |
| # trans. bet. matched firms | 86,000 | 55.1% | 173,000 | 82.0% |
| FOB value, matched firms | 13,770 | 83.4% | 4,660 | 83.2% |
| # FOB. matched trans. | 32,500 | 20.8% | 65,000 | 30.8% |

- Poor match rate for non-W/R transactions, but similar share of FOB value accounted for.

# Summary

- Discrepancies in aggregate flows trace to more Colombian shipments in LFTTD than in DIAN, and larger value per shipment.
  - possibly entrepot trade via Panama, not recorded by Colombians as destined for U.S.
  - not just a few problematic sectors.
- Aggregates hide more dramatic inconsistencies in customs records at the transactions level.
- Transactions that can be matched are accounted for by 2,500 firms–about 35% of the exporting firms in Colombia and 27% of the importing firms in the United states.
  - The firms with at least one matched record account for 97% of Colombian exports to the U.S. and 85% of U.S. imports from Colombia, by value
  - But even for these firms, most transactions cannot be matched.

# Summary, continued

- Match rates for shipments within matched buyer-seller pairs are low, especially for:
  - non-affiliated trade
  - small shipments
  - non-wholesale/retail trade

# Poor linkages mess things up

- **Reseach**
  - characterization of international B2B networks, GVC's:
    - missed links and imagined links affect network statistics, undermining inference
    - mismeasured longevity of relationships
  - analysis of exporter dynamics:
    - mismeasured entry costs, search costs, learning
  - analyses of technology transfers
    - mismeasured effect of interactions
- **Government**
  - construction of trade aggregates
  - enforcement of commercial policy
  - identification of bad actors abroad

$\Rightarrow$ Well-recognized payoff to doing better

# Better identifiers?

- **Shipment Invoice numbers**
  - Issued by the seller to the buyer, lists good, price, etc.; carries numeric code.
  - Main documentation of the sale between the two parties
  - U.S. import declaration form requires the importer to attest to its accuracy and use it to fill-out several vital fields
  - **but** required information on foreign export customs records?
    - In the U.S.: invoice # can be used to identify the "Importer of Record".
- **Bills of Lading (BOL) numbers**
  - BOL issued by the shipment carrier, carries a numeric code
  - establishes receipt of the goods, provide evidence of title to the goods' ownership.
  - **but** they can refer to multiple invoices and they may identify a container rather than a shipment
  - required information on foreign export customs records?
    - In the U.S.: BOL # can be used to identify the "Importer of Record".

# Better identifiers?

- **Private sector firm identifiers**
  - Dunne and Bradstreet
  - others?
- Global coordination on new recording norms may be infeasible.

But . . .

- Collecting data on a subsample could still be valuable
  - provides a sample of known true and false matches
  - opens the possibility of "supervised" matching algorithms that are based on "training" samples

# Entrepot Trade as an obscuring factor

- "[T]he majority of trade–80 percent–is shipped indirectly. The average shipment stops at two additional countries before its destination . . ." Ganipati et al. (2021)
- DIAN records exports according to their "last known destination."
  - If exporters don't know final destination, could bias trade statistics in either direction.
- LFTTD records list Colombia as country of origin (**CO**), shipping country (**CS**), or both. Suppose
  - **CO** = **Colombia, CS** $\neq$ **Colombia:** not a problem if properly recorded in U.S.
  - **CS** = **Colombia, CO** $\neq$ **Colombia:** *could* be a problem if such goods pass through Colombian customs and lose their country of origin identity, while importer knows CO $\neq$ Colombia.

# First stage: exact greedy matching rounds

1. Using standardized names, match on the first five words in each string.

   **example from DIAN:**

   "CEDAR BRIDGE NURSERIES DBA WORLD CLASS FLOWERS" becomes
   "CEDAR BRIDGE NURSERIES DBA WORLD"

2. If no exact match is found for a record, or if less than five words are available, it is passed to a second round based on the first four words.
3. Analogously, records that could not be exactly matched in the second round advance to a third round, which matches on only the first three words

# First stage: fuzzy matching criteria

- Definitions:
  - Let $\gamma$ be a string based on record characteristics
  - let $\mathbb{A}$ and $\mathbb{B}$ be the set of all upstream and downstream records, respectively.
  - let metric $s(\gamma_a, \gamma_b)$ measure similarity (inverse Generalized Edit Distance) between $a \in \mathbb{A}$ and $b \in \mathbb{B}$.
  - let $B \subseteq \mathbb{B}$ be the set of downstream records for which $a$ is the best match: $B = \{b' | a = \max_{a' \in \mathbb{A}} s(\gamma_{a'}, \gamma_{b'})\}$
  - let $I_a$ and $I_b$ be the domestic-record-based firm identifiers associated with records $a$ and $b$, respectively. (For us, $I_a$ is the exporting firm's NIT, and $I_b$ is the importing firm's EIN.)
- Trading partner identification
  - Then we say firms $I_a$ and $I_b$ are trading partners if (1) $b \in B$, (2) $b$ is the best match for $a$:

$$s(\gamma_a, \gamma_b) > \max_{b' \neq b} s(\gamma_a, \gamma_{b'}),$$

and (3) the similarity between $a$ and $b$, $s(\gamma_a, \gamma_b)$, exceeds a threshold value.

# First stage: fuzzy greedy matching rounds, continued

- the rounds:
  - Block on zip code, fuzzy match on name and street address
  - Block on state, fuzzy match on name and street address
  - Block on 2-digit zip code, fuzzy match on name
  - Still no match? **Give up**.

# Second stage: fuzzy matching on transactions

- Blocking on exporter-importer pairs, use transaction information to look for consistency in the transactions reported.
- Match on the similarity between the target transaction in DIAN and each of the potential counterpart transactions in LFTTD.
- Analogously with name/address matching we say records $a$ and $b$ are a match if
  - $a$ is the best match for $b$,
  - $b$ is the best match for $a$ and
  - the similarity between $a$ and $b$, $s(\gamma_a, \gamma_b)$, exceeds a threshold value.
- Now, howerer, $\gamma = [HS2, \textit{shipment date}, \textit{value}]$
- Similarly function somewhat ad hoc, but robustness tested.

**The index**: $$s' = \left(s_{HS2} + s_{date} + s_{value}\right)/3$$

where:

- 2-digit HS codes:

$$s_{HS2} = \begin{cases} |HS2_{DIAN} - HS2_{LFTTD}| = 0 & 1 \\ |HS2_{DIAN} - HS2_{LFTTD}| = 1 & 0.7 \\ |HS2_{DIAN} - HS2_{LFTTD}| = 2 & 0.5 \\ |HS2_{DIAN} - HS2_{LFTTD}| = 3 & 0.3 \\ |HS2_{DIAN} - HS2_{LFTTD}| > 3 & 0 \end{cases}$$

- export month: $s_{date} = 1 - |Month_{DIAN} - Month_{LFTTD}|/12$
- and F.O.B. values: $s_{value} = \frac{|Value_{DIAN} - Value_{LFTTD}|}{Value_{DIAN} + Value_{LFTTD}}$