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Bilateral Trade Asymmetries Between Nepal and India: Evidence from Mirror Statistics

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Abstract

International trade drives economic growth, but its measurement is undermined by discrepancies between partner countries' statistics. This paper examines scale and distribution of bilateral trade asymmetries and identifies their main drivers. Official published trade statistics for fiscal years 2017/18 to 2024/25 were harmonized across currencies and fiscal years, discrepancy indices were constructed, and weighted ordinary least squares regressions were applied at the product-year level. Results show modest aggregate discrepancies (imports 4.2%, exports 0.9%) but large variations across products. Import gaps were concentrated in textiles and medium-duty products, while consumer and intermediate goods exhibited significant asymmetries on both the import and export sides. Discrepancies also narrowed temporarily during COVID-19, suggesting convergence in reporting. The evidence suggests that valuation practices, classification issues, misinvoicing, and informal flows likely contribute to persistent asymmetries. Addressing these requires targeted Customs enforcement, systematic reconciliation of bilateral statistics, and stronger coordination across institutions to strengthen revenue assurance and the credibility of macroeconomic accounts.

Introduction

International trade has long been recognized as a fundamental driver of economic growth and development (Binos et al., 2023; Ji et al., 2022; Were, 2015). Reliable and consistent trade statistics are essential for evidence-based policy making, macroeconomic stability, and Customs revenue collection (Javorsek, 2016). Moreover, trade statistics are the key input for compilation of external sector statistics such as the Balance of Payments (BOP) and System of National Accounts (SNA) (International Monetary Fund, 2025). International trade is a concept that directly involves living standards and wealth creation (Markowicz and Baran, 2021b), thus the issue of trade statistics quality is no longer a matter of technique only but a determinant of wider development outcomes.

However, asymmetries that exist persistently decrease this trust and also lower the use of official trade data in international negotiations and economic governance (Guo, 2010). Discrepancies continue to be major, as each bilateral flow is recorded twice, once as an export and once as an import, but the two numbers often differ significantly (Shaar, 2019). For instance, the global trade in 2016 could have been estimated from US$11.8 trillion to US$14.7 trillion, the variation being due to whether partner-reported exports or imports were taken as the reference (Shaar, 2019). In other words, the discrepancy between trade figures reported by two different countries is still a very significant problem. The mirror statistics have become a global way of checking the consistency of the cross-border trade reporting and of the verification of the enforcement capacities of trade policies (Eurostat, 2006; Hien and Hung, 2020).

Despite continuous improvement in international standards, bilateral trade asymmetries still remain (Javorsek, 2016). As asymmetries exist, these asymmetries complicate the interpretation of trade balances, distort cross-country comparisons, and undermine the credibility of statistics (United Nations Statistics Division, 2019). While in principle exports and imports between two partners should match except for Insurance and freight costs, in reality they often diverge widely, particularly for developing countries with weaker statistical systems (Guo, 2010; Hamanaka, 2011). As various research has highlighted, there are several reasons for asymmetries seen in bilateral trade in goods such as valuation, classification (Markhonko, 2014; OECD, 2025), re-export (Guo, 2010), statistics recording systems (OECD, 2025). Yet even with such efforts, discrepancies remain large enough to affect empirical research, fiscal analysis, and international negotiations.

The systematic asymmetries reflects both technical and institutional factors. Some of the technical factors that can cause asymmetries are differences in classification, valuation (FOB vs. CIF), exchange rates, and timing of shipment recording (Hien and Hung, 2020; Shaar, 2019). And more fundamentally, they also represent the real cases of deliberate mis-classification, under/over invoicing, and smuggling. Some studies from different regions have indicated that tariff evasion, corruption, and weak enforcement amplify asymmetries (Hong and Pak, 2017; Kellenberg and Levinson, 2019). Besides, that misreporting has a link with illicit financial flows, as it is estimated that more than half (54%) of Africa's illicit outflows between 2001 and 2010 were associated with trade mispricing (Hong and Pak, 2017). Furthermore, the problem of the differences of CIF-FOB margins, exchange rate volatility, and "Rotterdam effects" has made reconciliation even more complicated (Hien and Hung, 2020). However, the concept of mirror statistics is no longer limited to macroeconomics, as they are now being used in Customs operations for various purposes, such as the detection of undervaluation, misclassification, and fraud (Cantens et al., 2013; Geourjon, 2023). So, Asymmetries analysis matters deeply because it extends beyond statistical and research applications to include enforcement functions as well.

Nowhere are these issues more pertinent than in the Nepal–India trade corridor. Nepal is a landlocked country with a high degree of trade concentration: India consistently accounts for the largest share of Nepal's trade, representing about 59 percent of total imports and more than 80 percent of exports (Department of Customs, Government of Nepal, 2025). Such close integration is the result of an open border, long-standing trade treaties, and dependence on the Indian transit infrastructure for third-country trade. Given this structural dependence, the accuracy of bilateral trade statistics is especially important. Accurate bilateral statistics are therefore important for both nations, as they strengthen the basis for trade policy, revenue administration, and bilateral cooperation. At the same time, while aggregate trade flows between Nepal and India are broadly aligned, closer inspection reveals significant product-level discrepancies that go beyond what can be explained by normal CIF-FOB margins. These factors make the Nepal–India case both policy-relevant and analytically challenging. While international organizations have long promoted mirror statistics as a tool to improve trade data quality and Customs oversight (Hien and Hung, 2020), systematic and product level analyses of Nepal–India asymmetries remain limited.

While there has been sustained international attention to the issue, empirical research on the bilateral trade asymmetries in South Asia is limited. Existing literature has largely focused on overall flows or on the well-established bilateral corridors such as the U.S.-China, thus, there is still a substantial amount of uncharted territory regarding the less-studied regions (Markhonko, 2014; Yurik et al., 2020), resulting significant gaps for under-researched regions. The number of asymmetry studies at the commodity level is still limited, although trade measurement can be very much affected by product-level misclassification and reverse asymmetries (Hamanaka, 2011). While mirror statistics have been deployed to detect fraud in Africa (Cantens et al., 2013) and to evaluate aggregate asymmetries in East Asia (Guo, 2010), no systematic analysis has examined Nepal–India flows at the HS6 level. This represents both an empirical and methodological gap. Addressing it is crucial because South Asian corridors share characteristics that are known to exacerbate discrepancies - porous borders, large re-export channels, and tariff-induced misinvoicing.

