Industry-level determinants of India's vertical and horizontal IIT

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Abstract

This paper mitigates the gap in the Indian context about the non-consideration of *vertical* and *horizontal* intra-industry trade (IIT) distinctly in testing empirical hypotheses about industry-level determinants of IIT. Our study indicates that failure to segregate *vertical* and *horizontal* IIT from the *total* IIT possibly leads to potential *bias* in econometric results. Drawing on annual multilateral trade data encompassing two and half decades of the liberalization period, we find India's IIT outpaced the growth of inter-industry trade over the years and its contribution mainly came from *six* manufacturing industry groups whose export baskets had been loaded with *low* vertically differentiated goods. However, horizontal and *high* vertical IIT have gained some momentum since the end of the last decade. Given the *fractional* nature of our dependent variable, we initially estimate a (random effects) Tobit model followed by the Exponential Regression of Fractional Response model. The robust econometric findings show that product differentiation has a *positive* impact *only* on *total* IIT. Whereas vertical and horizontal IIT are promoted in industries with *concentrated* and *competitive* market structures, respectively. The prevalence of concentrated market structure indicates that (large) Indian firms sustain import competition by specializing in *low* vertically differentiated goods, as they efficiently adjust to resource reallocation.

Keywords Horizontal and vertical IIT · Revealed comparative advantage · Manufacturing industry · (Random effects) Tobit model · Exponential regression of fractional response model

JEL Classification F14 · C23

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1 Introduction

In today's world, countries not only specialize in different products of different industries but also offer *different specialized varieties of a product within an industry*. Since the latter half of the last century, such specialization increasingly led to cross-country trade in both *horizontally* and *vertically* differentiated goods. The theoretical underpinnings of intra-industry trade (IIT) were first identified by Grubel and Lloyd (1971). In their seminal paper, the authors argued that the basis of IIT differs from the traditional Heckscher-Ohlin framework. They identified (*internal*) *economies of scale*, *monopolistic competition in the product markets* and *product differentiation* as the pivotal (industry) characteristics that give rise to IIT. The subsequent theoretical research had its principal focus on modelling trade in *horizontally* and *vertically* differentiated products. The initial theoretical attempts in the late 1970s and early 1980s, towards modelling IIT in horizontally differentiated products have been central to most of the early explanations on IIT. This strand of literature was primarily based on the assumptions of having (internal) scale economies, monopolistically competitive markets and incorporated horizontal product differentiation either through the Neo-Chamberlinian 'love for variety' approach by Krugman (1979) or the Neo-Hotelling 'favourite variety' approach of Lancaster (1980). In comparison to these seminal works, it was upon Helpman and Krugman (1985) to point out the theoretical reasons behind the simultaneous occurrence of both intra- and inter-industry trade in between two countries. By integrating scale economies and Chamberlinian type product differentiation with differences in factor endowments between two trading partners they explained the phenomena of horizontal IIT. In doing so, it also put forward empirical research hypotheses based on industry- and country-level characteristics to examine the basis of horizontal IIT. For instance, they argued the pattern of horizontal IIT will tend to be more intensified with greater similarity in factor endowments between countries and participating industries are likely to be characterized by *competitive* market structure. On the other hand, attempts to model IIT in vertically differentiated goods are rooted in the HO theory and are commonly referred to as the neo-Heckscher-Ohlin models. These models *without* generally relying on the assumption of economies of scale but consider industries with a *large* number of firms as an industry-level attribute of vertical IIT. The pattern of trade would follow a capital abundant country will engage relatively more in *high* vertical IIT while the labour-abundant country will participate in *low* vertical IIT (Falvey 1981; Falvey and Kierzkowski 1987). In the meantime, there were also other prominent theoretical studies arguing that *horizontal* and *vertical* IIT can occur in industries having relatively *small* number of firms (Eaton and Kierzkowski 1984; Shaked and Sutton 1984). Altogether, these seminal works have contributed towards building various testable *country-* and *industry-level* empirical hypotheses.

From the empirical standpoint, a significant majority of the existing studies while identify determinants of *horizontal* and *vertical* IIT (H-IIT/V-IIT) with respect to both *industry* and *country* attributes but are predominantly confined only to the 'advanced' economies and thus, empirical evidence pertaining to the 'emerging'

economies remains scanty.¹ In the Indian context, there have been only a few published studies that have dealt with *country*-level determinants of IIT and its broad forms (Bagchi and Bhattacharyya 2019; Aggarwal and Chakraborty 2017; Burange and Kelkar 2015; Varma 2015 and Veeramani 2002). However, *industry*-level studies are relatively much less, see Aggarwal and Chakraborty (2019); Burange et al. (2017) and Veeramani (2007).

Let us now put this empirical research into the proper perspective. Our study is on India's multilateral IIT and its generic origin could be traced back to Greenaway et al. (1995). Essentially, we focus on two specific aspects (1) identify from India's trade basket the dominance among horizontally and vertically differentiated goods by considering trade data at the disaggregated HS- 6 digit level; and (2) what industry-level attributes influence such trade. This study is in that sense pertinent and important for multifarious reasons.

To begin with, the Trade-GDP ratio of India has increased significantly over the past few decades—from around 15% in 1990 to around 40% in 2019 supplemented by a reduction in import tariff rate from 81.6% in 1990 to 9.03% in 2018 (2020: World Bank). The increased intensity in India's trading activity is also reflected in the increase in number of India's trading destination. It improved from 174 in 1990 to 226 in 2019 (2020: UN Comtrade). It is also noteworthy that in the overall Globalization Index prepared by Gygli et al. (2019), India's score improved from 14.73 [1990] to 26.57 [2000] to 42.90 [2018].²

Second, it is argued in the literature that a country's expansionary trade policies are not fundamental to its economic growth but rather *what it produces and exports are pivotal*; Hausmann et al. (2007).³ India is a typical example, where it has *moved up* from the category of *low-income* countries to the category of *lower-middle-income* countries in the year 2007 (2015: World Bank). It is expected that for an emerging (labour abundant) economy like India, the export basket will be loaded with more low-technological products as it has relative comparative advantage in producing such commodities, see Falvey (1981), Pittiglio (2012).⁴ On the other hand, gradual reforms over the past decades have eased the trade norms and increasing presence of India's manufacturing sector in its overall trade makes the empirical interest of this study to examine whether indeed India's multilateral trade basket is filled with technologically *low-quality* goods or not.

¹ A detailed survey for all sets of studies is well documented in Greenaway and Milner (1987); Greenaway and Torstensson (1997) and Greenaway and Milner (2006).

² Recently, the Indian Prime Minister has urged the Commerce Ministry "to make all efforts to double India's share in world exports from today's 1.6% to at least 3.4%", Mr. Modi at Vanijya Bhawan, New Delhi on 22nd June, 2018; GoI (2018). Subsequently, in January 2019, the Commerce Ministry had prepared a blueprint suggesting ways to increase size of the Indian economy to five trillion-dollar by 2025. Among them, the ministry aims to increase the size of the Indian manufacturing sector from around 390 to 900 billion-dollars by 2025, GoI (2019).

³ The emerging economies are expected to grow faster if these nations specialize in goods and services that the advanced economies exports.

⁴ The labour abundant economy is expected to have a comparative advantage in *low* technology products. In fact, Topalova (2010) argues that India is an unskilled labour abundant economy.

Our study with reference to Indian data makes a significant step forward since the earlier set of industry-level studies have examined hypotheses only on magnitude of *total* IIT. Greenaway and Torstensson (p. 255, 1997) argue that econometric models that consider *total* IIT as the dependent variable are *misspecified*. It is, therefore, important to disentangle the magnitude of vertical and horizontal IIT from total IIT and separately estimate the regression models to identify their determinants as from the theoretical point of view the impacts of determinants differ. We, therefore, identify distinctly the ‘industry-level’ determinants impacting India’s *vertical* and *horizontal* IIT over a data period that encompasses two and half decades of the post-liberalization phase using disaggregated trade data at the HS-6 digit level.

In doing so, we depart from the usual practice in the extant empirical literature of using *logit transformation* to the fractional nature of the dependent variable (i.e., magnitude of IIT as a percentage of total trade).⁵ Therefore, to increase robustness in our empirical analysis, we alternatively estimate a *Tobit* model, as well as, the *Exponential Regression of Fractional Response* (ERFR) model, see Ramalho et al. (2011), Ramalho et al. (2016) and Ramalho (2019) for details.

However, following Proença and Faustino (2015), estimation of the Tobit model does *not* seem to be a wise choice as the dependent variable might *not* have the *censored property*. But, given that a dominant majority of existing published empirical studies have estimated the Tobit model for identifying both country and industry-level determinants for the magnitude of IIT, we are maintaining the legacy of such a strand of literature.⁶ See Sect. 4.1.1 for necessary details on the ERFR model specification.

