Impact of Product Sophistication on Export Performance of India's Organized Manufacturing Plants, 2012-2019

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Abstract

This paper examines the impact of product sophistication on the export performance of India's organised manufacturing plants using ASI unit-level panel data for 2012–19. A plant-specific product sophistication score (PSS) is constructed by mapping plant-level NPCMS product codes to 6-digit HS PRODY values and aggregating sales-weighted PRODY across each plant's product mix. Descriptive analysis shows modest aggregate gains in PSS, accompanied by considerable cross-sectoral heterogeneity. Econometric estimates based on random-effects Probit, Tobit and Heckman selection model reveal an inverted-U relationship between PSS and both export participation and export intensity. The results also revealed that ICT investment, ISO-14000 certification, imported input use, in-house R&D, and foreign equity share have a positive association with export outcomes.

JEL Classification Codes: F14, O14, O33, L60.

Keywords: Product Sophistication, Export Performance, Indian Manufacturing, ASI Plant-level analysis.

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1 Introduction

The transformation of a country's production structure from low-productivity activities to higher-productivity activities is a fundamental driver of sustained economic growth and national prosperity. Recent development literature, however, emphasises that it is not only the structural shift itself that matters, but also the process through which countries accumulate the capabilities and learning necessary to undertake this transformation (Felipe *et al.* 2014). In this view, a country's prosperity depends significantly on the nature of its economic activities, particularly the type of goods it produces and exports, as different products have varying implications for economic growth.

In an influential study, Hausmann *et al*. (2007) showed that countries with more sophisticated export products tend to grow faster, suggesting that what a country exports matters for its subsequent growth.[1] Since sophisticated products capture embedded capabilities, technological content, and knowledge intensity, economies producing them are better positioned to climb the value chains, diversify into related industries, and achieve higher productivity growth (Schott, 2004; Hidalgo *et al.,* 2007). In this sense, economic development can be viewed as a process of learning how to produce (and export) more complex products (Felipe *et al.,* 2014)[2]. Differences in income across countries can thus be explained by differences in their ability to upgrade production and diversify into complex goods (McMillan and Rodrik, 2011). Ultimately, countries must sophisticate their productive structure to achieve higher levels of economic growth and social welfare (Hartmann *et al*., 2021; Hausmann *et al.,* 2014).

Generally, sophisticated products face relatively less price competition, enjoy higher demand elasticity, and enable deeper integration into global value chains (Jarreau and Poncet, 2012). Since participation in the global market involves significant sunk costs, firms capable of producing sophisticated products are more likely to enter export markets due to self-selection

[1] This research posits that countries specialising in products typically exported by richer nations would experience higher growth rates, as these products are generally more sophisticated.
[2] According to Hidalgo *et al.* (2007) and Hidalgo and Hausmann (2009) "theory of capabilities," a country's capacity to grow is contingent upon its ability to accumulate the productive knowledge required to produce a diverse range of sophisticated goods.

effects (Melitz, 2003; Bernard and Jensen, 1999). Continued export participation and foreign competition can also drive further upgrading through learning-by-exporting (Iacovone and Javorcik, 2010; De Loecker, 2013). The experience of East Asian economies, particularly China, where deliberate upgrading of the export basket contributed to rapid structural transformation, underscores the importance of product sophistication and capability building in the development process.

For a developing economy like India, enhancing product sophistication is not only relevant for improving growth performance but also crucial for strengthening export competitiveness. Despite considerable trade liberalisation and integration into the global economy, India has not achieved a significant breakthrough in manufacturing exports. Although there is evidence of a gradual shift in product composition from low-technology to more technology-intensive goods with a rise in sophistication (Veeramani and Saini, 2011), export competitiveness continues to be concentrated in labour-intensive products (Rijesh, 2025). While there is extensive literature on export determinants, the specific role of product sophistication in shaping export behaviour at the plant level remains largely unexplored.

This study addresses this research gap by examining whether product sophistication influences export performance in India's organised manufacturing sector. Using plant-level data from the *Annual Survey of Industries*[3] (2012–13 to 2019-20), we construct a Plant-specific Product Sophistication Score (*PSS*) by mapping detailed product codes of each plant to global income-based sophistication measures at the 6-digit HS level. We then assess the relationship between sophistication and export performance, providing new micro-level evidence for a large and diverse emerging economy. The empirical findings offer policy-relevant insights for industrial upgrading and export diversification strategies in India.

The remainder of the paper is organised as follows: Section 2 outlines the methodology and data construction framework. Section 3 presents detailed descriptive evidence on product sophistication in Indian manufacturing plants. Section 4 discusses the econometric results. Section 5 concludes.

[3] National Statistics Office, Ministry of Statistics and Programme Implementation, Government of India.

2 Analytical Framework and Data Construction

This section outlines the conceptual and empirical approach we adopted to study the impact of product sophistication on the export performance at the plant level in Indian organised manufacturing from 2012-13 (hereafter written as 2012) to 2019-20 (2019). We describe how we operationalise the concept of product sophistication using plant-level production data from the *Annual Survey of Industries* (ASI) and international trade data from UN Comtrade.

We determine the sophistication level of commodities produced by a manufacturing plant by constructing a plant-level product sophistication score (*PSS*). To identify *PSS*, we adapt the product-specific sophistication index developed by Hausmann *et al*. (2007), which has been used extensively in the trade literature[4] for studying the sophistication of a country's export basket. We operationalise this idea at the firm/plant level. The construction of *PSS* requires assigning the sophistication index, known as *PRODY*, a proxy for implied productivity, to each product. This process is explained below.

2.1 Construction of *PRODY* and Plant-Level Product Sophistication Score (*PSS*)

Hausmann*, et al.* (2007), building on the notion that products primarily exported by advanced economies likely embody higher levels of technology, quality or productivity, proposed a quantitative index—*PRODY*—to rank traded products based on the income level of countries that export them. The *PRODY* score for a product is essentially a weighted average of the per capita GDP of countries that export the product. The weight for each country reflects the importance of the product in that country's export basket, thereby incorporating the idea of revealed comparative advantage. For a product *k,* the *PRODY* is derived as follows:

$$PRODY_k = \sum_c \frac{x_{ck}/X_c}{\sum_j x_{jk}/X_j} * Y_c \qquad (1)$$

where:

$PRODY_k$ is the sophistication value of product *k*.
x_{ck} is the exports of product *k* by country *c*.
X_c is the total exports of country *c*.
Y_c is GDP per capita of country *c*.

[4] The construction of product sophistication using Hausman method is used widely in the literature. For example, see Jarreau and Poncet (2012), Eck and Huber (2016), Banga, (2023), among others.

The numerator of the weight $\left({x_{ck}}/{X_c}\right)$ represents the value share of product k in country c's overall export basket and reflects how specialised country c is in product k. The denominator $\left(\sum_j {x_{jk}}/{X_j}\right)$ is the sum of product k's share in total exports across *all* countries that export product k. It normalises across all exporting countries for k. Thus, by computing the weighted average of the income levels of countries that specialise in a product, the *PRODY* measure captures the average implied sophistication (technology) of that product (Eck and Huber, 2016). By using revealed comparative advantage as weight, the measure ensures that the country size does not distort the ranking of goods (Hausmann *et al*., 2007).

A product is associated with a higher sophistication level if, on average, higher-income countries have a revealed comparative advantage in its production. The index thus infers, from observed trade patterns, the products that require higher levels of development to be exported, thereby differentiating goods based on their implied productivity (Jarreau and Poncet, 2012; Bayudan-Dacuycuy and Lim, 2017)[5].

We have computed the *PRODY* index to determine the sophistication level of products manufactured by Indian industrial plants. The computation involves several steps, outlined below.

a) Computation of PRODY using export and GDP per capita data

To compute the index, we use trade and GDP per capita data. Following the HS 2007 classification, we compiled commodity-wise exports at the 6-digit level for all countries from 2012 to 2019. During this period, the number of unique HS product codes ranged from 5,011 to 5,048, depending on the year. The trade data are sourced from the UN Comtrade database, accessed via the WITS online portal.[6]

[5] It should be noted that our measure of product sophistication builds upon the "product space" framework developed by Hidalgo *et al*. (2007). This framework envisages the global economy as a network in which products are connected based on similarity of the capabilities such as skills, institutions, infrastructure etc. required for their production. Accordingly, a countries economic development path is determined by how it moves through this network, from simple, peripheral products to more complex, core ones. While the product-space literature primarily examines the between-product transitions and diversification patterns at the country level, our analysis of plant-level product sophistication captures average sophistication of a plant’s product-mix, reflecting across product shifts within plants.

[6] WITS is a software tool that allows users to access and analyse a wide range of trade data, including data from UN Comtrade, WTO Integrated Trade Intelligence Portal (ITIP), and UNCTAD's Trade Analysis and Information System (TRAINS).

The GDP per capita data are compiled from the World Development Indicators (WDI) Online database. We used GDP per capita based on purchasing power parity (PPP), expressed in constant 2021 international dollars and converted to thousand USD for uniformity. Based on the set of countries that are common across both databases (WITS and WDI), the *PRODY* calculation was carried out separately for each year from 2012 to 2019. Subsequently, we calculated the average *PRODY* score for each HS product code over the period. The resulting dataset contains 5,050 unique HS product codes with their average *PRODY* values.

b) Matching HS-based PRODY with NPCMS Data at the Plant-Level

Since our objective is to assess the sophistication of products manufactured in the Indian industrial sector, we matched the computed *PRODY* values (based on HS commodity classification codes) with the National Product Classification for Manufacturing Sector (NPCMS, 2011), which is used in the *Annual Survey of Industries* (ASI)[7]. NPCMS is a 7-digit product classification adopted in 2011 to provide a standardised coding structure for inputs and outputs recorded by Indian factories. It aligns with the international Central Product Classification (CPC) at the 5-digit level, with the remaining 2-digits adapted for Indian requirements.

Using the official United Nations Statistics Division concordance between HS-2007 and CPC version 2, we matched the computed *PRODY* scores with NPCMS at the 5-digit level. This enabled us to assign *PRODY* scores to products reported in the ASI data.

In the ASI unit-level dataset, information on products and by-products manufactured by plants is recorded in block-J using the 7-digit NPCMS. We extracted factory-wise data from the ASI panel data for the years 2012 to 2019. For the matching, we truncated the 7-digit NPCMS to its 5-digit form and then mapped it to the corresponding 6-digit HS codes (for which *PRODY* is available)[8].

[7]The *Annual Survey of Industries* (ASI), published by the National Statistics Office (NSO), Ministry of Statistics and Programme Implementation, Government of India, is the principal source for collecting statistics on manufacturing units registered under the Factories Act,1948 in India. The units are covered under two schemes: the Census scheme and the Sample scheme. The former generally includes large manufacturing units with 100 or more employees and is enumerated every year (the definition of the Census sector is more complex; see Goldar, 2024), while the latter covers the remaining smaller units through probability sampling. The unit-level data provides multipliers for each unit, indicating the inverse of the sampling probability.

[8] During the matching process, it was found that several factories reported the product code “9921100”, which serves as a catch-all category for “other products/by-products” not defined under the official NPCMS-2011 classification. In such cases, a *PRODY* score was assigned based on the average *PRODY* value of the other

c) Computation of Plant-Level Product Sophistication Score (PSS)

After computing the *PRODY* index for each manufacturing product, we constructed the **plant-level product sophistication score** (***PSS***), which measures the average level of product sophistication at the plant level. The *PSS* is defined as the sales-weighted average of *PRODY* scores for all products, $k = 1, \ldots\ldots K$, produced by plant i.

$$PSS_i = \sum_k \left({S_{ik}}/{S_i} \right) * PRODY_k \qquad (2)$$

This is a weighted sum of the product sophistication levels, where the weights are the shares of each product's ex-factory value in the plant's total product output. A higher *PSS* implies that the plant's production is skewed towards more sophisticated products, suggesting that the plant is producing commodities typically associated with higher levels of technological complexity and income.[9]

The computation of *PRODY* and *PSS* was carried out using only the *Census sector* of the ASI data. Additionally, we excluded units located in nine less industrially developed states and union territories (UTs).[10] We also excluded a small number of factories that reported zero output in each year (during the period studied).

2.2 Trend Analysis

To assess whether specific industries experienced a systematic increase in their average product sophistication score (*PSS*) over time, we estimated the following time trend regression for each 3-digit NIC-2008 industry (subscript i).

$$PSS_{it} = \alpha + \beta * time_t + \varepsilon_{it} \qquad (3)$$

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products manufactured by the same factory. In instances where a factory reported only the 9921100 code, the *PRODY* score was imputed using the average *PRODY* of all factories belonging to the same 5-digit NIC industry.