Against this backdrop, the paper aims to measure the overall magnitude and temporal profile of Nepal–India bilateral asymmetries from FY 2017/18 to 2024/25. It also examines product-level comparisons, which are critical for economic measurement and integration into the System of National Accounts. In addition, the study identifies reverse asymmetries and tests the statistical significance of these patterns using value-weighted OLS, aligning the weights with policy relevance through trade value and situating the analysis within ongoing international reconciliation efforts. Together, these aims operationalize mirror statistics for a high-dependence corridor and provide an empirically grounded basis for both statistical reconciliation and Customs enforcement.

The contribution of this paper is threefold. Empirically, it is the first product level analysis of Nepal–India trade asymmetries. Methodologically, it applies both conventional difference measures and econometric modeling. Policy-wise, it offers actionable insights for Customs and statistical reconciliation.

The remainder of the paper is structured as follows. Section 2 describes the data and empirical strategy, including formulas for asymmetry indices and the econometric methods. Section 3 presents result on aggregate trends, product-level drivers, event linkages, and econometric findings. Section 4 discusses the implications, situating the Nepal–India case within global literature and policy debates. Section 5 concludes with key policy recommendations for Customs, statistical agencies, and international cooperation.

Research Methods

Data

The empirical analysis in this study relies on officially published merchandise trade statistics from both Nepal and India. For India, bilateral export and import data at the six-digit level (HS6) of the Harmonized System were obtained from the Department of Commerce, Ministry of Commerce and Industry (Department of Commerce, Ministry of Commerce and Industry, Government of India, 2025b, 2025a). Corresponding data for Nepal were obtained from the Department of Customs, Government of Nepal (Department of Customs, Government of Nepal, 2025). Nepal's data were changed from the Nepalese fiscal year (mid-July to mid-July) to the Indian fiscal year (April to March) to ensure comparability. The study covers eight fiscal years (2017/18 -2024/25). For convenience these are referred to as 2017–2024 in the text.

Given that the Nepalese and Indian currencies are pegged, a uniform currency method was adopted to carry out the study. Indian data were retained in Indian rupees (INR), whereas values from Nepal were converted to INR for the analysis. This ensured that all bilateral discrepancies were measured consistently in a single currency. For presentation of aggregate flows, values were subsequently converted into United States dollars (USD) using the annual average exchange rate.

All initial analysis was done using HS6 level data, which is the most detailed level that is internationally comparable in trade statistics. For descriptive analysis and interpretation, HS6 codes were grouped into higher-order classifications. The chapter-level summaries (HS2) adhered to the official Harmonized System nomenclature of the World Customs Organization (World Customs Organization, 2022). For an economic breakdown, HS6 codes were mapped into the Broad Economic Categories (BEC, Rev.5) (United Nations Department of Economic and Social Affairs, 2018), which separate capital, intermediate, and consumption goods. To capture sectoral differences beyond HS, the HS6 codes were also merged with the Standard International Trade Classification (SITC Rev.4) (United Nations, 2006) using correlation tables provided by the World Integrated Trade Solution (WITS) (World Bank, n.d.). In addition, a separate concordance was applied to identify product categories subject to different levels of effective Customs duty, using a duty-effectiveness classification created for this study by the author, categorizing effective rates as low, medium, or high. Codes in administrative or special chapters (98 and 99) were excluded as they do not represent normal merchandise trade.

The raw datasets were cleaned and harmonized at the HS6 × year level. After aligning fiscal years and currencies, total trade flows and discrepancy indices were constructed for each HS6 product in each year. Additional binary indicators were created to capture product and sectoral characteristics. For example, textile products were identified using SITC sections 26, 65, and 84, and dummy variables were created for food and agricultural products based on SITC sections and HS ranges. A separate dummy was included to capture the COVID-19 shock for fiscal years 2020 and 2021. Duty categories were merged from external concordance tables. All categorical variables, including BEC and duty categories, were coded as factors for use in regression analysis. The dependent variable for the econometric analysis was defined as the natural logarithm of one plus the absolute value of the discrepancy index, i.e. ln(1+|"DIF" |), which reduces skewness and stabilizes variance across observations. Table 1 summarizes all variables used in the analysis, including type, coding, and definitions.

Table: 1
Summary of variables used in the analysis

Variable	Type	Description	Coding Notes
DIF	Continuous	Absolute bilateral trade discrepancy at HS6 level	Used ln(1+DIF) in regressions
Textile	Dummy	Indicates textile products	SITC sections 26, 65, 84; WITS
Food	Dummy	Indicates food products	Based on SITC/HS ranges; WITS
Agriculture	Dummy	Indicates agricultural products	SITC/HS ranges; WITS
COVID	Dummy	Captures COVID-19 shock	Fiscal years 2020/21 and 2021/22
BEC	Categorical	Broad Economic Category	Capital, Intermediate, Consumption goods
Duty Category	Categorical	Effective Customs duty	Low, Medium, High

Index and Model

Bilateral trade asymmetries arise when exports reported by one country to its partner do not equal the partner's reported imports from that country. To quantify these discrepancies, this study follows the standard Discrepancy Index of Foreign Trade (DIF) approach (Guo, 2010; Javorsek, 2016). Let M_{AB} denote imports reported by country B from country A, and E_{AB} denote exports reported by A to B. Because the same merchandise flow can be viewed from the perspective of either the exporter or the importer, two complementary versions of the index are defined.

When country A is treated as importer (and B as exporter), the import discrepancy index is given by:

$$\text{DIF}(I)_A = \frac{M_{BA} - E_{BA}}{M_{BA}} \times 100,$$

which measures the relative difference between the imports reported by A from B and the exports reported by B to A. Similarly, when country A is treated as exporter (and B as importer), the export discrepancy index is defined as:

$$\text{DIF}(E)_A = \frac{M_{AB} - E_{AB}}{M_{AB}} \times 100,$$

which measures the relative difference between the imports reported by B from A and the exports reported by A to B.
By construction, $\text{DIF}(I)_A = \text{DIF}(E)_B$. Thus, the same bilateral discrepancy can be expressed symmetrically from the perspective of either country. A positive value indicates that reported imports exceed reported exports, while a negative value indicates the reverse. The magnitude of the index reflects the severity of the discrepancy. For this study, A refers to Nepal and B to India. Import and export DIF have been calculated from Nepal's perspective.