It is against this backdrop that we focus on the following *three* empirical questions in this paper:

1. whether the manufacturing industries of a labour-abundant economy like India are destined to export *low*-quality goods and import their relatively superior counterparts;
2. whether India’s vertical IIT adhere to the *comparative advantage hypothesis*; and lastly,
3. which industry-level attributes are particularly important in explaining the *vertical* and *horizontal* IIT in India’s merchandise trade?

In summary, our contributions to the empirical literature on Indian data are the following. First, we provide a comprehensive map of the evolution of India’s IIT and its various types at the *multilateral* level of the post-liberalization era using HS- 6 digit data, which as far as we know, is one of the most detailed samples attempted so far in the literature. This study identifies the specific industry groups that contribute to India’s multilateral IIT and further explores whether it is vertical or horizontal IIT that dominates it. Second, it *separately* examines the hypotheses about

⁵ The econometric reason is that the logit transformation is usually considered only when *most observations* of the (fractional) dependent variable are *not* clustered at either *zero* or *one* values (Balassa and Bauwens 1987; Türkcan and Ates 2011 and Pittiglio 2012).

⁶ A quick comprehensive list of Tobit model estimation will be Greenaway et al. (1995), Hu and Ma (1999), Sawyer et al. (2010), Ambroziak (2012) and Kawecka-Wyrzykowska et al. (2017).

industry-level determinants of vertical and horizontal IIT. Lastly, econometrically we adopt a much robust estimation method that retains the fractional nature of the dependent variable.

The remainder of the paper is structured as follows: Sect. 2 mentions the choice of index to compute the magnitude of total IIT and the method used to segregate it into its different forms. Section 2.1 identifies the major manufacturing industry groups that cater to relatively high magnitude of India's IIT. Section 2.2 briefly explores the pattern of varied forms of IIT among the major industry groups and also delves to ascertain the degree of revealed comparative advantage in explaining India's vertical IIT. Section 3 sets out the *empirical hypotheses* examined in this paper. It also describes the variables considered for the empirical analysis. Construction of dataset and the chosen econometric methods are discussed in Sect. 4. The findings from the estimated regression models are presented in Sect. 5. Lastly, Sect. 6 concludes the paper.

2 IIT: measurement issues and evidence from India

The magnitude of total IIT at the HS-6 digit level is computed in this paper using the Grubel and Lloyd (1971) index. The weighted index is given by

$$IIT_j = \left[1 - \frac{\sum_{k=1}^K |X_k - M_k|}{\sum_{k=1}^K (X_k + M_k)} \right] \times 100,$$

where X_k and M_k represent India's export and import of the k th commodity group of industry group j at a given point of time with the world. IIT_j takes the value of *hundred* if all trade is *intra*-industry trade and *zero* if all trade is *inter*-industry trade.

Along with the *static index* (IIT_j), we also compute the *dynamic index* in terms of *marginal* IIT developed by Brühlhart (1994). The dynamic index calculates the percentage of IIT in *new* trade flows of a traded commodity over two time points and is

$$\text{expressed as } MIIT_j = \left[1 - \frac{\sum_{k=1}^K |\Delta X - \Delta M|}{\sum_{k=1}^K |\Delta X| + \sum_{k=1}^K |\Delta M|} \right] \times 100, \text{ where } MIIT_j = 100 \text{ represents pro-}$$

portion of changes in total trade to be *all* IIT and 0 indicates *no* share of IIT in total merchandise trade of a country; other notations have their usual meanings.

The need for such a dynamic measure emerged since trade liberalization generates an *adjustment cost* in the form of changes in the method of production, shift of productive resources from inefficient to efficient product lines, among others. The costs generated from these adjustment processes would be *less* if such changes occur *within* an industry. In other words, if trade liberalization brings about more *intra*-industry trade then these adjustment costs would be less. Thus, a dynamic index measures the composition of changes in trade flows for a country within an industry group. An increasing trend of $MIIT_j$ will signify that economic liberalization has

induced adjustment to be more *within* the industry reflecting a higher share of IIT in new trade flows.

The *unit value dispersion criterion* of Greenaway et al. (1994) is used to disentangle the magnitude of j th industry's total IIT into horizontal and vertical IIT and further vertical IIT into *low* and *high* categories (*l*-VIIT/*h*-VIIT). We consider the dispersion criterion at 15% as it remains empirically the most used criterion. Of course, we have also considered the Fontagné and Freudenberg (1997) measure and the results remain qualitatively the same for all cases. Upon categorizing the commodity groups of an industry group into the different forms of IIT, the magnitude of total IIT can be expressed as

$$\text{IIT}_j = \left\{ \underbrace{\left[\sum_{k=1}^l \left(\frac{X_j^k + M_j^k}{\sum_{k=1}^K (X_j^k + M_j^k)} \right) \cdot \left(1 - \frac{|X_j^k - M_j^k|}{X_j^k + M_j^k} \right) \right]}_{\text{H - IIT}} + \underbrace{\left[\sum_{k=l+1}^K \left(\frac{X_j^k + M_j^k}{\sum_{k=1}^K (X_j^k + M_j^k)} \right) \cdot \left(1 - \frac{|X_j^k - M_j^k|}{X_j^k + M_j^k} \right) \right]}_{\text{V - IIT}} \right\} \times 100$$

and further, the magnitude of *low* and *high* vertical IIT can be derived from vertical IIT as

$$\text{V - IIT}_j = \underbrace{\left[\sum_{k=l+1}^p \left(\frac{X_j^k + M_j^k}{\sum_{k=1}^K (X_j^k + M_j^k)} \right) \cdot \left(1 - \frac{|X_j^k - M_j^k|}{X_j^k + M_j^k} \right) \right]}_{\text{l-VIIT}} + \underbrace{\left[\sum_{k=p+1}^K \left(\frac{X_j^k + M_j^k}{\sum_{k=1}^K (X_j^k + M_j^k)} \right) \cdot \left(1 - \frac{|X_{ij}^k - M_{ij}^k|}{X_{ij}^k + M_{ij}^k} \right) \right]}_{\text{h-VIIT}},$$

where out of the set of K commodity groups that are engaged in IIT of industry j , a subset of l commodity groups are categorized under horizontal IIT, and the rest of $(K-l)$ commodity groups as vertical IIT.

It is of much significance to disentangle l -VIIT and h -VIIT from V-IIT because of two main reasons: (1) even after India moving up to a relatively higher income classification group in 2007, it has the perception of being a labour-abundant third-world country. Therefore, it certainly calls for an empirical investigation of whether India's vertical IIT is dominant with exports of *low* or *high* technological products; and (2) having explored what category of traded products dominate India's vertical IIT, it eventually led us to explain its industry-level determinants.

2.1 Trend and pattern of IIT in India's multilateral trade

Over the last three decades, India's total IIT has been found to play an increasingly pertinent role in India's total trade, Fig. 1. In comparison, to the base year of 1990, the growth in total IIT has outpaced the rise in inter-industry trade. The computation of simple annual average growth rate of trade value reveals that IIT grew by 10.28% while inter-industry trade rose by 9.1% annually over the period 1990–2019. Likewise, we also observe an *upward* trend in $MIIT_j$ signifying that trade liberalization brought about intra-industry trade, Fig. 2.

Growth potential that India's IIT witnessed during the decade of 2000s was neither experienced in the earlier decade (1990–1999) nor was it sustained in the decade later (2010–2019). Although, the lower levels of the magnitude of IIT in the initial years of economic reforms (1990s) cannot undermine its steady rise with minor fluctuations. The average magnitude of IIT during the decade of 1990s was 13.20%.

The decade of 2000s witnessed a continuous increase in the magnitude of IIT for all subsequent years. The average magnitude of IIT for this decade jumped to 20.60%. Such an increased activity of IIT can be attributed to the fact of India's increasing efforts to integrate itself with the world economy. For instance, the Trade-GDP ratio value in 2000 stood at around 27% and in 2008 it increased to a high of about 53% (2020: World Development Indicators). These facts are also represented

Fig. 1 Intra-industry trade vis-à-vis inter-industry trade: the case of India

Note: 1990 is considered as the base year

Fig. 2 Magnitude of marginal IIT
Data source: UN Comtrade

in the scores of Trade Globalization Index (*de jure*) prepared by Gygli et al. (2019). The decade started off relatively with a low score of 21.64 but in 2009 it ended with a decadal high of 47.82. In fact, from 2002 onwards India moved on to a tariff-only regime with specific focus being given to exports for employment generation and economic growth. Quite plausibly, the record high magnitude of marginal IIT of 28.16% in 2003 was an outcome of such policy change. In other words, gradual reforms point out that during the second decade of economic reforms, import competition had plausibly led to the shift of resources relatively more *within* as against between the industry. The relatively lower cost of resource reallocation within an industry encouraged Indian firms to attain economies of scale by specializing in narrow product lines. In other words, the liberalization process had thrown the Indian firms into a facet of import competition where it competed by specializing and producing only a subset of product lines within an industry while importing the different technological variations of the same product. It is worth mentioning here that very recently, Aggarwal and Chakraborty (2020) have carried out an in-depth analysis of labour market adjustment brought about by IIT in the Indian context. They found industry groups that have higher magnitude of marginal IIT witness greater adjustments in employment of labour.