[9] Although *PRODY/PSS* framework is widely used to assess product sophistication, it is not without limitations. A major concern is that it does not capture quality heterogeneity within a same product category, even at high levels of disaggregation (Minondo, 2010; Xu, 2010). Critics argue that this may lead to an overestimation of sophistication for low-income countries and an underestimation for high-income countries (Zhu and Fu, 2013). In this regard, Schott (2004) demonstrates that even at the most detailed tariff levels (e.g., HS 10-digit), unit values of exports within the same product category vary substantially across countries, reflecting significant within-product quality differences.

[10] The following states and UT were excluded from the empirical analysis: Andaman & Nicobar Islands, Arunachal Pradesh, Ladakh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura.

A significantly positive slope coefficient ($\beta > 0$) with $p < 0.05$ or lower suggests that the industry exhibited a statistically meaningful improvement in product sophistication during the study period. This would imply that the industry becomes more sophisticated, likely due to technological upgrading, improved production process, or shift towards higher-value products.[11] It should be noted that the above equation is estimated at the three-digit industry level using *PSS* at that level, which is derived from factory-level *PSS* computed by us.

A non-significant slope suggests no consistent trend in sophistication, implying stagnation in terms of the level of technological sophistication of the products produced. Such industries may be caught in low-sophistication production or may face barriers to technological upgrading. A significantly negative slope indicates a decline in *PSS*, suggesting a shift towards less sophisticated products—potentially due to competitive pressures, loss of technological capabilities or changing market demands.

At the 2-digit NIC-2008 level, we explored inter-factory differences using compound annual growth rates (CAGR). For this, we calculated the number of factories with a significant increase in *PSS*—defined as those with CAGR > 5 per cent—for each 2-digit industry.

2.3 Econometric Analysis – Impact of Product Sophistication on Export Performance

We now turn to the primary empirical issue raised in this study. Does a higher level of product sophistication enhance the likelihood or intensity of exporting by manufacturing plants in India? This is explored using unit-level data for the period 2012 to 2019. To empirically assess this, we model the export behaviour of manufacturing plants as a function of their sophistication level (*PSS*), along with other control variables.

We know that export behaviour can be defined either in binary form (whether a plant exports or not) or as a continuous variable (export intensity measured by taking the share of exports in total products and by-products manufactured). Therefore, we adopted two alternative econometric specifications. The first involves estimating a random effects probit model to

[11] Our measure of *PSS* is closely related to the concept of comparative advantage and its modern interpretations. Traditional trade theory explains specialisation in terms of factor endowments, whereas measures such as *PRODY* and PSS reflect a capability based dynamic view of comparative advantage. Thus, the concept of PSS extends the traditional theory of comparative advantage. When a country's export structure shifts towards high-*PRODY* products, it signals an upgrading of its comparative advantage (may be interpreted as progression up the comparative advantage ladder). As shown empirically by Hausmann and Klinger (2007), such structural upgrading tends to be path dependent, as countries export mix tend to move towards products that are closely related its existing production structure and knowledge base.

study the probability of exporting. In contrast, the second uses the Heckman selection model, which corrects for the potential bias arising from the fact that only a subset of plants enter the export market, and only those plants that we can identify export intensity meaningfully.

The econometric specification is outlined below:

Selection equation (export participation)

$$ExportDummy^{*}_{it} = \gamma_0 + \gamma_1 PSS_{it} + \gamma_2 Z_{it} + \mu_{it},$$
$$ExportDummy_{it} = 1\ if ExportDummy^{*}_{it} > 0 \qquad (4)$$

Outcome equation (export intensity)

$$ExportIntensity_{it} = \beta_0 + \beta_1 PSS_{it} + \beta_2 Z_{it} + \varepsilon_{it} \qquad (5)$$

where

$ExportDummy_{it}$: A binary variable indicating whether plant *i* exports in year *t*.

$ExportIntensity_{it}$: Share of exports in total output, observed only for exporting plants.

PSS_{it}: Product Sophistication score of plant *i* in year *t*

Z_{it}: A vector of control variables including plant size, ICT intensity, ISO14000 certification, share of contract workers etc.

$\mu_{it}, \varepsilon_{it}$: Idiosyncratic error terms.

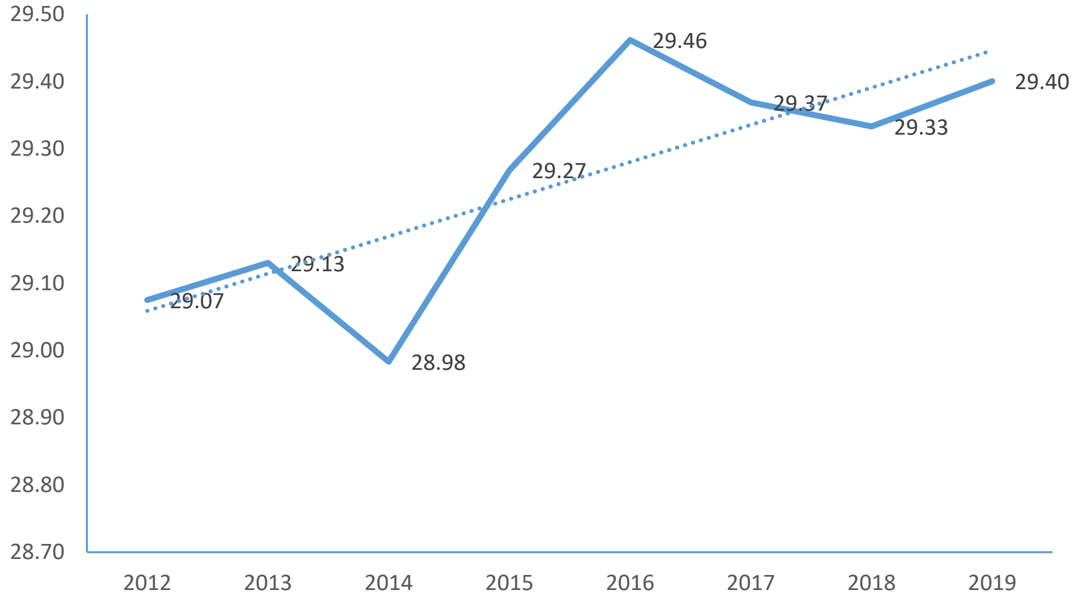
Both models include year and industry fixed effects to control for macroeconomic and sector-specific shocks.

An alternative to the Heckman selection model is to apply the Tobit model. Since panel data are used for the analysis, the random-effect Tobit model is used. Further details are provided later in sub-section 4.2. The analysis focuses on plants within 10 selected three-digit industries under the NIC 2008, which were selected based on their significant export activity (see Annexure-A, Table A.1 for the list of industries).

3 Trend in Product Sophistication in Indian Manufacturing

In this section, we present a descriptive overview of the trends in plant-level product sophistication in the Indian organised manufacturing sector during 2012—2019. As discussed in the previous section, the analysis draws on a comprehensive dataset covering plants in various industries, classified under the National Industrial Classification (NIC) 2008. We gauge the product sophistication trend by constructing the plant-level product sophistication score (*PSS*) using the census segment of the ASI data.

Figure 1: Trend in Average Plant–level Sophistication in the Indian Manufacturing Sector: 2012-2019



Source: Authors' computations.

In Figure 1, we illustrate the annual trend in average plant-level product sophistication for overall manufacturing over the period 2012 to 2019. We can notice that the *PSS* remained relatively stable in the initial years, with a noticeable upward trend from 2015 onwards. This modest improvement in the sophistication of products manufactured by organised sector plants may reflect underlying shifts in product composition within plants, possibly due to changes in the technology adoption, increased global market integration, or policy initiatives promoting industrial upgrading. However, the aggregate stability in the mean *PSS* masks significant heterogeneity across manufacturing sectors, which we explore in the following tables.

Table 1: Mean Product Sophistication Score (PSS) by 2-digit NIC, 2012-2019

2-digits	Description	2012	2013	2014	2015	2016	2017	2018	2019	2012-2019
10	Food products	21.6	21.6	20.6	21.6	21.8	21.7	21.8	21.7	21.6
11	Beverages	26.1	26.1	26.9	25.8	25.6	25.7	25.6	25.6	25.9
12	Tobacco Products	18.2	16.3	17.6	16.5	16.6	16.9	17.2	17.1	17.1
13	Textiles	18.2	17.8	18.3	19.0	19.3	19.1	19.0	19.2	18.7
14	Wearing Apparel	19.9	19.2	18.3	18.1	17.8	17.7	17.5	17.0	18.2
15	Leather and Related Products	23.6	23.6	24.0	23.6	23.4	23.6	23.6	23.7	23.6
16	Wood and Products of Wood	24.8	24.6	26.3	24.2	23.6	23.7	23.8	23.6	24.3
17	Paper and Paper Products	30.2	30.3	32.5	30.7	30.9	31.1	31.0	31.1	31.0
18	Printing and Reproduction of Recorded Media	39.1	39.1	40.9	39.6	39.5	39.5	40.4	40.7	39.9
19	Coke and Refined Petroleum Products	28.2	29.2	29.1	30.3	31.6	30.7	30.9	30.8	30.1
20	Chemicals and Chemical Products	30.5	30.7	31.6	31.3	31.7	31.7	32.0	31.9	31.4
21	Pharmaceuticals, Medicinal Chemical & Botanical Products	41.8	41.8	41.9	42.5	42.8	42.7	43.2	43.5	42.5
22	Rubber and Plastics Products	30.4	30.4	30.8	30.2	30.4	30.3	30.5	30.3	30.4
23	Non-metallic Mineral Products n.e.c	27.6	27.7	26.5	28.1	28.3	27.9	27.7	27.7	27.7
24	Basic Metals	31.7	32.0	32.8	32.7	33.0	32.7	32.8	33.2	32.6
25	Fabricated Metal Products	32.4	32.6	33.1	32.6	32.7	32.4	32.6	32.7	32.6
26	Computer, Electronic and Optical Products	39.7	39.7	39.9	40.3	40.3	40.5	40.9	40.7	40.2
27	Electrical Equipment	34.5	35.0	35.1	35.0	35.2	34.9	34.8	34.8	34.9
28	Machinery and Equipment n.e.c.	39.6	39.5	39.7	39.8	40.3	40.3	40.5	40.4	40.0
29	Motor Vehicles, Trailers and Semi-Trailers	36.6	37.2	36.9	36.8	36.9	36.9	36.9	36.7	36.9
30	Transport Equipment n.e.c	35.9	36.9	36.0	36.4	36.5	35.8	35.7	35.6	36.1
31	Furniture	26.0	25.8	26.4	25.3	25.0	25.0	24.5	24.5	25.3
32	Manufacturing n.e.c	34.5	34.8	34.7	35.0	35.5	35.3	34.9	34.2	34.9
33	Repair and Installation of Machinery and Equipment	37.6	36.4	38.6	37.2	37.6	36.0	37.9	34.9	37.0

Source: Authors' computation based on ASI Unit-Level panel data for the period 2012-13 to 2019-20.

Table 1 reports the average *PSS* across all major industrial sectors, defined at the 2-digit level of NIC, over the study period. We can observe considerable variation across sectors. In particular, sectors such as Pharmaceuticals (21), Computer, Electronic and Optical Products (26), and Machinery and Equipment n.e.c. (28), which belongs to medium to high technology-intensive segments with reliance on advanced technology and knowledge-intensive processes, consistently report high sophistication scores, with average *PSS* exceeding 40. On the other hand, traditional sectors such as Textiles (13), Wearing Apparel (14), and Tobacco Products (12), with relatively labour-intensive and less technologically complex production structures, report relatively lower scores, often below 20. In addition, we also observe marginal but steady improvements in several knowledge-intensive sectors such as Chemicals (20), Basic Metals (24), and Electrical Equipment (27).

Table 2: Distribution of Factories with a Significant Increase in PSS by 2-Digit Industries (2012-2019)

2-digit NIC	Description	Significant Increase
10	Food products	553 (12.7)
11	Beverages	52 (7.5)
12	Tobacco Products	55 (11.8)
13	Textiles	648 (24.7)
14	Wearing Apparel	250 (10.6)
15	Leather and Related Products	63 (7.2)
16	Wood and Products of Wood	55 (11.3)
17	Paper and Paper Products	69 (9.7)
18	Printing and Reproduction of Recorded Media	57 (11.1)
19	Coke and Refined Petroleum Products	76 (19.0)
20	Chemicals and Chemical Products	218 (10.1)
21	Pharmaceuticals, Medicinal Chemical & Botanical Products	76 (6.1)
22	Rubber and Plastics Products	185 (11.7)
23	Non-metallic Mineral Products n.e.c	218 (10.2)
24	Basic Metals	429 (22.6)
25	Fabricated Metal Products	168 (8.7)
26	Computer, Electronic and Optical Products	91 (10.4)
27	Electrical Equipment	204 (10.5)
28	Machinery and Equipment n.e.c.	180 (8.2)
29	Motor Vehicles, Trailers and Semi-Trailers	182 (10.5)
30	Transport Equipment n.e.c	117 (15.9)
31	Furniture	22 (5.2)
32	Manufacturing n.e.c	83 (6.8)
33	Repair and Installation of Machinery and Equipment	3 (5.6)

Note: The figure outside parentheses indicates the number of factories reporting a CAGR > 5 per cent. The figures in parentheses represent the percentage of factories within each sector showing a significant increase in PSS.
Source: Authors' computations.