To analyze and statistically validate the determinants of bilateral asymmetries, weighted ordinary least squares (WOLS) regressions were conducted at the HS6 × year level. The specification took the form:

$$y_{i,t} = \beta_0 + \beta_1 \text{Textile}_i + \beta_2 \text{COVID}_t + \beta_3 \text{BEC}_i + \beta_4 \text{Duty}_i + \beta_5 \text{Food}_i + \varepsilon_{i,t},$$

where the dependent variable $y_{i,t}$ is the log-transformed absolute discrepancy for product i in year t. Estimations were performed separately for import-based and export-based discrepancy indices. The regressions were weighted by the combined bilateral trade value of each HS6 product, reflecting the policy relevance of higher value items, and standard errors were clustered at the HS6 product level to account for correlation across years. All data processing, cleaning, and analyses were conducted in R (version 4.5.1), using packages such as tidyverse for data manipulation, flextable for table presentation, and fixest for OLS. Weighted OLS regressions were performed to assess determinants of bilateral discrepancies, with trade-value weights and clustering at the HS6 level to account for repeated observations over years. The workflow ensured consistent alignment of fiscal years, currency conversion, and classification of products across datasets.

Results

Aggregate bilateral trade flows

The initial analysis compared officially reported bilateral trade flows between Nepal and India, as presented in Table 2.

Table: 2
Reported bilateral trade flows between Nepal and India (USD million).

	India Reported Trade with Nepal		Nepal Reported Trade with India	
Year	Export	Import	Import	Export
2017	6,613	438	7,187	427
2018	7,766	508	8,229	494
2019	7,160	712	7,619	675
2020	6,838	673	6,941	662
2021	9,646	1,371	9,607	1,398
2022	8,079	842	8,223	858
2023	7,041	831	7,590	769
2024	7,386	1,289	7,822	1,318

At the aggregate level, the data shows that both countries report sizable flows with each other. Nepal's reported imports from India consistently exceed India's reported exports to Nepal, while India's reported imports from Nepal are generally larger than the exports recorded by Nepal.

During the reference period, on average, Nepal reported imports of $7.7 billion per year from India while India declared $7.3 billion of exports to Nepal. Likewise, India declared that on average per year it imported $896 million from Nepal, whereas Nepal registered $880 million as

exports to India. Expressed as bilateral discrepancy indices, the import-based measure (DIF_{import}) stands at 4.2 percent and the export-based measure (DIF_{export}) at 0.9 percent over the entire period 2017/18-2024/25.

Patterns of Trade Asymmetries

Annual dynamics reveal substantial variation behind the aggregate averages (Figure 1). In 2017, the import discrepancy approached 8%, and export asymmetry was 2.7%. Import asymmetries then declined and reached a trough near 1.5% in 2020 before turning negative in 2021. Similarly, export asymmetries rose sharply to above 7% in 2023 and turned negative in 2024.