On the other hand, we find the next decade of 2010s did not register a continued rise of IIT. Rather, the magnitude of IIT dropped in several years (2011, 2012, 2014 and 2017), while the rise in the remaining years was not large enough.⁷ The average magnitude of IIT for this decade was around 24%. These facts seem more worrying when we observe that in the decade of 2000s the highest magnitude of IIT was 25.49% in 2009 while the decadal peak of 2010s was 26.59% in the year 2019. More importantly, total trade value in 2019 stood at 1.86 times more than in 2009.

The slackness in IIT during the last decade is also represented by the low values of marginal IIT too. During these later years, the contribution of India's trade to its GDP began to fall consistently from 2013 onwards before marginally increasing in

⁷ The simple annual average growth rate of IIT for the decade of 2000–09 was 22.77% while for the decade of 2010–19, it was only 3.08%.

2018 (2020: World Development Indicators). These facts are too supported by the scores of Trade Globalization Index (de jure). The decade of 2010s started with a score of the index at 50.30 and then saw a continued steady decline all the way to a score of 36.78 in 2015 before again substantially increasing in 2017 and 2018. The extent of the drop during 2011–15 can be gauged from the observation that the scores were similar to those attained during the initial years of 2000s. Subramanian and Felman (2019) analyse the slowdown of the Indian economy during the decade of 2010s in details.

Our enquiry now goes one step further in exploring which specific industry groups from India have been contributing relatively high to India's IIT. Consequently, based on the values obtained for IIT_j of the 21 (manufacturing) industry groups as classified by the Indian Trade Clarification (ITC), we divide them into two groups, categorizing for *high* and *low* magnitude of IIT, respectively. We, therefore, consider only those industry groups that classify into the group with high magnitude of IIT across HS- 2, 4 and 6 digit classification levels, see Table 1.⁸

The common industry groups considered are *Chemical* [HS28–38], *Plastics & Rubber* [HS39, 40], *Stone, Cement & Glass* [HS68–70], *Base Metals* [HS72–83], *Machinery & Mechanical Appliances* [HS84, 85] and *Transport Equipment* [HS86–89] over the period 1990–2013.⁹

These industry groups exhibit a *positive* trend for the magnitude of IIT, Fig. 3. Beside the industry groups of Chemical and Machinery & Mechanical Appliances, all other industries yielded relatively high magnitude of IIT despite having a relatively meagre trade share in the country's total trade. One also observes that the magnitude of IIT across the industry groups has been more prevalent in the second decade of economic reforms. However, it is only Plastics & Rubber that witnessed a marginal decline in the magnitude of IIT during 2008–13. Moreover, the coefficient of variation computed across the industry groups over the time periods shows a *decline*.¹⁰ This indicates that compared to the early days of economic reforms the magnitude of IIT across the industry groups has been relatively more similar in recent times.

The share of commodity groups engaged in IIT has shown an *increasing* trend and the average share across the industry groups have been close to 90%, see Fig. 4. It is observed that compared to the magnitude of IIT the changes in the share of commodity groups engaged in IIT have been more rapid during the first decade of economic reforms. One of the plausible reasons for the spurt during the 1990s could be the impact of trade liberalization that began to spread across many commodity groups.

⁸ To control for the problem of 'categorical aggregation', we consider only those industry groups that cater to relatively high magnitude of IIT across the HS- 2, 4 and 6 digit classification levels.

⁹ We drop out miscellaneous manufacturers from the list of common entries. This is because one is not sure about the type of commodities that constitutes this industry group.

¹⁰ The coefficient of variation for IIT_j and marginal IIT across the industry groups during the period 1990–95, 1996–01, 2002–07 and 2008–13 have been 25.49%, 19.92%, 10.51%, 12.31% and 29.88%, 22.85%, 20.58%, 15.50%, respectively.

Table 1 Major manufacturing industries catering to India's IIT: 1990–2013

HS Classification Level	Industries	Avg. IIT _j	Avg. IIT _j of Other Industries
2 digit	Chemicals; Plastic & Rubber; Stone, Cement & Glass; Gems & Jewellery; Base Metals; Machinery & Mechanical App.; Transport Equip.; Arms & Ammunitions; Misc. Manufacturers	65.79	25.73
4 digit	Chemicals; Plastic & Rubber; Stone, Cement & Glass; Gems & Jewellery; Base Metals; Machinery & Mechanical App.; Transport Equip.; Optical, Photographic, Surgical & Clock; Arms & Ammunitions; Misc. Manufacturers	41.15	13.51
6 digit	Chemicals; Plastic & Rubber; Wood, Charcoal & Coke; Stone, Cement & Glass; Base Metals; Machinery & Mechanical App.; Transport Equip.; Optical, Photographic, Surgical & Clock; Transport Equip.; Misc. Manufacturers	30.60	10.44

Data source: UN Comtrade

Note: Average values were computed over time across industries

Fig. 3 Magnitude of IIT and trade share in select manufacturing industries: 1990–2013

Data source: UN Comtrade

Note: I, Chemical; II, Plastics and Rubber; III, Stone, Cement and Glass; IV, Base Metals; V, Machinery & Mechanical Appliances; and VI, Transport Equipment

Fig. 4 Share of commodities engaged in IIT in select manufacturing industries

Data source: UN Comtrade

2.2 Horizontal and Vertical IIT in select industry groups

Across these *six* major industry groups, the magnitude of total IIT has been *dominated* largely by vertical IIT and within vertical IIT it has been driven by *low* vertical IIT, Fig. 5.¹¹ To be precise, we found that across the industry groups, commodity groups that are engaged in IIT around 88% are involved in vertical IIT. Within vertical IIT, around 69% of the commodity groups are categorized in *low* vertical IIT. The annual growth rates for the share of magnitude of horizontal and vertical IIT in total IIT are reported in Table 2. Even though the magnitude of vertical IIT is *high* but its annual growth of its share in total IIT has *deteriorated* in lieu of increasing

¹¹ Bagchi (2018) discusses distinctly the trend of these six industry groups.

Fig. 5 Average share of magnitude of horizontal and vertical IIT in total IIT: 1990–2013
Data source: UN Comtrade

Table 2 Growth rate for the share of the magnitude of horizontal and vertical IIT

Industries	H-IIT	V-IIT	l-VIIT	h-VIIT
I Chemical	2.5 (6.38) ^a	−0.4 (4.78) ^a	−0.31 (1.29)	0.47 (1.54)
II Plastics and rubber	5.1 (9.62) ^a	−0.89 (10.51) ^a	−0.78 (1.03)	1.3 (0.93)
III Stone, cement and glass	5.3 (4.46) ^a	−0.48 (4.07) ^a	−1.66 (2.37) ^b	6.15 (3.75) ^a
IV Base metals	4.88 (16.19) ^a	−0.9 (14.74) ^a	−1.21 (1.44)	2.63 (1.88) ^c
V Machinery and mech. appliances	4.68 (6.79) ^a	−0.27 (5.65) ^a	−2.6 (3.61) ^a	6.32 (7.45) ^a
VI Transport equipment	1.09 (0.81)	−0.07 (0.72)	−1.68 (1.85) ^c	3.32 (2.25) ^b

Data source: UN Comtrade

Note: Two-tailed *t* statistics are reported in parentheses. ^{a,b,c}Indicate statistical significance at 1%, 5% and 10% level, respectively

share of horizontal IIT over the period 1990–2013 excepting the industry group of Transport Equipment.

Within vertical IIT, the magnitude of *high* vertical IIT has improved annually across the industry groups excepting Chemical and Plastics & Rubber. While in case of *low* vertical IIT, the decline in share has been observed only for Stone, Cement & Glass, Machinery & Mechanical Appliances and Transport Equipment.

We again consider 6-year intervals and compute the (average) share of magnitude of horizontal and vertical IIT in total IIT of these industry groups, see Table 12 in the “Appendix”. Apart from the industry group of Transport Equipment, we find that in all other groups, the share of magnitude of horizontal IIT has *improved* periodically while that of vertical IIT have *fallen* over the period 1990–2013. In case of Transport Equipment, during 1990–2007 the pattern of the magnitude of horizontal IIT and vertical IIT remained like the other five industry groups, but the share of horizontal IIT *declined* and that of vertical IIT *fell* during the years 2008–13. On the other hand, the pattern of *low* and *high* vertical IIT remained the same across the industry groups. The share of *low* (*high*) vertical IIT has *decreased* (*increased*) during 1990–2001. However, in the first half of the second decade of economic reforms

(2002–07), the share of *low* vertical IIT had improved marginally in lieu of deteriorating share of *high* vertical IIT before again reversing their respective patterns during 2008–13.