To identify factories that experienced a notable improvement in their sophistication levels, we computed the compound annual growth rate (CAGR) of *PSS* at the factory level for each 2-digit sector. We set a threshold of 5 per cent to classify whether a factory has experienced a 'significant improvement' during the reference period. The results are given in Table 2, which provides the share of such factories by major industrial sectors. Out of the total number of factories in our sample, only 4,054 (around 11 per cent) reported a significant rise in their sophistication levels. Sectors such as Textiles (13) and Basic Metals (24) reported the most significant growth, with 25 per cent and 23 per cent of their units, respectively, showing a marked improvement in *PSS*. Apart from them, factories in the following sectors recorded improvements comparable to the overall manufacturing average: Coke and Refined Petroleum Products (19), Transport Equipment n.e.c. (30), Food products (10), Tobacco Products (12), Rubber and Plastics Products (22), Wood and Products of Wood (16), Printing and Reproduction of Recorded Media (18), Wearing Apparel (14), Electrical Equipment (27), Motor Vehicles, Trailers and Semi-Trailers (29).

To complement the factory-level CAGR analysis, we conducted a linear time trend regression of *PSS* for each industry, defined at the 3-digit NIC level. As per the NIC-2008 classification, the entire manufacturing sector is distributed across 71 three-digit industries. Table 3 provides the distribution of these industries into three groups based on the slope and significance of the trend coefficients: (i) significant improvement, (ii) significant decline, and (iii) no significant change. Around 28 per cent of 3-digit industries reported a statistically significant increase in *PSS*, while 17 per cent reported a decline. For the majority of industries (55 per cent), there was no statistically discernible trend. Several high-technology and capital-intensive sectors such as Pharmaceuticals (210), Electronic Components (261), Measuring and Control Equipment (265), Irradiation, Electromedical and Electrotherapeutic Equipment (266), General Purpose Machinery (281), Special-Purpose Machinery (282), and Air and Spacecraft and Related Machinery (303) show statistically significant improvement in product sophistication over time. In contrast, industries such as Wearing Apparel (141), Consumer Electronics (264), Furniture (310) and Other Manufacturing n.e.c. (329) witnessed a significant decline.

To complement the sectoral and trend analysis, Table A.2 in the annexure provides an industry-level profile of the most and least sophisticated factories, ranked by their sophistication score in the initial year (2012) and final year (2019). For each year, we identified the top 20 factories with the highest *PSS* and the bottom 20 factories with the lowest *PSS*. We report their corresponding 5-digit NIC to illustrate the nature of products manufactured, so that we can explore the structural differences within manufacturing.

The analysis reveals a clear technology divide. As expected, the low-*PSS* category is dominated by low-technology, resource-based or traditional manufacturing units. In contrast, the high *PSS* category largely represents technology-intensive, capital-intensive, and high-value-added activities. One notable feature is that the low-*PSS* category has fewer 5-digit industries, as multiple low-ranked factories belonged to the same set of industrial codes. In contrast, the high-*PSS* category consists of diverse industry groups, reflecting a wider spread of high-technology activities in manufacturing.[12]

Another interesting pattern from the rank comparison is that, between 2012 and 2019, the composition of low-*PSS* industries remained broadly similar, dominated by textile and tobacco products. On the other hand, the high-*PSS* category industries expanded considerably to include a broader range of technology-intensive advanced manufacturing products, especially those belonging to communication equipment, industrial machinery, and medical devices. This pattern suggests that while certain plants continue to specialise in low-sophisticated commodities, others, especially the capital-intensive sectors, are building their capability to produce high-value-added manufacturing products over time.

[12] Rijesh (2024) has noted significant growth in GVA and wages in medium-to-high technology intensive industries in Indian manufacturing from 1991 to 2018.

Table 3: Trend Analysis of Product Sophistication Using Linear Regression by 3-digit Industries

Level of Significance	Significant Improvement	Significant Decline	No Significant change
p < 0.05	Processing and Preserving of Meat (**101**), Processing and Preserving of Fish, Crustaceans and Molluscs (**102**), Processing and Preserving of Fruit and Vegetables (**103**), Dairy Products (**105**), Other Textiles (**139**), Tanning and Dressing of Leather; Luggage, Handbags, Saddlery and Harness; Dressing and Dyeing of Fur (**151**), Other Chemical Products (**202**), Man-Made Fibres (**203**), Pharmaceuticals, Medicinal Chemical and Botanical Products (**210**), Glass and Glass Products (**231**), Electronic Components (**261**), Measuring, Testing, Navigating and Control Equipment; Watches and Clocks (**265**), Irradiation, Electromedical and Electrotherapeutic Equipment (**266**), Magnetic and Optical Media (**268**), Electric Lighting Equipment (**274**), General Purpose Machinery (**281**), Special-Purpose Machinery (**282**), Air and Spacecraft and Related Machinery (**303**), Sports Goods (**323**), Medical and Dental Instruments and Supplies (**325**)	Vegetable and Animal Oils and Fats (**104**), Wearing Apparel, except Fur Apparel (**141**), Knitted and Crocheted Apparel (**143**), Sawmilling and Planing of Wood (**161**), Products of Wood, Cork, Straw and Plaiting Materials (**162**), Reproduction of Recorded Media (**182**), Consumer Electronics (**264**), Other Electrical Equipment (**279**), Building of Ships and Boats (**301**), Weapons and Ammunition, (**304**), Furniture (**310**), Other Manufacturing n.e.c. (**329**)	Grain Mill Products, Starches and Starch Products (**106**), Other Food Products n.e.c. (**107**), Prepared Animal Feeds (**108**), Beverages (**110**), Tobacco Products (**120**), Spinning, Weaving and Finishing of Textiles (**131**), Articles of Fur(**142**), Footwear (**152**), Paper and Paper Products (**170**), Printing and Service Activities (**181**), Coke Oven Products (**191**), Refined Petroleum Products (**192**), Basic Chemicals, Fertilizer and Nitrogen Compounds (**201**), Rubber Products (**221**), Plastics Products (**222**), Non-Metallic Mineral Products n.e.c. (**239**), Basic Iron and Steel (**241**), Basic Precious and Other Non-Ferrous Metals (**242**), Casting of Metals (**243**), Structural Metal Products, Tanks, Reservoirs and Steam Generators (**251**), Weapons and Ammunition (**252**), Other Fabricated Metal Products; Metalworking Service Activities (**259**), Computers and Peripheral Equipment (**262**), Communication Equipment (**263**), Optical Instruments and Equipment (**267**), Electric Motors, Generators, Transformers and Electricity Distribution and Control Apparatus (**271**), Batteries and Accumulators (**272**), Wiring and Wiring Devices (**273**), Domestic Appliances (**275**), Motor Vehicles (**291**), Bodies (Coachwork) For Motor Vehicles; Trailers and Semi-Trailers (**292**), Parts and Accessories For Motor Vehicles (**293**), Railway Locomotives and Rolling Stock (**302**), Transport Equipment n.e.c. (**309**), Jewellery, Bijouterie and Related Articles (**321**), Musical Instruments (**322**), Games and Toys (**324**), Repair of Fabricated Metal Products, Machinery and Equipment (**331**), Installation of Industrial Machinery and Equipment (**332**)

Note: To assess whether certain industries experienced a systematic increase in their average Product Sophistication Score (*PSS*) over time, we estimated the following time trend regression for each 3-digit industry: $PSS_{it} = \alpha + \beta * time_t + \varepsilon_{it}$. A significantly positive slope coefficient (β > 0) with p < 0.05 or lower suggests that the industry has exhibited a statistically meaningful improvement in product sophistication during the study period.
Source: Authors' computations.

Overall, the descriptive analysis reveals that while the aggregate trend appears moderate, a sizeable number of factories and industries are experiencing structural transformations in terms of product sophistication. These changes may be driven by differences in investment behaviour, technological capability, global integration, or policy incentives.

4 Econometric Analysis

In the previous two sections, the methodology adopted by us to compute the product sophistication score (*PSS*) for each individual industrial plant in India's organised manufacturing from 2012 to 2019 has been discussed, and some preliminary analysis of the estimated *PSS* has been undertaken, looking at the trends. In this section, an econometric analysis is presented. The aim is to assess the impact of product sophistication on the export performance of Indian industrial plants. As explained above, our analysis in the paper covers only the organized sector manufacturing plants in India. In the analysis in this section of the paper, we use data on plants belonging to 10 three-digit industries, as explained further below. Two equations are estimated to study the impact of *PSS* on export performance: (1) an equation explaining plants' decision to participate in the export markets, and (2) another equation explaining the level of export intensity (share of exports in the value of products and by-products) for a plant that decides to participate in the export market.

As mentioned above, the econometric analysis of export performance is confined to plants belonging to 10 selected three-digit industries of NIC, 2008. The proportion of factories that have reported non-zero exports has been compared among various three-digit industries, and the top ten industries have been chosen (the list of industries chosen for the study is given in Annexure-A, Table A.1). There has been some further pruning of data of plants belonging to those industries. Data have been taken only for those plants which exported at least once during 2012 to 2019, and the plant was covered in the annual surveys undertaken for at least four years in the years 2012 to 2019. Thus, if a plant belongs to the aforesaid 10 three-digit industries but was covered in the annual surveys three times or less during 2012 to 2019, it is not included in the econometric analysis.

Our sample has about 3,300 to 4,800 plants in different years from 2012 to 2019. The mean export intensity (share of exports in the value of products and by-products) for the entire sample is about 27 per cent. Export intensity is positive in about 38 per cent of the observations, while in 62 per cent of the observations, it is zero. This may be contrasted with the situation among all plants of India's organized manufacturing. The comparison is presented in Table 4 for 2018-19. As shown in the table, among all manufacturing plants in ASI covered in 2018-19, about 92 per cent of plants reported no exports. By contrast, about 60 per cent plants in the chosen sample reported nil exports. Among all organized manufacturing plants, about 4 per cent reported that they are exporting more than half of their production. In the sample chosen for the econometric analysis, this proportion is much higher at about 29 per cent. Since the analysis in this section aims to assess the impact of *PSS* on export performance, a sample in which a relatively much higher proportion of plants are engaged in exports is advantageous to use.

Table 4: Distribution of plants according to export intensity, 2018-19

Export intensity, range	Percent of plants, out of all plants in the manufacturing sector	Percent of plants, among the plants selected for econometric analysis
Nil	92	60
1-10%	2	4
11-25%	1	3
26-50%	1	4
Above 50%	4	29

Source: Authors' computations.

4.1 Distribution of Product Sophistication Score (*PSS*) in the Sample

As stated above, the prime aim of the analysis is to assess the effect of *PSS* on export performance. The distribution of export intensity in the sample observations has been shown in Table 4. It would be helpful to discuss next the distribution of *PSS* in the sample observations. The distribution is depicted in Figure 2. The mean of *PSS* is 30.3 in the sample observation. The *PSS* is between 20 and 50 in about 80 per cent observations, and it is in the range of 20 to 40 in about 60 per cent observations. The mean value of *PSS* is relatively low in (i) Wearing apparel, except fur apparel (18.2), (ii) Knitted and crocheted apparel (17.7), (iii) Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, and harness; dressing and dyeing of fur (25.6) and (iv) Footwear (22.4). On the other hand, mean *PSS* is relatively high in (i) Special-purpose machinery (39.4) and (ii) air and spacecraft and related machinery (40.3).