Figure: 1
Annual bilateral trade discrepancy indices between Nepal and India

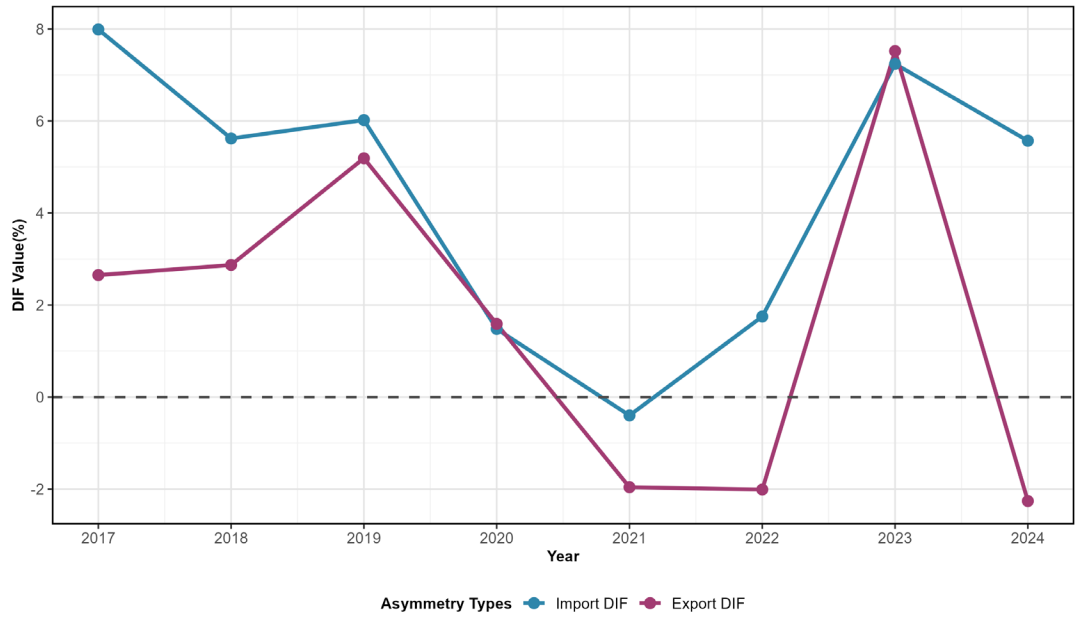
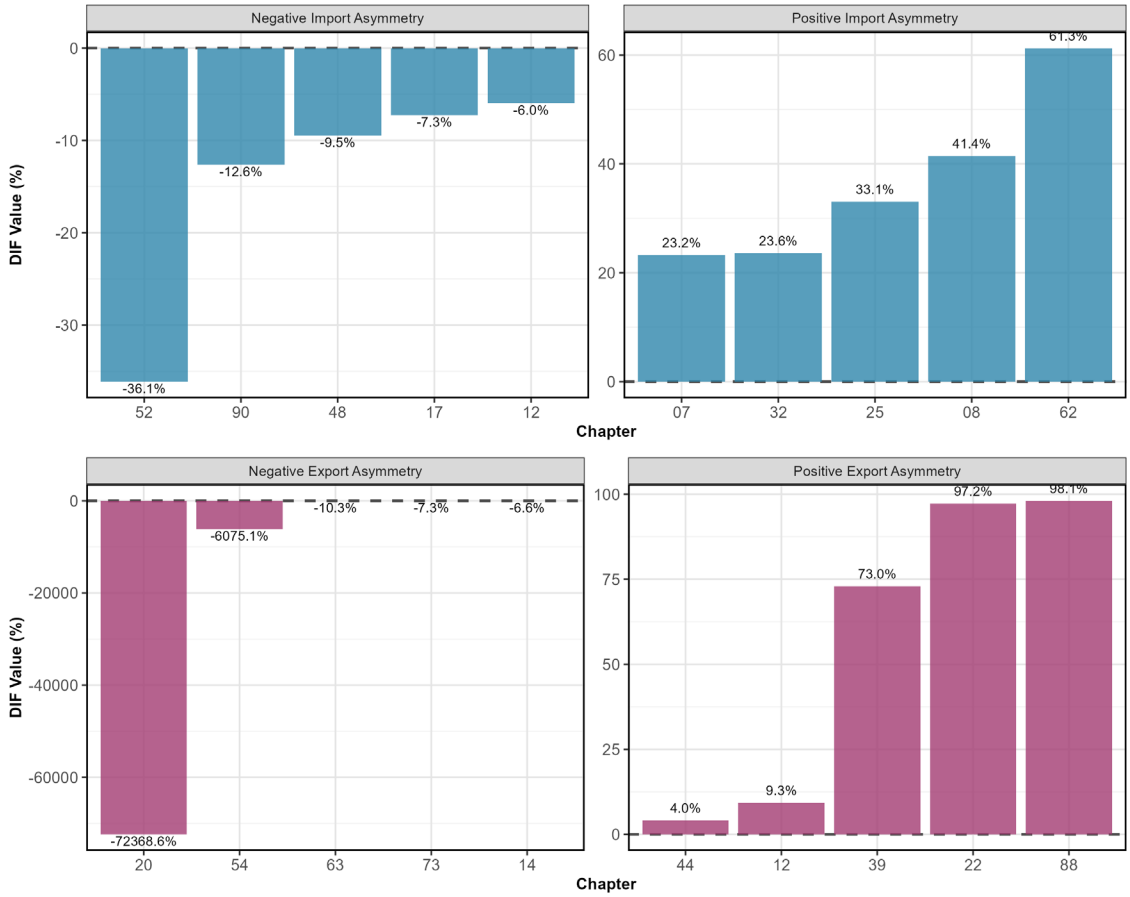


Figure highlights the cyclical nature of these discrepancies. Interestingly, during the pandemic period of 2020-2021, both indices approached zero. This suggests temporary convergence in reporting practices between the two countries during COVID-19.

Sectoral analysis highlights that asymmetries are concentrated in specific chapters of the Harmonized System (Figure 2). These variations suggest that product-specific factors; such as valuation methods, classification differences, and trade facilitation procedures contribute significantly to bilateral discrepancies.

Figure: 2
Top commodity chapters with highest positive and negative trade asymmetry indices



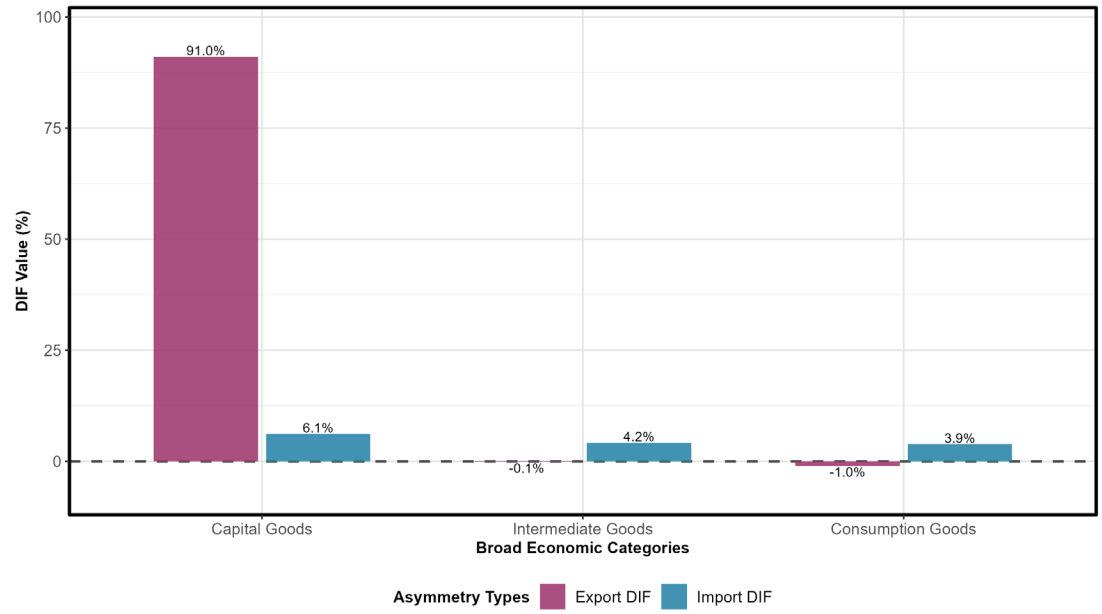
On the import side, the analysis shows substantial positive discrepancies in textiles and apparel (chapter 62, +61.3%), fruits and nuts (chapter 08, +41.4%), salt and minerals (chapter 25, +33.1%), dyes and pigments (chapter 32, +23.6%), and vegetables (chapter 07, +23.2%). Conversely, reverse asymmetries appeared in cotton (chapter 52, -36.1%), optical instruments (chapter 90, -12.6%), paper products (chapter 48, -9.5%), sugar (chapter 17, -7.3%), and oil seeds (chapter 12, -6.0%).