2.2.1 Vertical IIT and Revealed Comparative Advantage

The dominance of (*low*) vertical IIT in India is an exemplification of the country's relatively abundant supplies of labour (Bhattacharyya 1991). Even before this paper, following Falvey (1981) and Falvey and Kierzkowski (1987), one may argue that developing economies (such as India) with abundant supplies of labour would produce more of those goods that uses intensively the abundant factor of production and is expected have comparative advantage on them. To examine the relationship between vertical IIT and *relative factor abundance*, we compute the *revealed comparative advantage* (RCA) for each of the commodity groups engaged in both *low* and *high* vertical IIT across the six manufacturing industry groups, see Rodas-Martini (1998) for a similar exercise.¹² Even if most of the commodity groups within an industry have RCA it does *not* necessarily indicate that factor intensities of these commodity groups are widely different and consequently, the theory of relative factor abundance explains India's vertical IIT (Batra 2016).

Columns A and B of Table 3 depict the average number of commodity groups engaged in (*low* and *high*) vertical IIT and those among them having RCA over the period 1990–2013, respectively. The average share of commodity groups engaged in vertical IIT with RCA is reported in column C. We also perform the *mean test* to examine whether there is any statistically significant difference between the number of commodity groups engaged in vertical IIT and that with RCA.

Apart from the industry group of Chemical, all other industry groups have a relatively *low* share of commodity groups engaged in vertical IIT with RCA. Further, the mean test results indicate that the mean number of commodity groups engaged in *low* and *high* vertical IIT and that with RCA are statistically different from each other. While there may be a minor difference in the share of commodity groups engaged in vertical IIT with RCA across the industries, but the annual growth rate for the same varies widely (Table 4).

The share of commodity groups engaged in *low* vertical IIT with RCA have increased annually for all industry groups except Base Metals and Transport Equipment, whereas for *high* vertical IIT, the share has improved only in Chemicals, Plastics & Rubber and Machinery & Mechanical Appliances. The industry group of Chemical, which had a relatively high share of commodity group engaged in both forms of vertical IIT with RCA had a relatively smaller annual growth rate than the other industries. On the other hand, Machinery and Mechanical Appliances which had the lowest share of commodity groups in vertical IIT with RCA had the largest growth rate.

¹² This conforms the so-called *indirect* test of the Heckscher-Ohlin model. We consider the Balassa (1965) index to find out whether the *k*th product engaged in vertical IIT have RCA or not.

Table 3 Vertical IIT and RCA across industry groups

Industries	Form of IIT	Avg. no. comm. groups [A]	Revealed comparative advantage		
			Avg [B]	Avg. share (in %) [C]	Mean test <i>t</i>
I	<i>l</i> -VIIT	305.87	99.16	32.36	31.15 ^a
	<i>h</i> -VIIT	236.33	85.83	36.07	23.05 ^a
II	<i>l</i> -VIIT	107.67	20.62	18.78	19.66 ^a
	<i>h</i> -VIIT	47.62	7.58	15.99	9.29 ^a
III	<i>l</i> -VIIT	81.70	17.41	21.38	22.35 ^a
	<i>h</i> -VIIT	29.45	5.79	20.66	7.99 ^a
IV	<i>l</i> -VIIT	281.62	77.16	26.98	21.86 ^a
	<i>h</i> -VIIT	138.41	37.75	27.74	8.59 ^a
V	<i>l</i> -VIIT	475.5	69.41	14.94	21.8 ^a
	<i>h</i> -VIIT	170.29	28.91	15.61	11.3 ^a
VI	<i>l</i> -VIIT	59.17	14.70	26.49	14.09 ^a
	<i>h</i> -VIIT	24.58	4.95	25.48	5.97 ^a

Data source: UN Comtrade

Note: ^aStatistical significance at 1% level

I, Chemical; II, Plastics and rubber; III, Stone, cement and glass; IV, Base metals; V, Machinery and mechanical appliances; VI, Transport equipment

Table 4 Annual growth rate for share of RCA

Industries	<i>l</i> -VIIT	<i>h</i> -VIIT	Industries	<i>l</i> -VIIT	<i>h</i> -VIIT
I Chemical	1.22 (4.65) ^a	1.75 (7.55) ^a	IV Base metals	0.13 (0.30)	− 1.11 (1.58)
II Plastics and rubber	1.86 (2.25) ^b	2.88 (3.23) ^a	V Machinery and mechanical app	2.71 (7.72) ^a	4.20 (5.88) ^a
III Stone, cement and glass	1.26 (2.32) ^b	0.39 (0.31)	VI Transport equip	0.72 (0.74)	− 3.90 (2.24) ^b

Data Source: UN Comtrade

Note: Two-tailed *t* statistics are there in the parentheses

^{a, b}Statistical significance at 1% and 5% level, respectively

Altogether, our results indicate that the pattern of India's vertical IIT does *not* offer much support to the Heckscher–Ohlin model as the share of commodity groups engaged in vertical IIT with RCA in the major industry groups are found to be less and does not uniformly improve across all industry groups. In fact, our findings gain support from the results of Bagchi and Bhattacharyya (2019) that India majorly engages more in both *high*, as well as, *low* vertical IIT with the same set of trading partners that belong to high-income group countries. It appears that explanations from the *new trade theories* are required to explain the vertical IIT.

We now delve to ascertain as to what industry-level determinants essentially determine its magnitude. However, before proceeding to the empirical analysis, we briefly discuss the theoretical premise behind the industry-level determinants of IIT.

3 Industry-level determinants of IIT: the theoretical premise

Traditionally, the extent of product differentiation, presence of internal scale economies and market structure are considered as the important industry-level characteristics that determine the magnitude of IIT. However, extant empirical pieces of evidence are inconclusive in terms of both the coefficient sign and statistical significance. Nevertheless, before delving into the econometric analysis, we briefly highlight the theoretical underpinnings related to these industry-level determinants of *total, vertical and horizontal* IIT.

Under the alternative representations of production differentiation, Krugman (1979) and Lancaster (1980) demonstrated that within a monopolistically competitive framework the magnitude of IIT is *positively* related to the consumers' love for the diversity of preferences. This aspect of product differentiation is captured in this paper through the alternative proxies of (1) *ratio of marketing expenses to total expenses* (MKT); and (2) *advertising expenses as a percentage of net sales* (ADVT). Caves (1981) argued that the effect of these proxies does *not* always follow the conventional belief. The extent of product differentiation which depends greatly on advertising is prejudiced against trade since advertising is perceived to be specific to a country's culture and is rarely transnational. Indeed, advertising complements the styling of a product with regard to specific local tastes. In other words, the impact of these proxies on the magnitude of IIT is *not* linearly dependent. Hence, we hypothesize a nonlinear relationship between these two proxies of product differentiation and the magnitude of total IIT and its broad forms; see Veeramani (2007) for a similar argument.

On the other hand, Shaked and Sutton (1984) showed that that improvement in product quality by a firm is associated with its R&D expenditure. We include the ratio of R&D expenditure to total expenditure (RDE) as a degree of product innovation which by and large is also conceptualized as an alternative proxy of product differentiation. We hypothesize a linear *positive* relation between RDE and magnitude of IIT. See Hu and Ma (1999), Sharma (2004) for a similar exercise.

It was predominantly Helpman and Krugman (1985) drawing upon Krugman (1979) and Lancaster (1980) that framed empirically testable hypothesis based on industry characteristics about industry-level determinants of horizontal IIT. Within a monopolistically competitive framework, the scope for (horizontal) product differentiation is related to the *minimum efficient scale* (MES) of production and dependent upon the number of firms in an industry.¹³ A *smaller* MES would attract a relatively large number of firms associated with more unique varieties and thus a higher

¹³ *Minimum efficient scale* of production is commonly considered as a proxy for *scale economies*.

magnitude of horizontal IIT.¹⁴ Eaton and Kierzkowski (1984) however, argued that horizontal product differentiation is related to a large MES leading to a concentrated industry. Empirically, the MES is measured by the *output share of the median sized firm in the i th industry* (Beneito et al. 2015). While market structure is measured alternatively the *Herfindahl–Hirschman Index* (HHI) and the *four-firm concentration ratio* (CR₄); see Sharma (2004), Faustino and Leitão (2007).