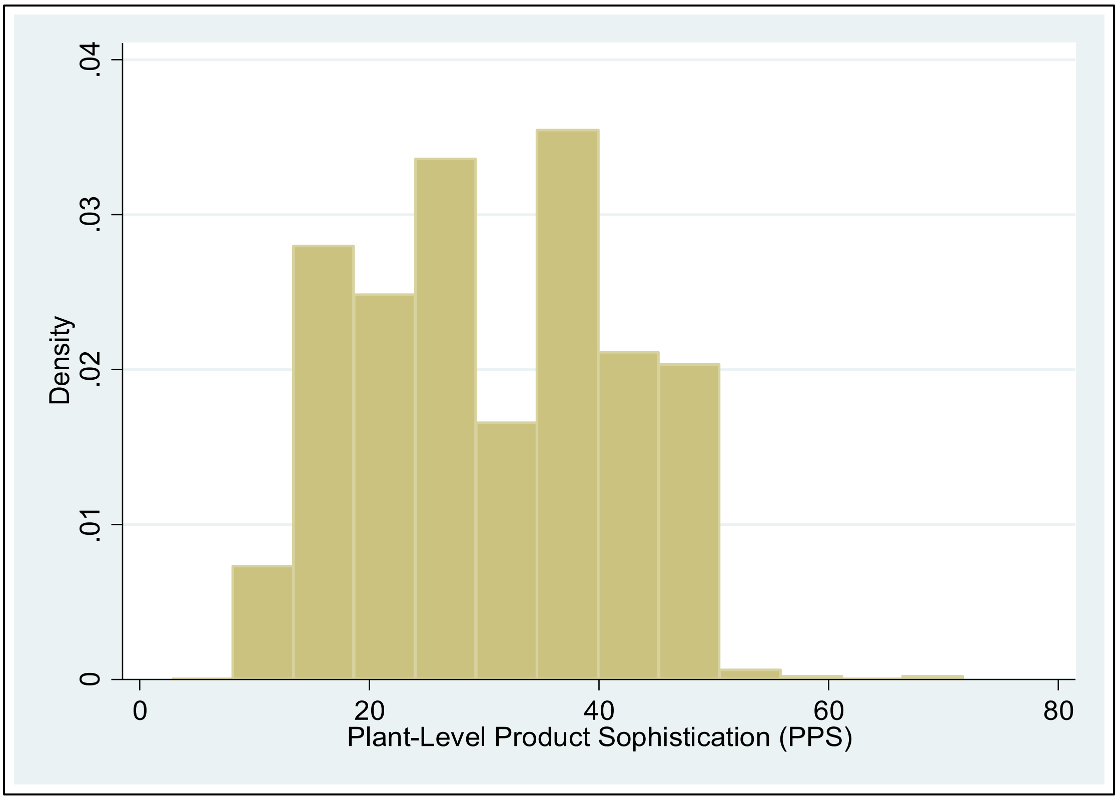


Figure 2: Distribution of PSS among sample observations, Histogram
Source: Prepared by Authors.

We have carried out further analysis of the distribution of *PSS* by studying the kernel distribution function for different categories of plants among the 10 selected 3-digit industries and plants specifically selected for the analysis, as explained above. We compare the *PSS* between plants with and without an R&D unit within factory premises, and between plants with and without foreign equity participation (i.e., foreign firms). Additionally, a comparison is made among the bottom one-third, middle one-third, and top one-third in terms of size measured by the deflated value of fixed capital stock. The data for 2015-2018 have been pooled for the analysis. The graphic presentations are made in Figures 3, 4, and 5.

The analysis reveals that the average *PSS* of plants having an R&D unit is higher than that of plants without an R&D unit, highlighting the key role R&D plays in attaining greater product sophistication. Similarly, foreign firms have, on average, higher *PSS* than domestic firms. The mid-size plants and small-size plants do not differ significantly in terms of the distribution of *PSS*, but the relatively bigger plants have, on average, a higher *PSS*. The mode for the bottom one-third plants is about 20, whereas the model for the top one-third plants is about 40.

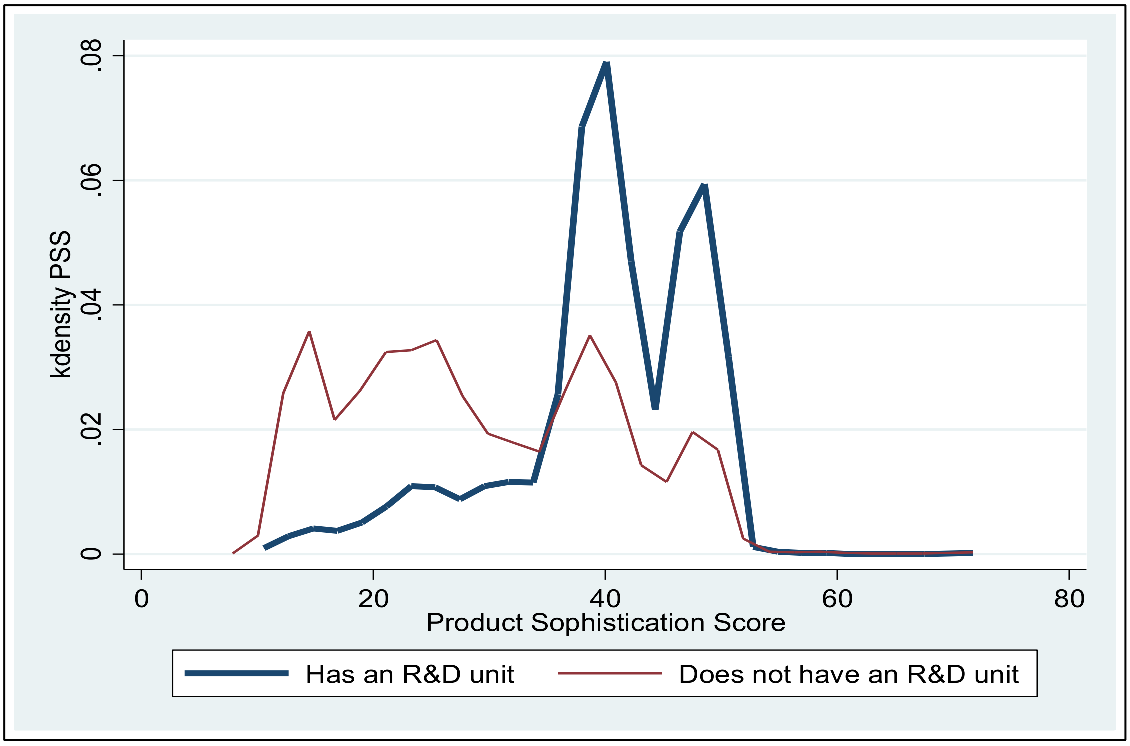


Figure 3: Kernel density distribution of PSS, comparison among industrial plants according to the presence of R&D within factory premises
Source: Prepared by Authors

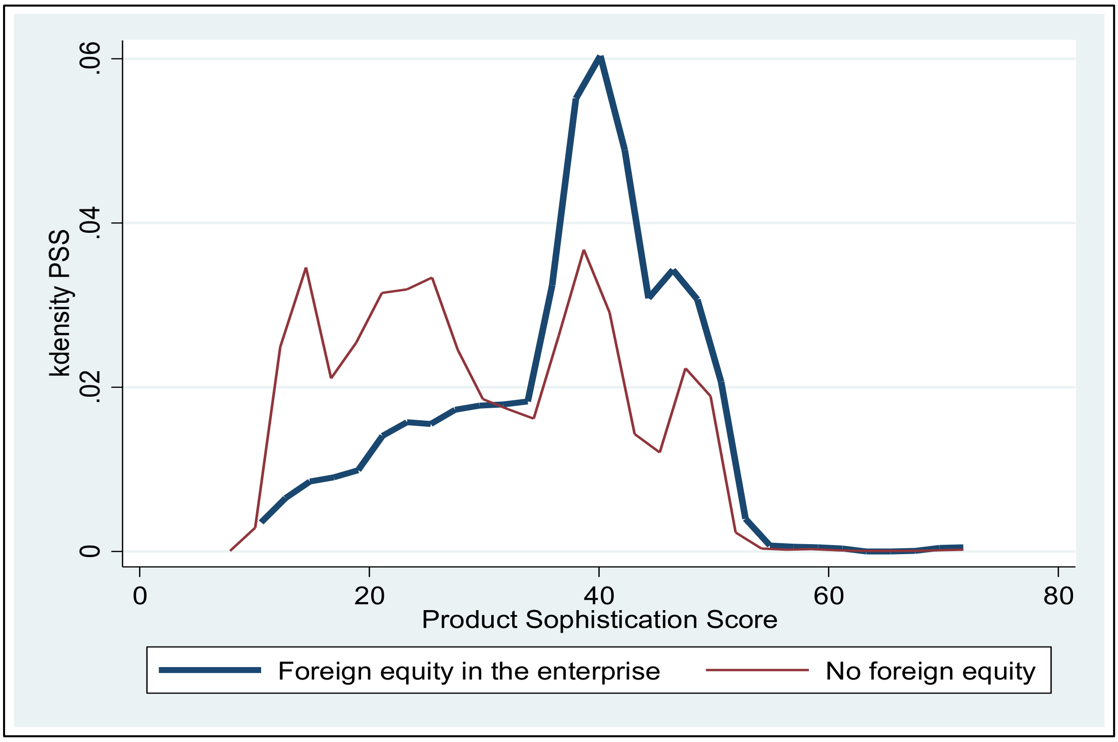


Figure 4: Kernel density distribution of PSS, comparison among industrial plants according to foreign equity participation in the firm to which the plant belongs
Source: Prepared by Authors

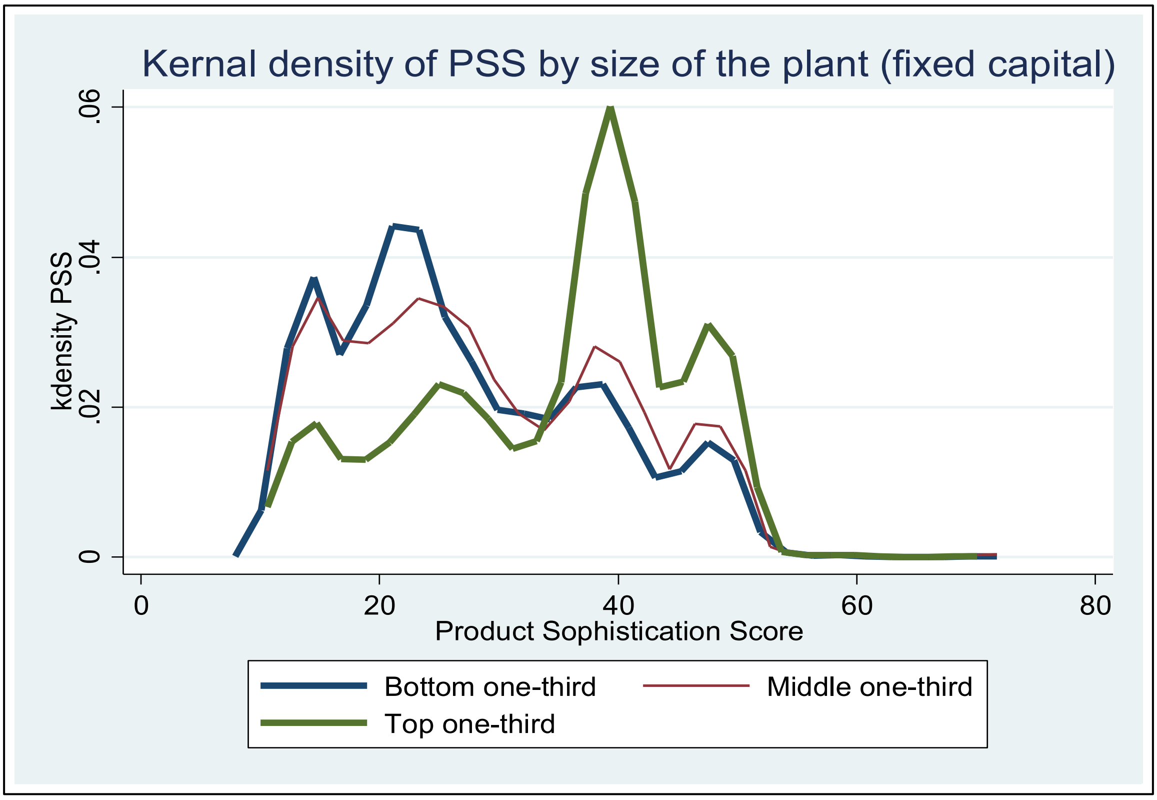


Figure 5: Kernel density distribution of PSS, comparison among industrial plants according to the size of the plant in terms of deflated value of fixed capital stock
Source: Prepared by Authors

4.2 Econometric Model Specification

(a) Model Explaining Decision to Participate in Export Markets

The model that explains the decision to participate in export markets is specified as follows:

$$Pr(EX_{it} = 1) = \alpha_i + \theta_t + \beta_1 PSS_{it} + \beta_2 PSS_{it}^2 + \gamma_1 lnK_{it} + \gamma_2 lnK_{it}^2 + \sum_r \phi^r X_{it}^r + u_{it} \qquad (6)$$

In this equation, subscript *i* is for plant and *t* is for time (year). *EX* denotes export status. It is a dichotomous (dummy) variable taking the value of one if the plant is exporting and zero otherwise. *PSS* denotes product sophistication score (described above). The size of the plant is measured by the logarithm of deflated fixed capital stock (net closing value), used previously in Figure 5. This is denoted by *lnK*. The quadratic terms for the product sophistication score and plant size are included in the model to allow for (possible) non-linearity of the relationship.