Export asymmetries showed even more pronounced variations. The highest positive discrepancies occurred in aircraft parts (chapter 88, +98.1%), beverages (chapter 22, +97.2%), and plastics (chapter 39, +73.0%), while oil seeds (chapter 12, +9.3%) and wood products (chapter 44, +4.0%) showed moderate positive asymmetries. On the negative side, Preparation of vegetable and fruits (chapter 20, -72368%), man-made fibers (chapter 54, -6075%), textile articles (chapter 63, -10.3%), iron and steel (chapter 73, -7.3%), and vegetable materials (chapter 14, -6.6%) exhibited substantial discrepancies.

Although some of these large values are inflated by small denominators at the HS6 level, the overall pattern confirms that trade asymmetries are highly commodity-specific. This concentration underscores that a relatively narrow set of chapters accounts for the bulk of Nepal- India discrepancies.

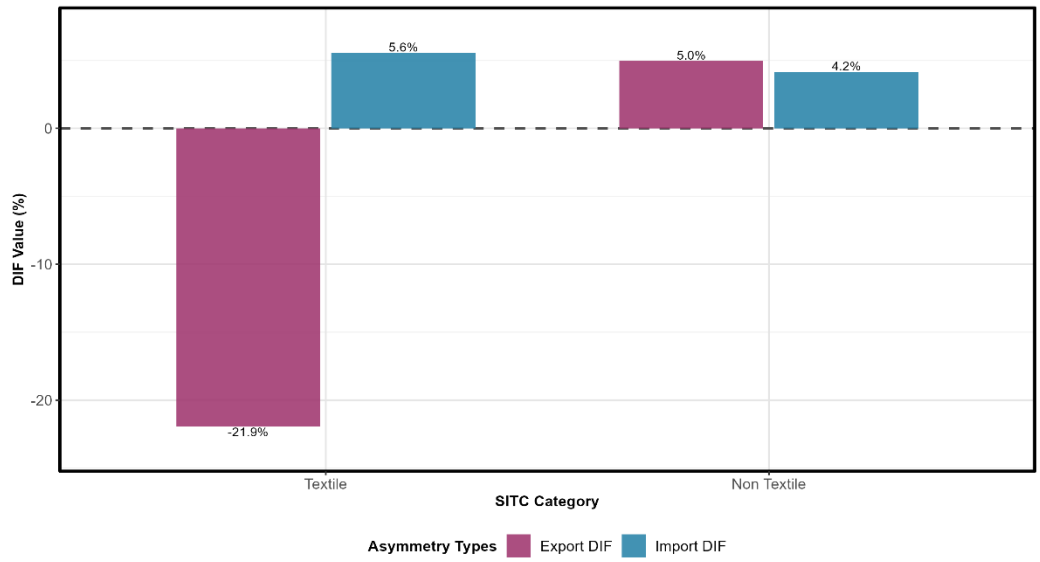
Beyond chapter-level patterns, asymmetries also varied across broad product categories. To examine whether the nature of goods contributed to systematic discrepancies, analysis grouped HS6 observations into Broad Economic Categories (BEC), textile versus non-textile products, and food versus non-food commodities.

Figure: 3
Bilateral trade discrepancy indices by Broad Economic Categories (BEC).



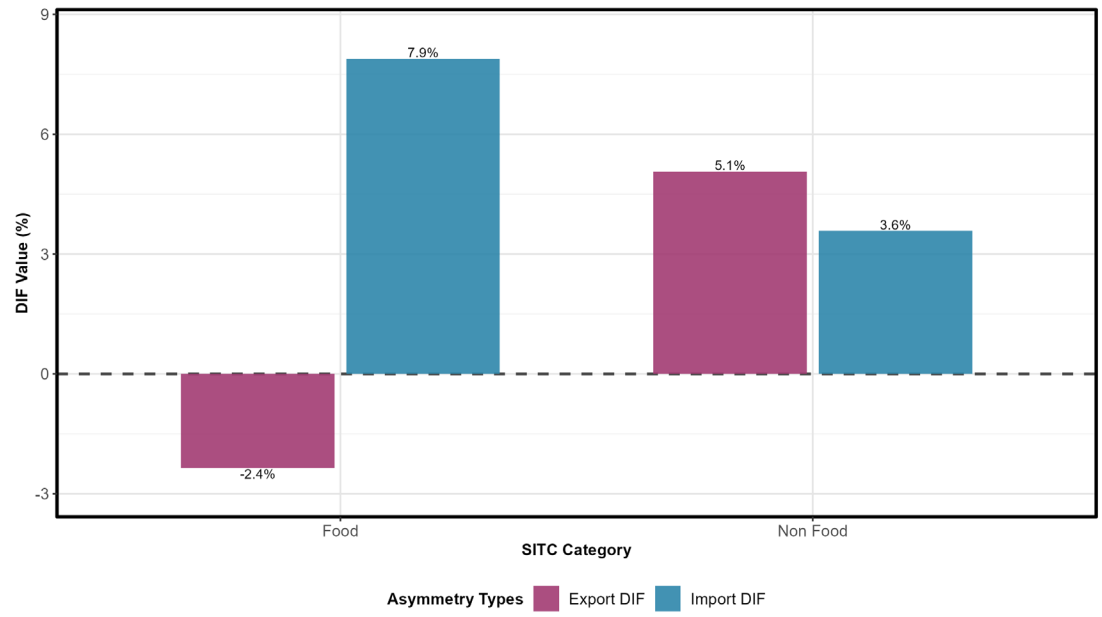
The BEC classification shows notable contrasts (Figure 3). Capital goods exhibited extremely large export-side discrepancies (91%), while import-side DIFs were more moderate (6.1%). Because capital goods accounted for only a very small share of total trade, even a few one-off transactions generated disproportionately large asymmetries. Intermediate goods recorded an import discrepancy of 4.2% and an export DIF close to zero (-0.1%). Similarly, consumption goods showed an import DIF of 3.9% and an export DIF of -1.0%. These results indicated that, Capital goods generated the most extreme trade discrepancies, but misreporting was also common in intermediate and consumer goods.

Figure: 4
Bilateral trade discrepancy indices for textiles and non-textile products.