On the other hand, theoretical models of vertical IIT date back to Falvey (1981). Both industry- and country-level factors are considered in explaining vertical IIT, but industry-level factor is not precisely defined as that of country-level factor; Greenaway et al. (p. 1507, 1995). Falvey (1981) relied on the theory of relative factor abundance as the country characteristic while considered the role of market with a large number of firms as the industry characteristic *but* assigns no role of scale economies to model vertical IIT. In other words, firms of a relatively capital abundant country would export higher quality goods, while firms of a labour-abundant country would export lower quality goods as they would have comparative advantage in it. The consideration of a large number of firms indicates that firms compete by producing a large number of unique varieties of vertically differentiated goods; Sharma (p. 1725, 2004). In this study, we consider only the industry attribute of vertical IIT. On the other hand, Shaked and Sutton (1984) emphasized a much more explicit role of market structure by assuming an oligopolistic framework. They demonstrated that vertical product differentiation can rise in industries characterized with relatively large MES and as a result giving rise to a concentrated market structure.

In a nutshell, with respect to the *industry* attributes that give rise to IIT, the theoretical literature presents the following features of *vertical* and *horizontal* IIT:

1. A market with a large number of firms but no role of scale economies is conducive for vertical IIT Falvey (1981);
2. A *concentrated* market structure accompanied with a *larger* MES is conducive for horizontal IIT Eaton and Kierzkowski (1984);
3. A *concentrated* market related with a *larger* MES is favourable for vertical IIT Shaked and Sutton (1984);
4. The *competitive* market structure associated with a *smaller* MES is conducive for horizontal IIT Helpman and Krugman (1985).

Our empirical exercise is primarily set to understand which of these channels lend an explanation to India's vertical and horizontal IIT.

We further argue that the determinants of magnitude of IIT and its two broad forms could be better understood by incorporating the *interaction* between them (i.e., 'market structure' and 'minimum efficient scale'; 'product differentiation' and 'market structure'; and 'product differentiation' and 'minimum efficient scale').

The coefficient of the interaction term associated with 'market structure and MES' signifies how changes in MES impact the relationship between market

¹⁴ Magnitude of horizontal IIT tends to be high when market structure inches towards a monopolistic competition; see Pittiglio (2012) for similar arguments.

structure and IIT. A *positive* coefficient value indicates that industries with concentrated market structure tend to have a higher magnitude of IIT, particularly when these industries experience an increase in MES over time. Similarly, to understand how changes in market structure impact the relationship between product differentiation and IIT, we include an interaction term of both these explanatory variables. A *positive* coefficient value reveals that the impact of product differentiation activities tends to be stronger on the magnitude of IIT in industries that inch towards concentrated market structures. Lastly, the interaction term of 'MES and product differentiation' depicts whether changes in MES have any impact on the relationship between product differentiation and magnitude of IIT. A *positive* coefficient points out that increased product differentiation activities are likely to positively impact the magnitude of IIT in industries that witness increases in MES over time.

4 Construction of data set and estimation methods

We consider trade data at the HS- 6 digit level from UN Comtrade database to compute the magnitude of total, vertical and horizontal IIT as the *dependent* variable. However, the *explanatory* variables corresponding to these six industry groups are constructed using the *firm-level* data from the ProwessIQ database of Centre for Monitoring Indian Economy (CMIE). One of the inescapable issues in the construction of such a sample is the 'process of concordance' between the (multilateral) trade data and firm-level data. Trade data obtained from UN Comtrade follows the HS classification while firm-level data from ProwessIQ is categorized according to National Industrial Classification [NIC] (2008). For example, the commodity group at HS 6-digit level, HS- 280620 (Hydrogen chloride and Chlorosulphuric acid) is needed to be matched with a corresponding similar industry defined in NIC 4-digit (2008) classification. In this case, it is found that the product can be broadly matched to be in NIC- 2011 (the industry that specializes in the manufacture of basic chemicals). A similar exercise is carried out, for all the commodity groups in each of the selected six major industry groups. This process of concordance, therefore, helps us to classify different commodity groups in the six industry groups to their corresponding similar industries defined at the NIC 4-digit level. In other words, this very exercise eventually ensures that the dependent and the explanatory variables are of the similar/same industry definition. The detailed process of harmonizing these two different data sets is done as follows.

Drawing upon the product concordance table available at the World Integrated Trade Solutions (WITS) database (The World Bank), we at first, obtain the match of each HS- 6 digit commodity groups in these *six* industries to their corresponding available International Standard Industrial Classification (ISIC) Revision 3 at the 4-digit level. As the nomenclature of the industries defined in ISIC and NIC are similar, we use the product concordance between HS and ISIC database from WITS database as a guide towards preparing the concordance table between HS-6 digit

and NIC-4 digit level (2008).¹⁵ The harmonization process categorizes all the commodity groups at HS-6 digit level across the said industry groups into 76 industries classified under the NIC-4 digit level over the period 1990–2013. However, given the *unavailability* of data on five industries in the CMIE ProwessIQ database, we are eventually left with 71 industries for subsequent empirical analysis in this paper. This is so because, after having matched and categorized the commodity group data at HS-6 digit level with NIC-4 digit level data, when we looked into the ProwessIQ database for firm-level data, on many occasions, there were *missing data* of variables such as net sales, advertisement expenses, R&D expenditures and the likes.

We observe a considerable variation in the number of commodity groups at the HS-6 digit classification level that are categorized (and matched) with a similar industry at the NIC-4 digit level. Therefore, we now compute the magnitude of total, vertical and horizontal IIT for the 71 industries defined at the NIC- 4 digit level using the Grubel and Lloyd (1971) index. It is worth mentioning here that because of the harmonization process of the two data sets, the magnitude of IIT in these 71 industries may get *biased*. Hence, to take care of this heterogeneity we include a measure of *industry aggregation* [IA] (i.e., number of commodity groups at the HS- 6 digit level engaged in IIT corresponding to each similar industry at the NIC- 4 digit level) as a *control variable*. Subsequently, we use the Greenaway et al. (1994) criterion at 15% to obtain the magnitude of vertical and horizontal IIT for these 71 industries. Eventually, we could construct an *unbalanced panel* of firm-level data encompassing 71 industries.

4.1 Estimation methods

The dependent variable in our case lies between 0 and 1.¹⁶ Given that observations are clustered at zero values, the *logit* transformed model will lead to considerable loss of observation and therefore becomes inappropriate. We consider two alternative estimation techniques (1) the (random effects) Tobit model; and (2) Exponential Regression of Fractional Response model.¹⁷ In that sense, this paper applies *ERFR* model for the first time in the empirical literature of IIT. However, before exploring the *ERFR* model, we begin with the *panel unit root test*.

¹⁵ For instance, in the industry of Transport Equipment, the match for HS- 880,220 (Airplanes and other aircraft, of an unladen weight not exceeding 2000 kg) in ISIC is found in the industry code of 3530 (Manufacture of Aircraft and Spacecraft). Subsequently, ISIC-3530 is matched to NIC- 3030 (Manufacture of Air and Spacecraft and Related Machinery) as the nomenclature and product categories of these industries are largely the same. Because of this exercise, trade data of HS- 880220 can be now correspondingly matched to the firm level data available with NIC-3030.

¹⁶ In case of *total* IIT, around 6.39% of observations have *zero* values. While vertical and horizontal IIT have about 7.72% and 41.49% of observations, respectively as zeros. There is no observation with the value of one.

¹⁷ The consideration of zero-truncated Poisson or Binomial model was also discarded as it would have also led to loss of observations and its applicability being restricted only when the dependent variable is *count data*.

As the time dimension in our sample [i.e., $T=24$ years] is relatively large there arises the need for controlling of nonstationarity in the series; Baltagi (2005) and Pesaran (2015). Given the *unbalanced* nature of our sample, we choose the combining *p value* test or *Fisher-type* test by Maddala and Wu (1999) and Choi (2001) to examine the stationarity on each panel observation. All the variables were found to be *stationary* (Table 5).

4.1.1 The exponential regression of fractional response model

The dependent variable in our case is denoted as y_{it} ($0 \leq y_{it} < 1$) for each cross-section unit i and time period t .¹⁸ In such a case, Papke and Wooldridge (2008) define the standard fractional regression model defined in a (one-way) fixed effects (balanced) panel data setting as $E(y_{it}|\alpha_i, x_{it}) = F(x_{it}\beta + \alpha_i)$, where $F(\cdot)$ is a function that bounds the dependent variable within the unit interval, x_{it} is a $1 \times k$ vector of explanatory variables, β is the vector of parameters and α_i denote the time-invariant unobserved heterogeneity.¹⁹ For consistent estimation of parameters, the econometric models for both balanced and unbalanced panel data structures require the normality assumption of individual effects with specific functional forms for their mean and variance to yield *consistent* estimates.²⁰

Recently, Ramalho et al. (2016) showed that one can obtain the parameter estimates when the dependent variable is defined on $[0, 1)$ and the regression model is defined as $y_{it} = F(x_{it}\beta + \alpha_i + v_{it})$, where v_{it} denotes the time-varying unobserved heterogeneity and $F(\cdot)$ is assumed to have a *logit* specification; i.e., $F(\cdot) = \frac{e^{(\cdot)}}{1+e^{(\cdot)}}$. Having the *logit* specification allows us to convert the regression model into a form of *exponential regression*. It is essential to convert into exponential regression so as to handle observations at the endpoints of the unit interval.