X denotes other plant characteristics, and ϕ is the corresponding vector of parameters. The following variables have been considered (constituting X): (i) share of ICT (information and communication technology) capital stock in total fixed capital stock,[13] (ii) a dummy variable representing whether the plant has ISO 14000 series certification, and (iii) a dummy variable representing whether the plant has more than 25 per cent of workers employed through contractors. Goldar (2023) found a significant positive effect of ICT investment and ISO 14000 certification on the export performance of Indian manufacturing plants. This gives a good reason for the use of these two explanatory variables. As regarding the use of contract workers in industrial plants, it is reasonable to argue that a plant having a significant portion of workers employed through contractors has greater flexibility in adjusting its workforce in response to year-to-year variation in demand in export markets. This flexibility in managing its workforce is likely to have a favourable impact the plants decision to participate in the export markets. This is the rationale underlying the use of the dummy variable representing significant use of contract workers. To define the dummy variable, the cut-off is taken as 25 per cent, which is the median value in the sample observations used for the analysis.

(b) Model Explaining in Export Intensity

The model explaining export intensity has a similar specification. This equation applies only when *EX=1*, i.e., the plant is participating in export markets. The explanatory variables are the same as in equation (6) above. An additional variable is included, namely, the share of imported materials in total materials consumed, which is expected to have a positive effect on export intensity. The equation may be written as:

$$XI_{it} = \mu_i + \lambda_t + \rho_1 PSS_{it} + \rho_2 PSS_{it}^2 + \pi_1 lnK_{it} + \pi_2 lnK_{it}^2 + \sum_r \delta^r X_{it}^r + \sigma M_{it} + \xi_{it} \qquad (7)$$

In this equation, *XI* denotes export intensity (share of exports in the value of products and by-products produced), which is the dependent variable. *M* denotes the share of imported materials in total materials consumed.[14]

The estimation of equation (6) has been done by the random effects probit model.[15] In making this estimate, industry dummy variables at the three-digit NIC have been included in the model to take into account heterogeneity across the 10 industries chosen for the study.

[13] The variable is winsorized at the 99th percentile.
[14] This variable is winsorized at the 95th percentile.
[15] The 'xtprobit' command in STATA is used, which applies the probit model to panel data. The fixed-effects probit model is not available.

The estimation of equation (7) has been done by the Heckman selection model applied to panel data, allowing for fixed effects.[16] The estimation is done in two steps. In the first step, a selection model is estimated explaining export market participation decision (equation 6 above), and the probability of a plant in a specific year deciding to export is computed. In the second step, the outcome equation (equation 7 above) is estimated, in which the inverse Mills ratio (based on the estimated probability) computed in the first step is included as an additional explanatory variable (for correcting for selection bias).

Besides estimating equation (6) by the random effects probit model and estimating (7) with an underlying selection model using the Heckman selection model applied to panel data, an alternate approach to model estimation has been taken by applying the random effect Tobit model.[17] In this case, a latent variable XI* is used. The model is specified as follows:

$$XI_{it}^{*} = \mu_i + \lambda_t + \rho_1 PSS_{it} + \rho_2 PSS_{it}^{2} + \pi_1 lnK_{it} + \pi_2 lnK_{it}^{2} + \sum_r \delta^r X_{it}^{r} + \sigma M_{it} + \xi_{it} \qquad (8)$$

$$XI_{it} = XI_{it}^{*}\ if\ XI_{it}^{*} \geq 0;\ XI_{it} = 0\ if\ XI_{it}^{*} < 0$$

4.3 Regression Results

The regression results are presented in Table 5. Plant-level panel data for the aforementioned 10 three-digit industries for 2012-13 to 2019-20 (2012-2019) are used for the estimates. The parameter estimates of equation (1) using the random effects Probit model are shown in Regression (1). The parameter estimates of equation (2) based on the Heckman selection model applied to panel data are shown in Regression (2). The estimates of the random effects Tobit model as specified in equation (3), which combines equations (1) and (2), are shown in Regression (3).

The results presented in Regression (1), estimates of equation (6) show that the size of the plant has an inverted-U shaped relationship with export status or the decision to participate in export markets. As the size of the plant goes up, the probability of participating in export market increases. However, beyond a point, an increase in the size of the plant tends to lower the probability in participating in export markets – probably such firms tend to focus more on the domestic market.

[16] The software module 'xtheckmanfe' has been used in STATA to apply the Heckman selection model to panel data.
[17] Estimation is done by applying the 'xttobit' command in STATA. The fixed-effects Tobit model is not available.

Table 5: Models Explaining Export Performance of Industrial Plants, Regression Results Plant-level Panel data for 2012-13 to 2019-20

Explanatory Variable	Regression-1 Random effect probit model Dependent Variable: XS (dummy var.)	Regression-2 Heckman selection model, fixed effects Dependent Variable: XI (%)	Regression-3 Random effects Tobit model Dependent Variable: XI (%)
PSS	0.037 (0.008)***	0.390 (0.286)	3.011 (0.478)***
PSS^2	-0.0006 (0.0001)***	-0.010 (0.006)*	-0.050 (0.007)***
Plant size	0.185 (0.027)***	1.087 (0.842)	10.614 (1.288)***
Plant size squared	-0.012 (0.003)***	-0.091 (0.130)	-0.785 (0.168)***
Share of ICT assets total fixed capital stock (%)	0.014 (0.006)**	0.038 (0.243)	0.557 (0.365)
Plant has ISO 14000 series certification (dummy variable)	0.082 (0.037)**	-0.060 (1.504)	4.468 (2.206)**
Plant employing more than 25% of workers through contractors (dummy variable)	0.143 (0.032)***	-0.770 (0.991)	11.912 (1.875)***
Share of imported materials in total materials consumed (%)		0.030 (0.032)	0.734 (0.061)***
Year dummies	Yes	Yes	Yes
Industry dummies	Yes	No	Yes
No. of observations	33,103	33,073	33,073
No. of plants	6,774	6771	6,771
Wald chi-square and prob.	1566.6 (0.000)		2439.2 (0.000)

Note: Standard errors of estimated coefficients are shown in parentheses.
*, **, *** statistically significant at the 10, 5, and 1 percent, respectively.
Source: Authors' Computations.

Similarly, an inverted-U-shaped relationship is found between the product sophistication score (*PSS*) and export status. As PSS increases, the probability of participating in the export markets increases. However, once the *PSS* reaches about 30, further increases in *PSS* do not augment the probability of participating in export markets. Instead, the aforesaid probability may even go down.

A significant positive effect of ICT investment and ISO 14000 certification is found. Also, a positive association is found between substantial (above median) use of contract workers in the plant and the probability of participating in export markets. These results are as expected.

The results of the random effects Tobit model presented in Regression 3 are similar to those in Regression 2. An inverted-U-shaped relation is found between the size of the plant and export intensity (XI). Similarly, an inverted-U-shaped relationship is found between *PSS* and XI. The results suggest that till *PSS* reaches 30, there is a positive effect on XI. However, beyond that level, further increases in *PSS* do not have a positive effect and may have an adverse effect. A significant positive effect of ISO 14000 certification and substantial use of contract workers in the plant on XI is found, confirming the results in Regression (1). The coefficient of the ICT variable is positive, as in Regression (3), though not statistically significant. A significant positive effect of the use of imported intermediate input on export performance is found, as expected.

Table 6: Models Explaining Export Performance of Industrial Plants, Additional Regression Results, Heckman Selection Model with Fixed Effects

Plant-level Panel data for 2012-13 to 2019-20 Dependent Variable: XI (%)

Explanatory variable	Regression-4	Regression-5	Regression-6	Regression-7 Data for 2015-2019
PSS	0.391 (0.272)	0.389 (0.297)	0.390 (0.280)	0.582 (0.324)*
PSS^2	-0.010 (0.005)**	-0.010 (0.005)**	-0.010 (0.005)**	-0.014 (0.005)***
Plant size	1.046 (1.054)	0.366 (0.675)	1.045 (0.878)	2.954 (2.734)
Plant size squared	-0.098 (0.134)		-0.090 (0.131)	-0.335 (0.308)
Share of ICT assets total fixed capital stock (%)	0.009 (0.242)			0.103 (0.362)
Plant has ISO 14000 series certification (dummy variable)	-0.081 (1.007)			-0.181 (1.672)
Plant employing more than 25% of workers through contractors (dummy variable)	-0.823 (1.006)			
Share of imported materials in total materials consumed (%)			0.030 (0.043)	2.278 (5.021)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No
No. of observations	33,103	33,103	33,073	22,646
No. of plants	6,774	6,774	6,771	6,134
Wald chi-square and prob.	NA	NA	NA	NA

Note: Standard errors of estimated coefficients are shown in parentheses. In Regression (7), data for 2015-16 to 2019-20 are used. The model specifications have been slightly modified as discussed in the text.
*, **, *** statistically significant at the 10, 5, and 1 percent, respectively.
Source: Authors' computations.

The results of the Heckman selection model, presented in Regression (2), are unsatisfactory as almost all estimated coefficients are statistically insignificant. However, some support is found for the core finding above that *PSS* has an inverted-U-shaped relationship with export performance. In Regression (2), the coefficient of *PSS* is positive, and that of the squared term is negative. The latter coefficient is statistically significant at the 10 per cent level of significance. In Table 6, more regression results based on the Heckman selection model (allowing fixed effects) are presented, using alternate specifications of equation (7). A consistent pattern seen in the results is that the coefficient of *PSS* is positive and that of the squared term is negative and statistically significant. Thus, further support is found for the above finding of an inverted-U-shaped relationship between *PSS* and XI.

One econometric issue with the specification of equations (6) and (7) when estimated with the Heckman selection model is that the model explaining selection does not have an explanatory variable that is not included in the equation for the outcome variable, i.e., export intensity. To address this issue, the contract worker variable has been dropped from equation (7) because it is likely to have a more significant impact on the decision to participate in export markets than on the extent of export intensity. Two other variables have been included in the model explaining export participation decision: (1) whether the plant belongs to a company in which there is foreign equity participation, and (2) whether there is an R&D unit within the factory premises. Data on foreign equity participation and the presence of an R&D unit are available from 2015-16 onward. Hence, the estimates of the models have been made using data for 2015-16 to 2019-20. The results are reported in Regression 7 of Table 6. In these results, *PSS* has a positive and statistically significant coefficient, and the squared term has a negative and statistically significant coefficient, corroborating the estimates based on the Tobit model in Table 5.

4.4 Robustness Checks

One important econometric issue in the analysis above that needs to be addressed is that of endogeneity of explanatory variables, particularly the ICT investment, ISO 14000 series certification, employment of contract workers, and the imported input intensity variable. Goldar (2023) has recognised the possible endogeneity of the ICT intensity variable and the ISO 14000 certification variable in modelling export performance of Indian manufacturing plants using plant-level panel data drawn from ASI, and shown that even after addressing this issue, a positive effect of ICT investment and ISO 14000 certification on export performance is found. Goldar and Majumder (2022) have studied the factors that influence the acquisition of ISO 14000 series certification by Indian manufacturing plants using ASI unit-level data and find that exports are a significant reason why industrial firms adopt ISO 14000 (exporting adds to the probability of adopting ISO 14000). Goldar (2024) has studied the impact of exports on the decision of industrials regarding the use of contract workers. A positive effect of export on the use of contract workers is found, the effect varying among industry groups and plant size classes.

Turing now to the import intensity variable measured by the share of imported materials in total materials consumed, several studies have noted a positive correlation between import intensity and export intensity of manufacturing firms (see, for example, Goldar, 2013). Thus, export intensity could be treated both as a cause and an effect of import intensity.[18]

Table 7: Models Explaining Export Performance of Industrial Plants, Explanatory Variables Lagged by One Year, Regression Results

Plant-level Panel data for 2012-13 to 2019-20

Explanatory variable	**Regression-8 Random effect probit model Dependent Variable: XS (dummy var.)**	**Regression-9 Random effect probit model Dependent Variable: XS (dummy var.)**	**Regression-10 Random effects Tobit model Dependent Variable: XI (%)**	**Regression-11 Random effects Tobit model Dependent Variable: XI (%)**
PSS	0.028 (0.009)***	0.027 (0.009)***	2.444 (0.574)***	2.410 (0.574)***
PSS^2	-0.0005 (0.0001)***	-0.005 (0.0001)***	-0.046 (0.009)***	-0.045 (0.009)***
Plant size	0.338 (0.033)***	0.365 (0.030)***	23.163 (1.922)***	25.055 (1.942)***
Plant size squared	-0.023 (0.004)***	-0.024 (0.004)***	-1.781 (0.233)***	-1.830 (0.233)***
Share of ICT assets total fixed capital stock (%)	0.018 (0.007)**	0.010 (0.007)	1.210 (0.446)***	0.764 (0.451)*
Plant has ISO 14000 series certification (dummy variable)	0.063 (0.040)	0.049 (0.040)	3.557 (2.630)	2.809 (2.631)
Plant employing more than 25% of workers through contractors (dummy variable)	0.159 (0.034)***	0.148 (0.034)***	14.255 (2.258)***	13.362 (2.260)***
Share of imported materials in total materials consumed (%)			0.565 (0.073)***	0.515 (0.073)***
ln (TFP)		0.214 (0.029)***		13.584 (1.953)***
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
No. of observations	25,321	25,316	25,317	25,313
No. of plants	5,345	5,345	5,345	5,345
Wald chi-square and prob.	1413.4 (0.000)	1491.6 (0.000)	1937.1 (0.000)	1960.0 (0.000)

Note: Standard errors of estimated coefficients are shown in parentheses. ln (TFP)= logarithm of total factor productivity.