Textiles stood out as a category with asymmetric patterns in both directions (Figure 4). On a comparative basis, textile imports in Nepal were on average 5.6% higher than the exports reported by India. In particular, textile exports had a negative DIF of -21.9%, which suggested that import records of India were always higher than the exports declared by Nepal for textile products. In stark contrast to these results, non-textile products only showed a very small discrepancies: imports showed a discrepancy index of 4.2% and exports 5.0%. The difference emphasized that textiles were more in line with the divergent reporting of the two countries.

Figure 5
Bilateral trade discrepancy indices for food and non-food commodities.

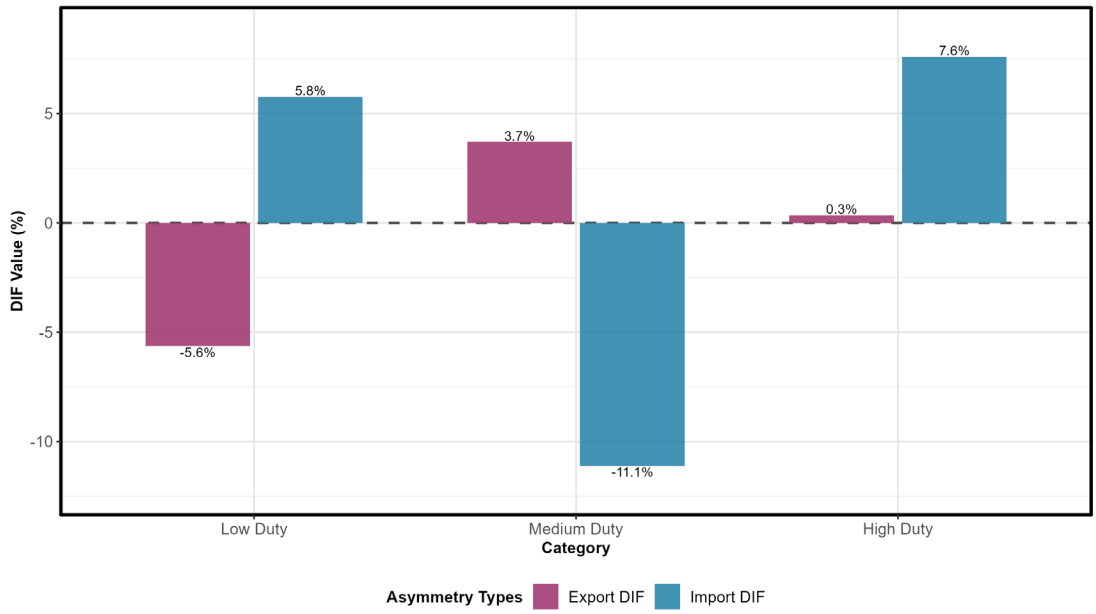


Food and non-food commodities also showed consistent differences (Figure 5). Food imports were associated with a discrepancy of 7.9%, more than double the 3.6% observed for non-food imports. On the export side, food commodities showed negative asymmetries (-2.4%), while non-food commodities exhibited positive discrepancies (5.1%). These results indicated that food trade, in particular, was characterized by greater divergence in bilateral statistics.

Taken together, the product category analysis revealed that the most pronounced asymmetries were concentrated in capital goods, textiles, and food commodities. Capital goods showed the highest export-side discrepancies (91%), textiles displayed the largest negative export asymmetries (-21.9%), and food products exhibited the greatest import-side discrepancies (7.9% vs 3.6% for non-food imports).

The analysis looked at trade discrepancies for products with different levels of taxes for import, including import duty, excise, VAT, and other taxes collected at Customs point. Products were grouped as low-tax (effective tax rate less than or equal to 20%), medium-tax (effective tax rate more than 20% but less than or equal to 30%), and high-tax (effective tax rate more than 30%). Figure 6 shows the trade discrepancies for these groups.

Figure: 6
Bilateral trade discrepancy indices for duty categories.



Trade asymmetries varied systematically across duty effective rate categories (Figure 6). Products with low duties showed import discrepancies of 5.8% and negative export discrepancies of -5.6%. Commodities with medium duties had the largest import-side asymmetries at -11.1%, while export discrepancies were positive at 3.7%. Products with high duties had import discrepancies of 7.6% and modest export discrepancies of 0.3%.

The discovered trend indicated that medium-duty groups were the main source of the most significant import-side discrepancies as Nepal's reported imports were 11.1% lower than India's recorded exports. This contrasted with low-duty and high-duty categories, where Nepal consistently reported higher import values.

Econometric evidence: weighted OLS models

The weighted Ordinary Least Squares (OLS) models were estimated to examine the relationships between product characteristics and the bilateral trade asymmetries. Both import and export models incorporated product categories, BEC, tariff category, food vs non-food, and the COVID-19 period, while standard errors were clustered at the HS6 level. Table 3 presents the estimated coefficients, standard errors, and model statistics.

Table: 3
Weighted OLS estimates of bilateral trade asymmetries

	Import Model		Export Model	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Textile	1.258***	(0.313)	0.057	(0.337)
COVID-19	-0.230*	(0.111)	-0.060	(0.233)

	Import Model		Export Model	
Variable	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Consumer goods	-1.107***	(0.199)	-1.185**	(0.457)
Intermediate goods	-0.512**	(0.169)	-0.857**	(0.298)
Medium Duty	0.327*	(0.163)	-0.461	(0.368)
High Duty	0.163	(0.177)	-0.330	(0.370)
Food	0.326	(0.241)	0.152	(0.375)
Constant	3.193***	(0.134)	4.404***	(0.144)
Observations	31,113		2,786	
R-squared	0.099		0.068	
RMSE	7.219		14.0	

Notes: Dependent variables: ln(1 + import/export DIF). Standard errors clustered at HS6 level.

Reference categories: Capital goods (product), Low Duty (tariff).