With this assumption the regression model can be expressed as $y_{it} = G\left[e^{(x_{it}\beta + \alpha_i + v_{it})}\right]$, where $G(c) = \frac{c}{1+c}$, where $c = e^{(x_{it}\beta + \alpha_i + v_{it})}$. The above regression model can be transformed into an exponential model of the form $Z(y_{it}) = e^{(x_{it}\beta + \alpha_i + v_{it})}$, where $Z(y_{it}) = \frac{y_{it}}{1-y_{it}}$ and y_{it} is restricted to the interval $[0, 1)$.²¹ Apart from retaining fitted values *within the unit interval* and handling *zero* observations of the dependent variable, this estimation method does *not* require any distributional assumption on the unobservable heterogeneity and is applicable to both balanced as well as unbalanced panel data structures. Besides these, the estimation method *only* requires the

¹⁸ For econometric simplification, we rescale the magnitude of IIT to lie between 0 and 1.

¹⁹ Wooldridge (2018) extends the fractional regression model to an unbalanced panel data setting.

²⁰ Loudermilk (2007) and Elsas and Florysiak (2015) argued for the use of *doubly censored Tobit models* for both the *balanced* and *unbalanced* panels. But such models assume a normal distribution of the individual effects and additionally require the assumption of a normality and homoscedastic distribution of the error term. This method is applicable when the fractional variable has values at both zero and one. Nevertheless, these techniques allow for the inclusion of one endogenous variable in the empirical model but require *strict exogeneity* assumption of the remaining regressors.

²¹ In case of linear-fractional model, the model is defined as $L(y_{it}) = x_{it}\theta + \alpha_i + v_{it}$ where $L(y_{it}) = \ln[Z(y_{it})]$. However, it loses the ability to handle zero values of the dependent variable.

Table 5 Result of Fisher-type panel unit root test

Variables	p_m statistic	Interactions	p_m statistic
Y_{IIT}	6.93 ^a	$MES \times CR_4$	29.73 ^a
Y_{VIIT}	14.43 ^a	$MES \times HHI$	30.38 ^a
Y_{HIIT}	10.83 ^a	$CR_4 \times ADVT$	12.09 ^a
MKT	7.51 ^a	$CR_4 \times MKT$	4.48 ^a
MKT^2	5.31 ^a	$CR_4 \times RDE$	13.73 ^a
$ADV T$	14.08 ^a	$HHI \times ADV T$	10.44 ^a
$ADV T^2$	28.92 ^a	$HHI \times MKT$	6.16 ^a
RDE	12.50 ^a	$HHI \times RDE$	14.94 ^a
HHI	15.25 ^a	$ADV T \times MES$	15.51 ^a
CR_4	9.78 ^a	$MKT \times MES$	14.01 ^a
MES	28.89 ^a	$RDE \times MES$	16.41 ^a
IA_{IIT}	9.49 ^a		
IA_{V-IIT}	5.47 ^a		
IA_{H-IIT}	9.49 ^a		

Note: The test was performed using the *augmented* Dickey–Fuller equation. ^a The statistical significance at 1% level. Results of the other test statistics are *qualitatively the same*

assumption of *weak exogeneity* of the regressors and the standard errors obtained are *cluster-robust* in nature. For more details, see Ramalho et al. (2016).

4.2 The empirical model

Our *basic* regression model is of the following form:

$$y_{it} = \alpha + \beta_1 (\text{Prod Diff})_{it} + \beta_2 (\text{Prod Diff})_{it}^2 + \beta_3 (\text{Mkt Str})_{it} + \beta_4 (\text{MES})_{it} + \beta_5 (\text{Ind Agg})_{it} \\ + \beta_6 (\text{Mkt Str} \times \text{MES})_{it} + \beta_7 (\text{Prod Diff} \times \text{Mkt Str})_{it} + \beta_8 (\text{Prod Diff} \times \text{MES})_{it} + \varepsilon_{it},$$

where y_{it} is the magnitude of either *total*, *vertical* or *horizontal* IIT in the i th industry at time period t ; α is the intercept term, β 's are the regression coefficients and ε_{it} captures the random error component in the model. Table 13 reports the construction of the variables.

5 Regression results

This section is divided into two parts. Section 5.1 discusses the estimated results of the (random effects) Tobit model and Sect. 5.2 presents the results from the ERFR model estimation. In doing so, we attempt to highlight the similarities, as well as, the inconsistencies in the empirical findings obtained from the two estimation methods. In this context, please recall our footnote 6.

5.1 The Tobit model estimation

The regression results specifying the industry-level determinants of the magnitude of *total*, *vertical* and *horizontal* IIT are reported in Tables 6, 7 and 8, respectively.

The estimated coefficient of the marketing to total expenditure ratio (*MKT*) as the measure of *product differentiation* is found to be *positively* significant at 1% significance level and the coefficient of its quadratic term has the expected *negative* sign at 5% significance level. Such a non-linear (inverted-*U*) relationship between *MKT* and the magnitude of total IIT implies that initially *MKT* positively influences the magnitude of total IIT, but after a certain threshold level of *MKT* is reached, increasing the *MKT* further eventually lead to a fall in total IIT. In other words, this indicates that over a range, expenses in marketing activities *positively* influence the magnitude of total IIT. However, beyond that, there is a negative relationship. This is because marketing activities are rarely transnational; recall our discussion from Sect. 3.

The estimated coefficient of *MES* is *negatively* significant at 1% level across *all* model specifications. Note that, this finding is consistent with the negative coefficient of *HHI* which has been relatively weakly significant at 10% level in Model 1 but strengthened to 5% significance level in the alternative specifications of Model 2 and 3. These findings are consistent with the argument that a relatively *small* *MES* permits the entry of a large number of firms within an industry and therefore, eventually opens up more opportunities for IIT. In other words, it is the monopolistically competitive market structure that encourages growth in India's IIT; see Greenaway et al. (1995), Černoša (2009) and Andersen (2010) for a similar result.

The estimated coefficient of the *interaction term* associated with industry concentration and *MES* yields a *positive* sign at 5% level in Model 1 and further strengthened to 1% significance level in Model 2 and 3. This suggests that industries with a concentrated market structure tend to have a higher magnitude of IIT, particularly when these industries experience an increase in *MES* over time. Such a result, however, is inconsistent with the standalone independent impact of *MES* and *HHI*, respectively.

The estimated coefficient of the interaction term between product differentiation and market structure also has a *positive* sign at 10% and 5% level in Model 1 and 3, respectively. Industries that are prone to concentrated market structures are likely to improve their magnitude of IIT with additional expenses in product differentiation in the form of R&D and Marketing activities. Our result plausibly indicates that dominant firms in concentrated industries are able to sustain import competition by spending on product differentiation activities that create a niche in their products. Such an act eventually improves the magnitude of IIT.

The *positive* impact of industry aggregation has been relatively weak at 10% significance level only in Model 2 and 3. The estimated constant term is consistently statistically significant at 1% level across the model specifications.

Let us now turn to the estimated results for industry-level determinants of India's vertical IIT reported in Table 7. We find that none of the alternative measures of product differentiation has any significant impact in determining the magnitude of

Table 6 Determinants of magnitude of total IIT

Variables	Model 1	Model 2	Model 3
MKT	4.70 (2.78) ^a		
MKT ²	−0.28 (2.29) ^b		
ADVT		−0.42 (0.17)	
ADVT ²		0.12 (0.43)	
RDE			−0.13 (0.18)
MES	−0.28 (5.64) ^a	−0.27 (5.47) ^a	−0.28 (5.69) ^a
HHI	−7.15 (1.70) ^c	−10.16 (2.46) ^b	−8.49 (2.04) ^b
HHI × MES	0.37 (2.43) ^b	0.39 (2.81) ^a	0.39 (2.86) ^a
MKT × HHI	55.65 (1.73) ^c		
ADVT × HHI		−18.44 (0.70)	
RDE × HHI			147.74 (1.98) ^b
MKT × MES	−0.48 (1.00)		
ADVT × MES		0.18 (0.42)	
RDE × MES			0.38 (0.56)
IA _{IIT}	0.02 (0.76)	0.60 (1.88) ^c	0.05 (1.67) ^c
Constant	32.34 (12.22) ^a	34.64 (13.72) ^a	34.53 (13.95) ^a
Log-Likelihood	−6399.70	−6405.05	−6403.44
Wald Statistic	$\chi^2_{(8)} = 78.93^a$	$\chi^2_{(8)} = 68.46^a$	$\chi^2_{(7)} = 72.13^a$

No. of obs. = 1581. No. of left-censored obs. at zero = 101

Two-tailed *z* statistics are there in parentheses

^{a,b,c}Statistical significance at 1%, 5% and 10% level, respectively

vertical IIT; see Sharma (2004) for a similar result.²² However, as in the case of total IIT, when MKT and RDE are interacted separately with HHI, the estimated coefficients turn out to be *positively* significant at 10% level. This result follows from the earlier obtained result of total IIT. It directs us to identify that expenses in product differentiation activities by dominant firms in concentrated industries are on vertically differentiated products.