*, **, *** statistically significant at the 10, 5, and 1 percent, respectively.

Source: Authors' computations.

It is evident from the above that there is an issue of endogeneity in the estimates of equations (6), (7), and (8) presented in Tables 5 and 6. We have adopted a rather simplistic method to

[18] The theoretical model in Annexure-B brings out that industrial firms may jointly decide on both *PSS* and XI considering cost and revenue functions. Hence, this could be a source of endogeneity in the estimated econometric model that needs to be addressed.

address this econometric issue, which probably provides only a partial solution. All explanatory variables have been lagged by one year, and then the regression equations have been estimated. Another change made in the model is that total factor productivity (TFP) estimated by the Levinsohn-Petrin (2003) method[19] has been introduced as an explanatory variable in some regressions. The aim is to find out if the results remain mostly unchanged if variations in TFP are controlled for.

The regression estimates have been made for the Random-Effect Probit model and the Random-Effects Tobit model. Since the results of the Heckman Selection model with Fixed Effects are not found satisfactory in most regression equations estimated, this modelling approach is not adopted anymore in the analysis that follows. The estimated regressions with all explanatory variables lagged by one year are presented in Table 7. In Regressions (8) and (10), the specification includes the same explanatory variables as in Table 5 above. In Regressions (9) and (11), a new explanatory variable, namely TFP, is introduced.

It is seen in Table 7 that the results remain qualitatively the same as in Table 5 when all explanatory variables (except the industry and year dummies) are lagged by one year to address the issue of potential endogeneity. In particular, it should be noted that the coefficient of *PSS* is positive and statistically significant, and the coefficient of the square of *PSS* is negative and statistically significant, indicating an inverse-U-shaped relationship between *PSS* and export performance (as in the results in Table 5). The results do not change much when TFP is introduced as an explanatory variable. The coefficient of TFP is found to be positive which is expected since productivity increases (hence gains in competitiveness) should be reflected in better export performance. In these regressions using TFP as one of the explanatory variables, the coefficient of PSS is positive and that of the coefficient of the square of *PSS* is negative – both coefficients are statistically significant. Thus, an inverted-U shaped relationship is found as in the results in Tables 5 and 6. This issue has been investigated further by estimating the Tobit model in equation (8) for different subsets of observations based on *PSS* values. These results are shown in Table 8.

[19] The estimation of TFP by the Levinsohn-Petrin method is based on the gross output function, using materials input as a proxy. Output is deflated with the WPI (wholesale price index) at the NIC 3-digit level, and materials are deflated using the materials deflators from India KLEMS database which provides the indices for 27 industries comprising the Indian economy. Capital is deflated using the machinery and machine tool WPI indices. All Price series are of base 2011-12 = 100.

Table 8: Models Explaining Export Intensity of Industrial Plants, Panel (Random effects) Tobit Model, Subsets of observations according to PSS, Regression Results

Plant-level Panel data for 2012-13 to 2019-20

Explanatory variable	Reg. -12	Reg. -13	Reg. -14	Reg. -15	Reg. -16
	PSS≤25	PSS≤30	PSS>30	PSS>35	PSS>40
PSS	4.092 (0.483)***	1.619 (0.259)***	-0.702 (0.215)***	-0.297 (0.237)	-0.443 (0.389)
Plant size	12.484 (2.063)***	13.496 (1.865)***	14.480 (1.805)***	15.087 (1.883)***	14.823 (2.494)***
Plant size squared	-1.977 (0.316)***	-2.025 (0.278)***	-0.787 (0.204)***	-0.805 (0.206)***	-0.727 (0.269)***
Share of ICT assets total fixed capital stock (%)	0.203 (0.650)	-0.299 (0.560)	1.241 (0.435)***	0.686 (0.458)	0.886 (0.572)
Plant has ISO 14000 series certification (dummy variable)	9.844 (4.748)**	5.777 (3.955)	3.169 (2.357)	2.773 (2.278)	-3.453 (3.105)
Plant employing more than 25% of workers through contractors (dummy variable)	18.260 (3.366)***	13.765 (2.815)***	4.734 (2.288)**	2.291 (2.285)	2.291 (3.046)
Share of imported materials in total materials consumed (%)	1.032 (0.123)***	0.897 (0.107)***	0.589 (0.065)***	0.464 (0.067)***	0.531 (0.086)***
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
No. of observations	12,589	16,882	16,191	13,566	6,879
No. of plants	3,235	3,966	3,183	2,753	1,769
Wald chi-square and prob.	757.0 (0.000)	1045.2 (0.000)	926.9 (0.000)	543.9 (0.000)	309.5 (0.000)

Note: Standard errors of estimated coefficients are shown in parentheses.
*, **, *** statistically significant at the 10, 5, and 1 percent, respectively.
Source: Authors' computations.

Four points emerge from the results presented in Table 8. First, the coefficient of plant size is positive and statistically significant, and the coefficient of the squared term is negative and statistically significant in all five regressions. This indicates an inverted-U-shaped relationship between plant size and export intensity, as in the results presented in Tables 5 and 7. Export intensity increases as the size of the plant goes up. However, beyond a certain level, further increases in the size of the plant bring down the export share in production.

Second, the import intensity of materials used has a significant positive relationship with export intensity. The coefficient is positive and statistically significant in all five regressions, which also tallies with the results presented above.

Third, among plants engaged in the production of less sophisticated products, the use of contract workers at a substantial scale enhances their export intensity. Such plants probably belong to labour-intensive industries, and flexibility in labour use is likely to be an important factor influencing their decision to enter the export markets.

Fourth, the coefficient of *PSS* is positive when observations with *PSS* up to 25 or up to 30 are used. In contrast, the coefficient is negative when observations with *PSS* above 30, 35, or 40 are used. This is consistent with the inverse-U-shaped relationship found in the results presented above.

To complement the empirical analysis, a theoretical note has been developed to explain the inverted-U relationship observed between *PSS* and export-intensity among manufacturing plants. This theoretical discussion is presented in the Appendix-B.

5 Conclusion

In this paper, we have studied the degree of product sophistication achieved by organized-sector industrial plants in India. We used plant-level panel data of ASI from 2012 to 2019. The plant-level estimates of product sophistication score (*PSS*) were aggregated to the 3-digit industry level to study the trends in *PSS* for various 3-digit industries. We also identified the plants that achieved a significant increase in the *PSS* during the study period.

An analysis of product sophistication assumes significance since it is rooted in technological advances and results in improved competitiveness of industrial firms both in the domestic market and in export markets. Since the impact of *PSS* on export competitiveness has a good deal of policy relevance, we have studied econometrically the impact of *PSS* on the decision to engage in export markets and the share of exports in the production of industrial plants in India. For this purpose, we estimated models explaining export status and export intensity of industrial plants using panel data for 2012-2019 for ten selected 3-digit industries.

Previous studies on the product sophistication of Indian manufacturing firms, for example, Banga **(**2023), have used firm-level data drawn from the ProwessIQ Database of the Centre for Monitoring Indian Economy (CMIE). In our understanding, ASI provides much richer data on the products produced by Industrial plants in India. To our knowledge, this is the first study in which *PSS* has been computed for manufacturing enterprises in India using ASI data.

Our analysis revealed that the estimates for the manufacturing sector and those for two-digit industries show only a modest increase in *PSS*. However, a detailed examination revealed that about 11 per cent of the plants attained a significant increase in *PSS* during the study period. About 24 per cent of plants in Textiles and 23 per cent of plants in the basic metals industry achieved a significant increase in *PSS* during 2012-2109.

The analysis undertaken at the 3-digit industry level revealed that around 28 per cent of 3-digit industries attained a statistically significant increase in *PSS*, while 17 per cent experienced a decline. For the majority of industries (55 per cent), there was no statistically discernible trend. Several high-technology and capital-intensive sectors such as Pharmaceuticals (210), Electronic Components (261), Measuring and Control Equipment (265), Irradiation, Electromedical and Electrotherapeutic Equipment (266), General Purpose Machinery (281), Special-Purpose Machinery (282), and Air and Spacecraft and Related Machinery (303) show statistically significant improvement in product sophistication over time. In contrast, industries such as Wearing Apparel (141), Consumer Electronics (264), Furniture (310) and Other Manufacturing n.e.c. (329) witnessed a significant decline.

From our analysis, we find that a sizeable number of factories and industries are experiencing structural transformations in terms of product sophistication. Differences in investment behaviour, technological capability, global integration, or policy incentives may be driving these changes.

As mentioned above, using plant-level panel data on 10 selected 3-digit industries, an econometric analysis of the impact of *PSS* on export performance was undertaken. Preliminary analysis of these data revealed that plants that have an R&D unit within factory premises have, on average, a higher *PSS* than plants that do not have an R&D unit. Similarly, plants belonging to firms in which there is foreign direct investment (FDI) have, on average, a higher *PSS* than plants that do not have foreign equity participation. These findings highlight the critical role played by R&D and FDI in enhancing the *PSS* of Indian industrial plants.

The estimates of the econometric models showed the importance of ICT investment for enhancing the export competitiveness of Indian industrial plants. An inverted-U-shaped relationship was found between *PSS* and export performance, for both export market participation and export intensity. The implication is that an increase in *PSS* raises export performance. However, once the *PSS* reaches a certain level, further increases in *PSS* do not augment export performance further.

Since we find that R&D and FDI augment *PSS* (as depicted in Figures 3 and 4) and *PSS* bear a positive relationship with export performance, at least to a certain level, our results point to a positive effect of R&D and FDI on export performance.

Why the effect of *PSS* on export performance does not remain favourable beyond a particular level of *PSS* is an important question. One possibility is that a portion of the plants that achieved significant hikes in *PSS* use their competitiveness to consolidate their position in the domestic market, competing against imports of technologically sophisticated products, and the supplies of multi-national firms operating from their production facilities in India. A theoretical analysis of the issue has been done in Annexure-B. The analysis brings out that an inverse relationship between *PSS* on export performance could arise because of revenue realization from export market at higher levels of *PSS*.

In Annexure-B, attention has been drawn to the findings of a recent study on the impact of India's Quality Control Orders (QCOs) undertaken by Prabhakar (2025). From the econometric analysis undertaken, Prabhakar finds that QCOs significantly reduce imports, especially of intermediate goods, indicating import-substitution effects. However, there is no evidence of export gains arising from QCOs. These findings of Prabahkar (2025) are broadly in line with the findings of the present study.

Annexure-A

Table A.1 List of three-digit industries chosen for econometric analysis

Industry, 3-digit NIC	Description	Share in aggregate gross value added in the factory sector (aggregate ASI) in 2022-23, %	Share in aggregate employment in the factory sector (aggregate ASI) in 2022-23, %
102	Processing and preserving of fish, crustaceans, and molluscs	0.33	0.60
141	wearing apparel, except fur apparel	1.94	4.87
143	knitted and crocheted apparel	0.75	2.26
151	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, and harness; dressing and dyeing of fur	0.22	0.63
152	footwear	0.59	1.57
210	pharmaceuticals, medicinal chemicals, and botanical products	7.73	5.01
259	metal products; metalworking service activities n.e.c.	2.24	2.75
282	special-purpose machinery	2.89	2.56
303	air and spacecraft and related machinery	0.18	0.16
321	Jewellery, bijouterie, and related articles.	1.20	1.42
All		**18.07**	**21.83**

Source: Prepared by Authors.