*All models weighted by trade volume. *** p<0.001, ** p<0.01, * p<0.05*

For imports, textile products are associated with substantially larger discrepancies compared to non textile product (β = 1.258, SE = 0.313, p < 0.001). This indicates that the magnitude of import asymmetries in textiles is significantly greater, holding other factors constant. The COVID-19 period showed a modest negative effect (β = -0.230, SE = 0.111, p < 0.05), indicating that reporting discripencies were somewhat reduced during the pandemic. Regarding BEC categories, consumer goods (β = -1.107, SE = 0.199, p < 0.001) and intermediate (β = -0.512, SE = 0.169, p < 0.01) goods exhibit significantly larger import discrepancies relative to capital goods. Consumer goods and intermediate goods exhibit significantly larger import discrepancies relative to capital goods, while medium duty tariffs show a positive association with discrepancies. Food imports, despite showing noticeable variation in the descriptive analysis, were not statistically significant, implying that discrepancies in food trade may be more sporadic or transaction-specific rather than systematic. Food category do not show statistically significant effects. The model explains approximately 10% of the variation in the log-transformed magnitude of import discrepancies (adjusted R^2 = 0.099), with a root mean squared error of 7.219.

For export discrepancies, the magnitude of asymmetries is generally lower. only borad economic categories are statistical significant. Both, consumer goods (β = -1.185, SE = 0.457, p < 0.01) and intermediate goods (β = -0.857, SE = 0.298, p < 0.01) are associated with larger export discrepancies relative to capital goods. but share of the capital goods in export is very low. Moreover, the coefficients for the categories textile, COVID-19, tariff, and food are not statistically significant, which shows that these factors do not contribute systematically to export discrepancies. The export model explains approximately 6.8% of the variance in log-transformed absolute export discrepancies, with an RMSE of 14.0.

To assess the stability of the baseline estimates, a series of robustness checks were conducted using alternative model specifications (Table 4). These include unweighted estimation, models

without clustering, clustering at a broader HS2 level, and a trimmed sample excluding extreme observations.

Table: 4
Robustness Checks for Weighted OLS Estimates of Import Discrepancies

Variable	Baseline	Unweighted	No Clustering	Alt. Clustering	Trimmed Sample
Textile	1.258*** (0.313)	0.514*** (0.053)	1.258*** (0.041)	1.258** (0.376)	1.091*** (0.266)
COVID-19	-0.230* (0.111)	0.137*** (0.018)	-0.230*** (0.017)	-0.230 (0.145)	-0.224* (0.111)
Consumer goods	-1.107*** (0.199)	0.029 (0.060)	-1.107*** (0.031)	-1.107*** (0.181)	-1.121*** (0.192)
Intermediate goods	-0.512** (0.169)	0.042 (0.044)	-0.512*** (0.029)	-0.512** (0.178)	-0.555*** (0.164)
Medium Duty	0.327* (0.163)	-0.033 (0.042)	0.327*** (0.024)	0.327* (0.150)	0.320* (0.151)
High Duty	0.163 (0.177)	0.176*** (0.050)	0.163*** (0.019)	0.163 (0.238)	0.148 (0.166)
Food	0.326 (0.241)	0.213** (0.072)	0.326*** (0.023)	0.326 (0.325)	0.283 (0.220)
Constant	3.193*** (0.133)	3.550*** (0.034)	3.193*** (0.027)	3.193*** (0.128)	3.190*** (0.133)
Observations	31,113	31,113	31,113	31,113	30,804
R-squared	0.099	0.020	0.099	0.099	0.110

Notes: Dependent variable: ln(1 + Import DIF).

Baseline: weighted OLS with HS6 clustering. Unweighted: no trade weights. No Clustering: SE not clustered.

Alt.Clustering: clustered at HS2 level. Trimmed Sample: 1% extremes excluded.

*Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05*

Across these specifications, the main result remains consistent. The association of textile products with import discrepancies is positive and statistically significant. The COVID-19 variable is still negative in most cases, but it is sensitive to different specifications in terms of its significance. Consumer and intermediate goods consistently exhibit negative coefficients, reinforcing the baseline conclusion that product type plays a role in shaping reporting asymmetries. The effects of other covariates, like tariff categories and food products, are suggested by their less stable behavior across specifications, indicating that they are weaker and more context-dependent. Overall, the robustness checks confirm that the substantive findings of the analysis are not dependent on a single modeling approach.

Discussion

This study examined product-level determinants of bilateral trade asymmetries in the Nepal India merchandise trade. The analysis found that asymmetries are systematic rather than random. The empirical evidence showed that among the considered factor for textile products consistently exhibited larger magnitudes of import discrepancies in weighted regressions, similarly, consumer and intermediate goods, and medium-duty tariff categories were statistically associate with discrepancy magnitude. The COVID-19 period also affected measured discrepancies, and this effect was visible in several specifications. Robustness checks including unweighted estimation, HS2 level clustering, and trimmed samples that exclude extreme observations confirmed the persistence of the textile result and the broad role of end-use and tariff structure, while showing that some covariates (notably certain tariff dummies and COVID effects) are sensitive to specification. Interpreting these associations requires care. Because the regressions used the log of one plus the absolute value of the discrepancy, the coefficients identify variation in the magnitude of asymmetries, not their direction. Thus, a large and positive textile coefficient indicates that textile HS6 lines tend to produce larger reporting gaps, but it does not, by itself, imply systematic net over reporting by one partner. Several mechanisms plausibly explain the observed magnitudes. First, valuation and mis-invoicing incentives (under- or over-invoicing) are likely important where tariff wedges are salient. Second, product classification ambiguity common in textile and some food lines can produce persistent HS6 misclassifications, creating apparent asymmetries even where economic flows are similar. Third, methodological differences across compilers (timing of recording, CIF versus FOB valuation, and treatment of re-exports) generate systematic measurement offsets. Finally, informal cross-border transactions known to be substantial along some Nepal–India routes further complicate reconciliation. These mechanisms are not mutually exclusive; the empirical patterns reported here are best understood as the outcome of interacting economic incentives, administrative practices, and statistical conventions.