As earlier, both MES and HHI have *negative* standalone impact on the magnitude of vertical IIT; while the interaction between HHI and MES has a *positive* impact. The standalone impact of MES and HHI signifies that a *smaller* MES permits greater entry of firms in industry promoting competitive market structures. Such market structures, in turn, influence vertical IIT. While the result of the interaction term suggests industries with the concentrated market structure are conducive for vertical IIT. These results obtained are, therefore, inconclusive in nature.

The estimated coefficient of industrial aggregation is found to be *positively* significant only in Model 2 at 10% significance level; the constant term remained positively significant at 1% level in all the three alternative model specifications.

²² We also estimated the model by including the *linear* terms of MKT and ADVT. Even then product differentiation did *not* turn out to be statistically significant. In fact, this result reconfirms our justification to attempt separate estimation to determine the magnitude of vertical and horizontal IIT.

Table 7 Determinants of the magnitude of vertical IIT

Variables	Model 1	Model 2	Model 3
MKT	1.87 (1.19)		
MKT ²	−0.11 (0.98)		
ADVT		−0.56 (0.24)	
ADVT ²		0.11 (0.44)	
RDE			−0.15 (0.18)
MES	−0.25 (5.27) ^a	−0.24 (5.03) ^a	−0.25 (5.26) ^a
HHI	−6.79 (1.69) ^c	−9.14 (2.31) ^b	−7.56 (1.90) ^b
HHI × MES	0.52 (3.54) ^a	0.49 (3.70) ^a	0.48 (3.71) ^a
MKT × HHI	51.93 (1.69) ^c		
ADVT × HHI		−20.29 (0.81)	
RDE × HHI			132.33 (1.87) ^c
MKT × MES	−0.18 (0.39)		
ADVT × MES		0.28 (0.67)	
RDE × MES			0.21 (0.32)
IA _{V-IIT}	0.04 (1.14)	0.59 (1.67) ^c	0.05 (1.55)
Constant	29.90 (11.79) ^a	30.97 (12.67) ^a	30.75 (12.79) ^a
Log-Likelihood	−6260.18	−6262.10	−6260.70
Wald Statistic	$\chi^2_{(8)} = 57.29^a$	$\chi^2_{(8)} = 53.41^a$	$\chi^2_{(7)} = 56.48^a$

No. of Obs. = 1581. No. of left-censored obs. at zero = 122

Two-tailed *z* statistics are there in parentheses^{a,b,c}Statistical significance at 1%, 5% and 10% level, respectively

With respect to industry-level determinants of India's horizontal IIT, the major observations are as follows, see Table 8.²³ Yet again, product differentiation has *no* impact in determining the magnitude of horizontal IIT, see Greenaway et al. (1995) for a similar result. Perhaps, the extent of product differentiation has been too low to make any impact on the magnitude of horizontal IIT.

MES has a *negative* impact on horizontal IIT; the statistical significance drops to 5% level in Model 1, otherwise remains significant at the 1% level. Industry concentration *negatively* affects the magnitude of horizontal IIT in Model 2 and 3 at 10% significance level. The findings of MES and industry concentration are consistent with each other. In that sense, our findings corroborate the argument that a *smaller* MES would attract a relatively large number of firms associated with more unique varieties and thus a higher magnitude of horizontal IIT. Further, the estimated coefficient associated with the interaction term between market structure and scale economies is *negative* and statistically significant at 10% level only in Model 1. Such a result is consistent to the standalone independent impact of HHI and MES.

Unlike the earlier cases, industrial aggregation is observed to have a *positive* coefficient value at 1% level of significance across all the regression model

²³ The statistically best fit empirical models of horizontal IIT are found to be with the alternate proxy of market structure (i.e., the four-firm concentration ratio).

Table 8 Determinants of the magnitude of horizontal IIT

Variables	Model 1	Model 2	Model 3
MKT	1.02 (1.20)		
MKT ²	−0.07 (1.07)		
ADVT		−0.29 (0.22)	
ADVT ²		0.07 (0.47)	
RDE			0.18 (0.43)
MES	−0.06 (2.07) ^b	−0.08 (2.87) ^a	−0.09 (3.15) ^a
HHI	−1.29 (0.53)		
CR ₄		−4.11 (1.72) ^c	−3.90 (1.96) ^c
HHI × MES	−0.18 (1.72) ^c		
CR ₄ × MES		−0.26 (0.69)	−0.30 (0.80)
HHI × MKT	16.04 (0.82)		
CR ₄ × ADVT		−2.31 (0.25)	
CR ₄ × RDE			−15.60 (0.78)
MKT × MES	−0.30 (0.89)		
ADVT × MES		0.77 (1.24)	
RDE × MES			1.63 (1.19)
IA _{H-IIT}	0.44 (7.44) ^a	0.45 (7.76) ^a	0.45 (7.83) ^a
Constant	−1.82 (1.67) ^c	1.37 (0.73)	1.22 (0.69)
Log-Likelihood	−3730.45	−3730.31	−3729.98
Wald Statistic	$\chi^2_{(8)} = 96.18^a$	$\chi^2_{(8)} = 93.35^a$	$\chi^2_{(7)} = 92.52^a$

No. of Obs. = 1581. No. of left-censored obs. at zero = 656

Two-tailed *z* statistics are there in parentheses^{a,b,c}Statistical significance at 1%, 5% and 10% level, respectively

specifications. The constant term has been statistically significant only in Model 1 at 10% level.

In a nutshell, our findings from the Tobit model estimation are as follows. *Product differentiation* has a *non-linear* relationship *only* with the magnitude of total IIT. However, the estimated models also revealed that investment in marketing and R&D activities promotes magnitude of not only total IIT but also vertical IIT too particularly in industries that are more prone to have concentrated market structures. While in case of the horizontal IIT, product differentiation has *no* impact whatsoever. In terms of the respective impacts of *scale economies* and *market structure*, the results obtained for total and vertical IIT are inconclusive in nature. However, for horizontal IIT, we find that its magnitude gets boosted in industries characterized by competitive market structures.

In what follows, we now present the econometrically robust findings from the ERFR model. As mentioned earlier, this model specification apart from handling the fractional nature and the zero observations of the dependent variable is also able to accommodate endogenous covariates. We, therefore, argue that the subsequent

findings of the *ERFR* model would better present the industry-level determinants of India's IIT.

5.2 Exponential regression of fractional responses model estimation

The obtained parameter estimates in the *ERFR* model show a handful of dissimilarities from the results of the Tobit model.²⁴ However, the results obtained across the model specifications in the *ERFR* model appear to be relatively more consistent than the Tobit model. It is worth mentioning here that to substantiate the findings from the *ERFR* model, the standard errors were bootstrapped at 4000, 10,000 and 20,000 replications. The results of the model remained qualitatively the same across all these replications.

In contrast to the Tobit model, we observe *no* non-linear relationship between product differentiation and total IIT. It is only the *RDE* that is found to be *positively* significant at 5% level (Table 9). For similar results, see Hu and Ma (1999) and Sharma (2004).

The estimated coefficient of HHI yields a *positive* sign at 1% significance level across the model specifications. The result shows that magnitude of total IIT is enhanced in industries with concentrated market structures. However, the estimated coefficient of the interaction term of $HHI \times MES$ is found to be *negatively* significant at 10% level in Model 1 and 2. The result of the interaction term suggests the magnitude of total IIT is promoted in industries with competitive market structures. Such a finding does *not* lend support to the results of the standalone impact of HHI.

When we turn to vertical IIT, it is seen that *RDE* has lost its statistical significance (Table 10). One of the plausible reasons for such a result in our case is that India's IIT is dominant with *low* vertical IIT over the entire study period. It seems that there is not much R&D led innovation and/or technology-driven product differentiation that have been boosting India's vertical IIT with the rest of the world over these years. If there is no worth mentioning product differentiation then it does not call for any significant advertising efforts and/or marketing expenses.