Table A2: Major 5-digt NIC industries with highest and lowest PSS per factory (2012, 2019)

2012	2019
Low (PSS range: 2.8 to 3.4)	**Low (PSS range: 2.6 to 3.4)**
Metal fasteners (**25991**), Preparation and spinning of cotton fiber including blended cotton (**13111**), Other textile products n.e.c. (**13999**), Weaving, manufacture of cotton and cotton mixture fabrics (**13121**), Medical impregnated wadding, gauze, bandages, dressings, surgical gut string etc. (**21006**), Wadding of textile materials and articles of wadding such as sanitary napkins and tampons (**13996**), Processing of edible nuts (**10793**), Vegetable oils and fats excluding corn oil (**10402**), Zarda (**12006**), Pan masala and related products (**12008**), Other tobacco products including chewing tobacco n.e.c. (**12009**), Stemming and redrying of tobacco (**12001**).	Sun-drying of fruit and vegetables (**10301**), Preparation and spinning of cotton fiber including blended cotton (**13111**), Synthetic or artificial filament staple fibre not textured (**20302**), Tapes, newar and wicks (**13946**), Hydrogenated oil and vanaspati ghee (**10401**), Stemming and redrying of tobacco (**12001**), Zarda (**12006**), Other tobacco products including chewing tobacco n.e.c. (**12009**), Snuff (**12005**).
High (PSS range: 90.5 to 59.4)	**High (PSS range: 90.5 to 61.3)**
Other rubber products n.e.c. (**22199**), Other structural metal products (**25119**), Other special-purpose machinery n.e.c. (**28299**), Other fabricated metal products n.e.c. (**25999**), Parts and accessories for the machine tools (**28223**), Casting of non-ferrous metals (**24320**), Diverse parts and accessories for motor vehicles (**29301**), Forging, pressing, stamping and roll-forming of metal; powder metallurgy (**25910**), Steel in ingots or other primary forms, and other semi-finished products of steel (**24103**), Cable television equipment, transmitting and receiving antenna including dish, VSAT (**26304**), Bearings, gears, gearing and driving elements (**28140**), data communications equipment (**26303**), Wind instruments, accordions, harmonium and similar instruments and mouth organs (**32202**), Repair and maintenance of irradiation, electromedical and electro theraputic equipmemts (**33132**), Aluminium from alumina and by other methods and products of aluminium and alloys (**24202**), Printing directly onto textiles, flexographic plastic, glass, metal, wood and ceramics (**18115**).	Rubber plates, sheets, strips, rods, tubes, pipes, hoses and profile -shapes etc. (**22191**), Metallised yarn or gimped yarn, rubber thread or cord covered with textile material (**13997**), Preparation and spinning of cotton fiber including blended cotton (**13111**), Other textiles/textile products n.e.c. (**13999**), Machinery for metallurgy (**28230**), other machinery for textiles, apparel and leather production n.e.c. (**28269**), Other machinery for the industrial preparation or manufacture of food or drink n.e.c (**28259**), Steel in ingots or other primary forms, and other semi-finished products of steel (**24103**), Hot-rolled and cold-rolled products of steel (**24105**), Other communication equipments n.e.c. (**26309**), Cable television equipment, transmitting and receiving antenna including dish, VSAT (**26304**), Televisions, television monitors and displays (**26401**), Diverse parts and accessories for motor vehicles (**29301**), Other musical instruments n.e.c. (**32209**), Machinery for working soft rubber or plastics or for the manufacture of products of these materials (**28292**), Other general purpose machinery n.e.c. (**28199**), Bone plates and screws, syringes, needles, catheters, cannulae, etc. (**32504**), Irradiation, electromedical and electrotherapeutic equipment (**26600**).

Note: The "Low" category lists industries whose plants recorded the lowest Product Sophistication Scores (PSS) in the given year, while the "High" category lists those with the highest PSS.
Source: Authors' computations.

Annexure-B

Possible Explanation for the empirically observed inverted-U relationship between *PSS* and export intensity among Indian manufacturing plants

The econometric analysis presented in Section 4 of the paper revealed an inverted-U relationship between *PSS* (product sophistication score) and export intensity (share of exports out of production) of organized sector industrial plants in India. This annexure aims to look for a possible explanation for the observed negative relationship between *PSS* and export intensity beyond a particular level of *PSS*. A theoretical framework of firm (producer) behaviour is used for this purpose.

Several simplifying assumptions are made to examine theoretically how a firm decides on the level of product sophistication and the allocation of its production into domestic and export markets. Let us consider a firm that produces a particular product, Q. The level of product sophistication is denoted by *PSS*.[20] This is a decision variable for the firm. The level of production of Q is also a decision variable. However, we ignore this aspect for the time being and focus instead on the cost per unit of production and the revenue per unit of production, which yield profits per unit of production. Another crucial decision variable is export intensity (*XI*), i.e., what proportion of the production is exported (the rest is sold in domestic market).

The firm uses five inputs: capital (K), ordinary labour input (ordinary workers along with contract workers) (L_1), skilled labour input (i.e., skilled workers) (L_2), domestic intermediate inputs (including energy and services) (M_1) and imported intermediate inputs (M_2). It is reasonable to assume that as *PSS* is raised, the requirement of L_1 falls and that of L_2 rises. Also, the requirement of M_2 rises.[21] The rise in the use of M_2 may be compensated, to some extent, by a fall in the use of M_1. However, it seems reasonable to assume that the sum of M_1 and M_2, i.e., the total value of intermediate inputs would go up as the firms raised the level of sophistication of its product.

Another reasonable assumption to make is that an increase in the *PSS* of production is associated with an increase in capital intensity. This assumption is not necessary for the

[20] While we consider a single-product firm for simplicity, the core logic extends to a multi-product firm, where *PSS* represents the sales-weighted average level of product sophistication.

[21] The important role imported intermediate input have played in enhancing export sophistication of Chinese manufacturing firms has been studied by Wang *et al*. (2024). It may be noted here that the increase in M_2 caused by increase in *PSS* could translate into lower domestic value added in exports. Tandon (2020) in her analysis of India's exports finds a negative relationship between domestic value addition and product sophistication.

theoretical results presented later. However, there is a strong possibility that capital cost per unit of output tends with rise with the level of product sophistication, and this assumption should therefore be made.[22]

Figure A.1 depicts how aggregate input cost per unit of output changes as the level of sophistication of the product produced by the firm is raised. It is assumed that the aggregate input cost per unit of production increases with *PSS* because of higher costs of skilled labour, imported materials and capital input.

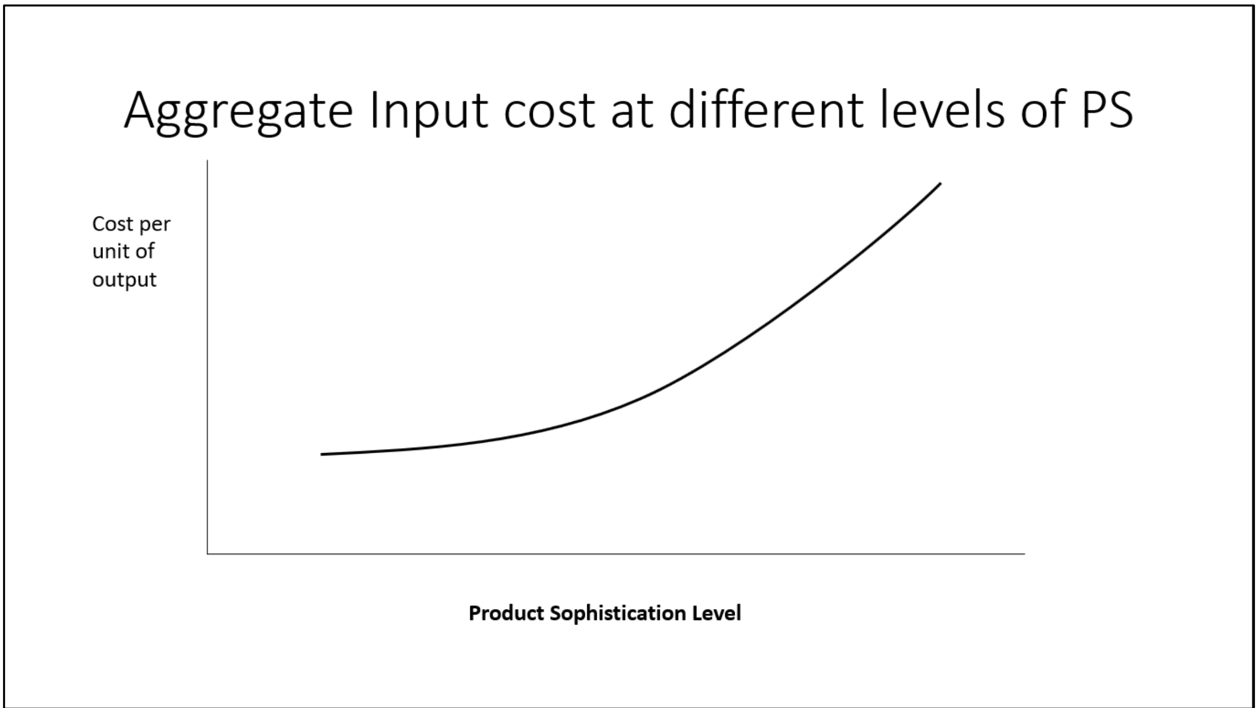


Figure A.1: Aggregate input cost at different levels of product sophistication
Source: Prepared by authors.

The assertation of a rising cost of skilled labour with increases in the level of product sophistication needs some further discussion. It is known that organized sector industrial firms in India are facing a significant shortage of skilled workers, which is partly traceable to the uneven quality of technical education and training and the course curriculum, in many cases, not being aligned to the needs of the industry. According to *India Skills Report, 2025*, only 71.5% of BE/B. Tech., 40% of ITI trained persons and 29% of persons trained at Polytechnics

[22] The way *PSS* is defined in the literature and in the paper (see Section 2), the score for a particular product will be relatively high if its production (and hence exports) is concentrated in high income (industrialized) countries. The techniques of production employed in those countries are likely to be highly capital-intensive because of the prevailing factor prices in those countries. When such a product is produced in an emerging economy, the available technology and capital equipment will dictate the technology choice and thus cause the capital intensity of production to be high in the emerging economy too.

are employable. In the *Global Talent Shortage Survey, 2025,* undertaken by *the Manpower Group,* about 3000 employers in India were surveyed. Among them, about 80% reported difficulty in recruiting required talent. There are other reports or media articles drawing attention to a shortage of skilled workers being faced by industrial firms in India. Given the shortage of skilled labour in India's organized manufacturing, the problem faced by an industrial firm is expected to become more intense, resulting in increased labour cost, if it decides to raise product sophistication.

It may be mentioned here that in the theoretical model incorporating product quality in the analysis, a cost curve rising with the level of product quality is often assumed (see Sutton, 1986). Thus, the assumption made about the behaviour of cost as *PSS* is raised is justified.

Let us now turn to the side of revenue and consider how revenue realization changes as the level of product sophistication of an industrial firm goes up (could also be interpreted as the impact of product quality improvement on revenue realization). The revenue realized is obviously expected to rise with *PSS*. However, there could be differences between the way revenue realization from domestic market varies with *PSS* and how revenue realization from the export market varies.

Let the revenue per unit sold in domestic market be denoted by p_d, which is taken as a function of the level of product sophistication. $p_d = p_d(PSS)$. We assume a positive linear relationship between p_d and *PSS*.

Let the revenue per unit sold in the export market be done by p_x, which is again a function of the level of product sophistication. $p_x = p_x(PSS)$. We assume that $p_x(PSS)$ is also increasing in *PSS*, but potentially at a diminishing rate (could even fall beyond a level). The reason for the tapering effect of product sophistication on the revenue realization per unit of output in the export market is as follows. At low levels of *PSS*, international market is mainly driven by cost competition and Indian firms are competing mainly with firms from other emerging economies. By contrast, at a high level of *PSS*, the competition in international markets is mainly in product quality and embedded technology and Indian firms are competing mainly with firms from industrialized countries. It is reasonable to argue that a large part of global trade in sophisticated products is intra-firm or within closely connected networks. Hence, significant discounts may have to be given by Indian firms to sale the product in such market if the chosen *PSS* is high.

The assumed behavior of $p_d = p_d(PSS)$ and $p_x = p_x(PSS)$ is depicted in Figure A.2. It should be pointed out the aforesaid tapering effect on revenue realization from export market will occur if the firm is not participating in GVCs (Global Value Chains) or has a shallow participation in GVCs. In case the firm has a deep participation in GVCs, the enhancement of product sophistication may take place at the request of the buyer firms. Therefore, the revenue realization from exports need not fall as *PSS* is raised. This is a special case and treated later in discussion. Most industrial firms in India have limited or shallow participation in GVCs or at best a moderate participation in GVCs, and therefore the pattern depicted in Figure A.2 is expected to hold commonly.