Placing the Nepal–India results in a global context strengthens the case for both targeted and system-wide responses. Javorsek (2016) large-sample assessment found that, across 90 trading relationships, fewer than half (42.2%) exhibited discrepancy indices smaller than 20% in absolute value, and aggregate discrepancies amounted to roughly 8% of trade value across ten major economies. That cross-country evidence underscores that concentrated, sizable discrepancies are common and that the Nepal–India patterns are not anomalous. the results show both convergence and nuance. Consistent with earlier mirror-trade and asymmetry studies, this analysis confirms that discrepancies concentrate in a small set of commodities and that valuation and classification issues are central. At the same time, the emphasis on medium-duty categories and the observed pandemic convergence yields new perspectives: medium tariffs emerge here as a more important correlate than some global studies suggest, and the COVID-19 period produced a temporary narrowing of gaps in the Nepal–India case a pattern that differs from some international experience. This invites closer investigation into border procedures and reporting behavior during crisis periods. These contrasts underscore that while broad drivers of asymmetries are shared across contexts, the precise manifestation and policy levers are country and corridor-specific. The findings have immediate implications for statistical reconciliation and macroeconomic compilation. Trade statistics feed directly into SNA and BOP frameworks; persistent product-level asymmetries therefore translate into distortions in GDP and in the current account, even when aggregate bilateral totals appear relatively aligned. Such disaggregated mismatches disrupt supply use balancing and alter the perceived structure of external trade. The reconciliation of bilateral trade data is essential not only for accurate trade balance measurement but also for constructing reliable global input-output tables and value-added trade metrics that inform macroeconomic policy (Markhonko, 2014). For compilers, the

results point to the value of combining targeted bilateral reconciliation with broader harmonization of metadata to reduce structural offsets. For Customs, the evidence supports risk-based targeting and enhanced post-clearance audit. More broadly, these results argue for institutional arrangements that enable secure exchange of transaction-level metadata between Customs, statistical offices, and central banks so that reconciliation becomes operational rather than purely diagnostic. Beyond compilation, such mechanisms would enhance the credibility of Nepal's trade and macroeconomic statistics in international reporting systems.

Beyond trade data harmonization, financial transaction records offer a valuable parallel source for validation. Since all trade-related foreign exchange transactions in Nepal must pass through the formal banking system under the supervision of central bank, bank-reported payment data can serve as an independent cross-check for declared trade values. Linking or reconciling aggregated Customs and banking data would help detect potential misinvoicing and under-reporting, thereby improving the credibility of both trade and balance of payments statistics. This approach is consistent with the IMF's BPM7 guidance, which encourages the integration of trade and financial transaction records to strengthen external sector statistics.

Conclusion and Policy Recommendations

The Nepal–India corridor analysis demonstrates that bilateral trade asymmetries are concentrated, partly systematic, and policy-relevant. The empirical evidence shows that a manageable set of product groups and institutional factors account for much of the observable magnitude of discrepancies, which implies that targeted interventions can produce meaningful improvements in data quality. Because mirror-statistic gaps directly affect national accounts and balance-of-payments measures, reducing them is both a statistical priority and a policy imperative.

For Customs administrations the immediate priority is operational: implement focused risk-management and post-clearance audit programs aimed at HS6 lines with persistent, high-magnitude discrepancies. Practical steps include maintaining a dynamic priority list of problematic HS6 codes; deploying electronic data interchange; strengthening tariff classification training for examiners; and piloting artificial intelligence (AI) based automated anomaly detection algorithms to flag suspicious valuation or quantity patterns for follow-up. These measures improve both revenue assurance and statistical fidelity.

For SNA and BOP compilers, the recommendation is to institutionalize reconciliation procedures that operate at product-level granularity and that explicitly document and propagate any adjustments into national accounts and balance-of-payments tables. This requires agreed metadata on valuation basis (FOB/CIF conversion methods), timing of recording, and treatment of re-exports. Compilers should experiment with routine bilateral exchanges of anonymized aggregated reconciled tables with major partners and incorporate the outcomes of reconciliation into supply-use balancing processes. Where discrepancies persist after methodological alignment, compilers should publish reconciliation notes that describe the adjustments made to national aggregates to aid transparency and international comparability.

International organizations and regional bodies have a central enabling role. Capacity building targeted at improving classification accuracy, valuation checks, and digital reporting infrastructure is essential for lower-capacity economies. Donor and technical partners should prioritize: (i) training and tools for HS classification and post-clearance audit; (ii) implementation support for electronic data exchange system; and (iii) pilot reconciliation platforms that allow secure partner exchanges of mirror statistics. These efforts should be framed within BPM7 and

SNA2025 implementation support, because harmonized manuals and guidance give national compilers the methodologies needed to reconcile trade with broader macroeconomic statistics.

Cross-cutting institutional measures are also required. National technical working groups bringing together Customs, the national statistical office, and the central bank,should be formalized and empowered to perform recurrent reconciliation, to define priority HS6 lists, and to coordinate capacity development. Regular publication of a short reconciliation bulletin (e.g., annual or biannual) that reports on aggregate DIFs, the top high-discrepancy HS6 lines, and actions taken will increase accountability and help external partners target support. Finally, setting modest, time-bound objectives will make progress verifiable and actionable.

In parallel, bilateral cooperation between Nepal and India should be institutionalized to ensure consistency between the two countries' trade statistics. Establishing a Nepal–India Trade Data Reconciliation Committee would enable periodic joint reviews of asymmetries, alignment of HS classification practices, and harmonization of valuation and timing methods. Moving beyond ex-post reconciliation, both administrations could implement pre-arrival information sharing, through which export declarations filed in India are electronically transmitted to Nepal Customs before the goods arrive at the border. Such early data exchange would allow Customs to verify HS codes, quantities, and declared values in advance, reducing reporting discrepancies and facilitating legitimate trade. Over time, this bilateral data-sharing framework could be linked with banking and statistical systems, ensuring that trade, payment, and accounting data converge across institutions.

This study offers both a caution and an opportunity. The caution is that persistent asymmetries, if ignored, propagate into misleading macroeconomic signals and weaken policy analysis. The opportunity is that asymmetries are in large part concentrated and thus amenable to targeted, cost-effective remedies that combine modern data systems, improved classification and valuation practices, and institutionalized partner reconciliation. Implementing such measures will strengthen statistical credibility, support better economic management, and help operationalize the BPM7 and SNA2025 agenda for more reliable, comparable international statistics.

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