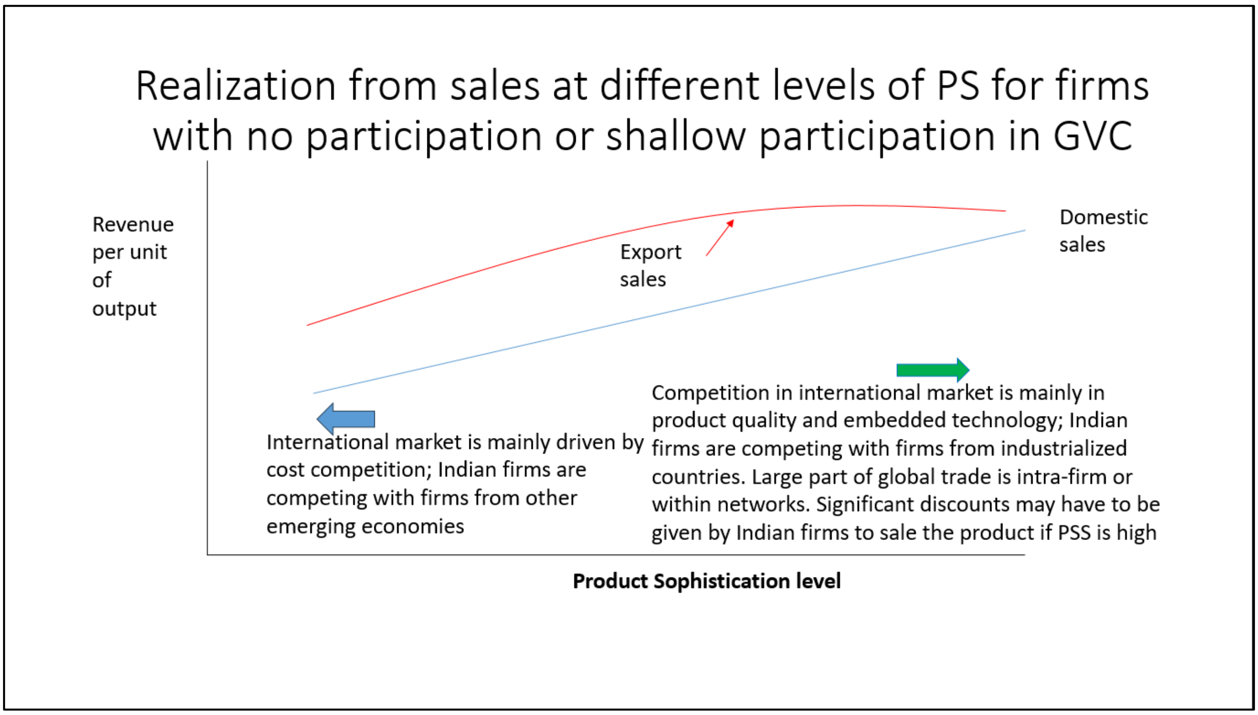


Figure A.2: Revenue realization from sales in the domestic market and export market at different levels of product sophistication
Source: Prepared by authors.

Let us consider next an industrial firm that is not exporting. What is the optimal level of *PSS* for such a firm? A simplifying assumption to make for determining the optimal *PSS* is that the firm maximizes profits per unit of output sold. This will depend on the cost per unit of output, depicted in Figure A.1 and revenue realization per unit of output depicted in Figure A.2. The optimum level can easily be determined – this is depicted in Figure A.3.

In the next step, the optimum level of *PSS* is determined for an exporting firm. An illustrative case is taken in Figure A.4. Two levels of export intensity are considered: 5% and 15%. If the export intensity is relatively high, the tapering effect of *PSS* on the overall revenue realization is also high. As a result, the optimal *PSS* is reached at a relatively low level of *PSS* in such a case. As a result, an inverse relationship arises between the chosen export intensity and the optimal *PSS*. In other words, if the firm opts for a relatively high *PSS*, then this is consistent with a relatively low export intensity.

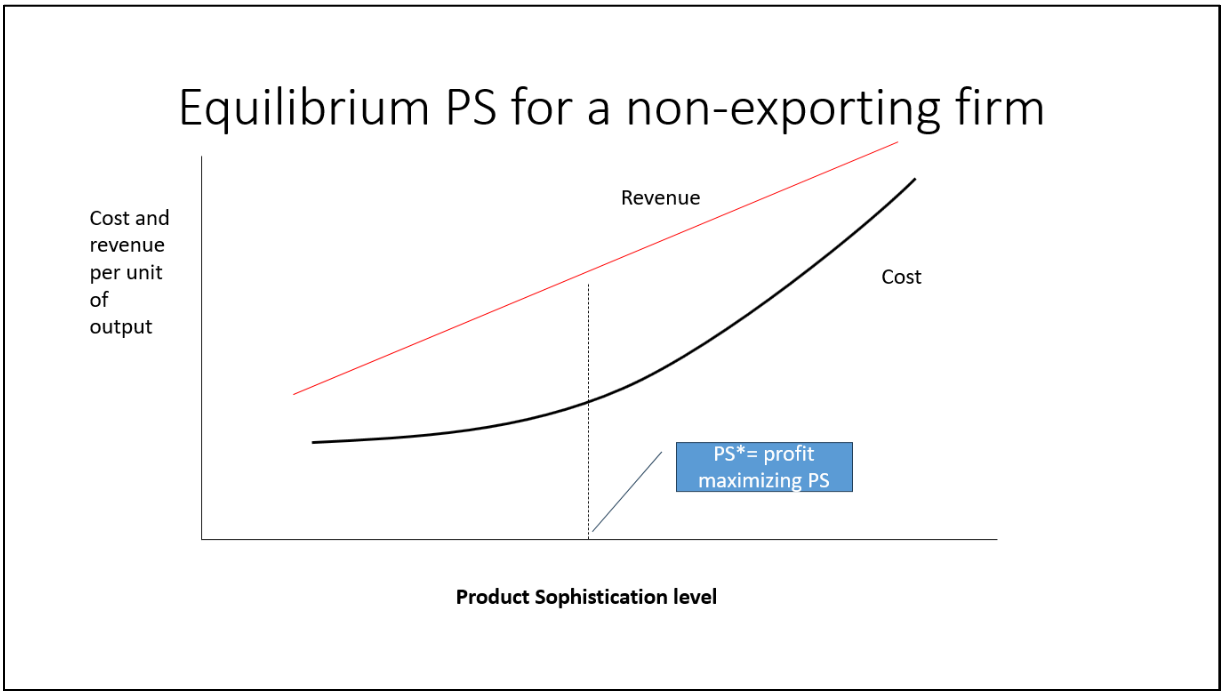


Figure A.3: Optimate level of product sophistication for a non-exporting firm
Source: Prepared by authors.

For a more complete analysis of the firm behaviour in the context discussed above, one should consider a curve representing revenue per unit of output at different *PSS* for each level of export intensity, yielding a map of the relationship. Then, for each level of export intensity, the optimal *PSS* (denoted *PSS**) and the corresponding profit per unit (denoted π*) should be computed. Once profit per unit of output (π*) is computed for each level of export intensity and the corresponding optimal *PSS* (i.e., *PSS**), then the levels of profits (π*) should be compared, and accordingly the optimum combination of export intensity (*XI***) and sophistication level (*PSS***) for the firm may be derived which yields the highest value among π* for different *XI* values. A more complete analysis also needs that the following points be taken into consideration: (a) one should consider the aggregate level of profits rather than profit per unit of output for deriving the firm equilibrium, which is determined by total quantity of production and profits per unit of output; (b) it is more appropriate to assume that capital stock is fixed (or sticky) in the short run and the variable cost goes up with the level of production; (c) selling a larger part of production in diverse export markets may impose an additional cost on the firm which needs to be taken into account while deriving the equilibrium, and (d) changes in cost conditions, for instance, availability of skilled workers, will impact the shape of the cost curve (making the cost curve flatter or steeper) and lead to changes in the optimal levels of *PSS* and *XI*, and whether these two move in the same direction or in opposite directions needs to be ascertained.

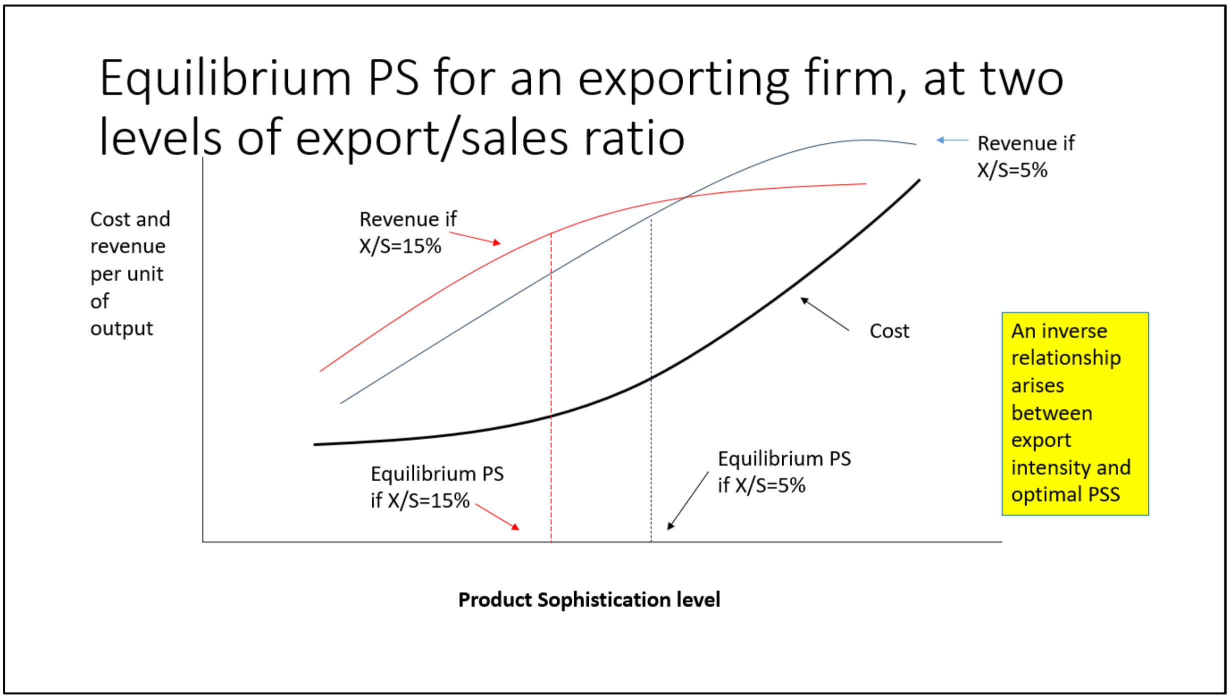


Figure A.4: Optimate level of product sophistication for an exporting firm at two levels of export intensity
Source: Prepared by authors.

A complete analysis as outlined above is outside the scope of the present paper and is not attempted here. Thus, the analysis in Figure A.4 may be treated as rudimentary, merely illustrating a possible case when an inverse relationship could arise between the optimum PSS and optimum export intensity. Nevertheless, the figure does provide a helpful insight on why increases in *PSS* need not be associated with increases in export intensity. The moot point is that the decision about exports is governed by the cost of production for domestic and export markets and the returns from sales in the domestic and export markets. An increase in product sophistication will raise the returns from the domestic market as well as that from the export market. But, if the increase in the returns from the domestic market because of the increased *PSS*/ improvement in the quality of the product is more than the increase in the return from the export market (which is expected to occur commonly beyond a level of *PSS*), the firm may reduce the proportion of the production sold in the export market and instead direct its sales relatively more in domestic markets since import substitution has now become more attractive.

The above observation on the relative attractiveness of exports versus import substitution finds support from the findings of a recent study on the impact of India's Quality Control Orders (QCOs) undertaken by Prabhakar (2025). From the econometric analysis undertaken, Prabhakar finds that QCOs significantly reduce imports, especially of intermediate goods, indicating import-substitution effects. Exports decline two years post-QCO, particularly for intermediate goods, and no impact over the long run. There is no evidence of export gains arising from QCOs, raising concerns over QCO effectiveness in boosting competitiveness (see, in this context, the theoretical analysis of Schubert, 2017). These findings of Prabahkar (2025) are broadly in line with the findings of the present study. The implication of the empirical findings is that an improvement in product sophistication (or product quality) enables Indian firms to substitute imports profitably and need not always lead to increased export intensity.

One issue that should addressed at the end of the annexure is the impact of *PSS* on a firm that is deeply embedded in GVCs. As stated above, such a firm might raise *PSS* on demand from its buyers and thus there is no reasons to expect a tapering effect of *PSS* enhancement on revenue realization from exports. For such a firm, the relationship between *PSS* and *XI* may not be negative, and may even be positive. However, only a small minority of Indian industrial firms have deep integration into GVCs (see Manghnani et al., 2021; Ray and Miglani, 2020) and therefore in the results of empirical analysis in Section 4 of the paper based on a large sample of industrial plants covered by ASI, the observed relationship is valid since the relationship arising from the plant-level data will be dominated by the relationship between *PSS* and *XI* prevailing among firm that have shallow or moderate integration into GVCs, i.e. a negative relationship is expected to hold beyond a level of *PSS*.

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