The sign of the parameter estimate of *MES* is *positive* and is significant only in Model 1 at 10% level. HHI has a *positive* impact on vertical IIT; the statistical significance is at 5% level in Model 1 and strengthens to 1% level in Model 2 and 3. These results indicate that India's magnitude of vertical IIT is promoted in industries characterized by a *concentrated* market structure. In this regard, following Caves (1981), we argue that large and dominant firms operating in a liberal trade regime are relatively better prepared to absorb the process of resource reallocation to nurture their efficiencies and competitiveness. This ability ensures that the large Indian manufacturing firms compete against import competition by specializing in

²⁴ Even after considering alternative proxies, the *interaction term* between 'Product Differentiation and Market Structure' and 'Product Differentiation and MES' did *not* turn out to be statistically significant in any of the model specifications of total, vertical and horizontal IIT. Hence, we drop these interaction terms from the specification of the empirical model.

Table 9 Determinants of the magnitude of Total IIT

Variables	Model 1	Model 2	Model 3
MKT	− 2.6726 (0.24)		
MKT ²	1.9786 (0.14)		
ADVT		0.7921 (0.05)	
ADVT ²		− 3.1408 (0.13)	
RDE			21.0629 (2.15) ^b
MES	0.0305 (0.46)	0.0402 (0.57)	0.0653 (0.77)
HHI	10.2674 (3.02) ^a	11.5710 (3.45) ^a	10.6895 (3.57) ^a
HHI × MES	− 0.1463 (1.70) ^c	− 0.1373 (1.66) ^c	− 0.1034 (1.16)
IA _{IIT}	− 0.0199 (0.59)	− 0.0129 (0.48)	− 0.0365 (1.14)

Two-tailed *t* statistics are there in parentheses

The results reported are bootstrapped up to 4000 replications

^{a,b,c}Statistical significance at 1%, 5% and 10% level, respectively

low vertically differentiated goods. As a result, the varieties of products to be limited whereas the magnitude to be high. This finding seems to be consistent with the ‘small’ number model, i.e., concentrated market structures with large MES; Shaked and Sutton (1984). Lastly, Industrial aggregation has a *negative* impact at 10% level only in Model 3.

In determining the magnitude of horizontal IIT, the estimated coefficient of MES has a *positive* sign with statistical significance at 5% level in Model 1 which got stronger to 1% level in Model 2 and 3 (Table 11). In other words, industries with large MES promotes horizontal IIT. Since the MES and therefore, firm-level cost (dis)advantage can act as an entry barrier within an industry group and thus make the industry market structure concentrated. On the other hand, HHI has a *negative* impact; the statistical significance is observed in Model 2 at 5% level and got weaker to 10% level in Model 3. This result indicates that industries characterized with competitive market structures promote the magnitude of horizontal IIT. Further, the sign of the estimated coefficient of the interaction term between HHI and MES is *negatively* significant at 5% level in Model 1 and at 1% level in Model 2 and 3. Altogether, the obtained impacts of HHI, MES and their interaction are not consistent with each other.²⁵ We, therefore, rely on the result of the interaction term and also market structure to find out which theoretical basis explains India’s horizontal IIT. The finding seems to be consistent with the theory of ‘large’ numbers model, i.e., competitive market structures boost horizontal IIT; Helpman and Krugman (1985).

The estimated coefficient of industrial aggregation has a *positive* sign and is statistically significant at 5% level only in Model 2.

²⁵ In many of the existing literature such ambiguous evidence of market structure and scale economies prevailed; see for instance, Greenaway et al. (1995) and Menon et al. (1999), among others. In dealing with such findings, a handful of research articles have considered the result of *only* market structure over scale economies to explain the magnitude IIT. They opined that because of the nature of proxies, impact of scale economies is somewhat an unreliable indicator.

Table 10 Determinants of the magnitude of vertical IIT

Variables	Model 1	Model 2	Model 3
MKT	3.3557 (0.37)		
MKT ²	– 2.4683 (0.22)		
ADVT		3.4226 (0.23)	
ADVT ²		– 4.2574 (0.20)	
RDE			9.8036 (1.02)
MES	0.1324 (1.84) ^c	0.0589 (0.78)	0.0703 (0.78)
HHI	8.3919 (2.31) ^b	10.4572 (3.60) ^a	9.7750 (3.52) ^a
HHI × MES	0.0456 (0.49)	– 0.1275 (1.33)	– 0.1073 (1.31)
IA _{V-IIT}	– 0.0210 (0.73)	– 0.0316 (1.14)	– 0.0446 (1.68) ^c

Table 11 Determinants of the magnitude of horizontal IIT

Variables	Model 1	Model 2	Model 3
MKT	4.6724 (0.47)		
MKT ²	– 5.0213 (0.49)		
ADVT		– 12.0086 (0.95)	
ADVT ²		3.6515 (0.09)	
RDE			3.8607 (0.53)
MES	0.0976 (2.16) ^b	0.2060 (5.36) ^a	0.1325 (3.42) ^a
HHI	– 2.6652 (0.84)	– 5.9403 (2.26) ^b	– 4.3419 (1.80) ^c
HHI × MES	– 0.2407 (2.01) ^b	– 0.4353 (4.52) ^a	– 0.2988 (3.12) ^a
IA _{H-IIT}	– 0.0789 (0.18)	0.6754 (2.42) ^b	– 0.1033 (0.56)

Two-tailed *t* statistics are there in parentheses

The results reported are bootstrapped up to 4000 replications

^{a,b,c}Statistical significance at 1%, 5% and 10% level, respectively

6 Summing up

This paper is pitched at mitigating the observed gap in the extant empirical literature about the non-consideration of *vertical* and *horizontal* IIT *separately* in analysing the industry-level determinants of India's IIT. We believe that this missing aspect of India's IIT was worth attempting for as (1) empirical studies analysing the industry-level determinants on India have only considered total IIT as the dependent variable and have *biased* results, see Greenaway et al. (1995); (2) studies of industry-level determinants of IIT for emerging economies are still very scanty; and (3) exploring what constitutes the trade basket of India's IIT and its determinants could supplement policy makers in analysing India's growth story.

Our analysis reveals an increasing importance of IIT in India's total merchandise trade over the past two and half decades of trade liberalization was substantially dominated by (*low*) vertical specialization. However, the magnitude of horizontal and *high* vertical IIT across the industry groups have also shown an increasing trend in the latter half of the second decade of economic reforms. It, therefore, appears that India being a labour-abundant country stress more on vertical IIT. In that sense, one can argue that it is important for India to improve the quality of its exports to have sustained economic growth. In an indirect test of the Heckscher-Ohlin model, our result reveals that vertical IIT has less support of the comparative advantage hypothesis. In other words, the result is indicative of the fact that India's vertical IIT is more linked with the explanations from the *new* trade models.

The econometric exercise provides new insight to the literature on IIT. The analysis shows that not only do the results change with changing the definition of the dependent variable from a *censored* variable to *fractional* one but they distinctly *differ* for vertical and horizontal IIT too even for an emerging economy. The results from the Tobit model show that product differentiation only in the form of marketing expenses has a *non-linear* impact on the magnitude of total IIT; while the magnitude of total and vertical IIT improved with investment in marketing and R&D activities, particularly in the industries that inches towards concentrated market structures. The result also revealed that horizontal IIT is promoted in industries with competitive market structure while for vertical IIT there appears to have no distinct evidence.

On the other hand, in the ERFR model, it is only R&D activities that made a significant *positive* impact on total IIT. However, in the case of vertical and horizontal IIT, product differentiation had *no* significant impact. Plausibly, such a result points to India's dominance on *low* vertical specialization. India's vertical IIT is promoted in industries characterized by *concentrated* market structures. The large firms within the concentrated market structures sustain import competition by reallocating their resources into specializing in *low* vertically differentiated goods. In other words, the liberal trading regime has pushed the Indian firms towards producing *labour-intensive lower-technology* products and components while they import the high and intermediate technology products and components under the same product classification.²⁶ In case of horizontal IIT, it was consistently found that its magnitude is favourably influenced in industries characterized by *competitive* market structures.

In the context of policy implications, we think our results may have ensuing suggestions for India, particularly when the government in its mid-term review of the foreign trade policy (2015–2020) has laid out specific plans to push India's export by promoting the Micro, Small and Medium Enterprises that seek large-scale employment opportunities. In fact, looking to increase India's participation in the Global Value Chains (GVCs), the Government of India introduced the scheme of 'Assemble in India for the World' into the 'Make in India' program, see Economic Survey 2019–20; GoI (2020a). Through this process, GoI plans to rise export share in the world market to

²⁶ For example, data from UN Comtrade reveals that in 2013, the type of "steam or other vapour generating boilers" and "household or laundry-type washing machines" that leave Indian ports are found to be relatively less technical. In fact, data from World Development Indicators point out that in 2013, of the total Indian manufactured exports only 8.68% are high technology exports.

3.5% by 2025 and subsequently to 6% by 2030 and create additional 4 and 8 crore jobs by the end of this year. It is worth mentioning here that, India's pull-out from RECP in 2019 was in the direction to make level playing ground for Indian industries via the 'Make in India' program; see Ghosh (2019) for further details.

Needless to say, such hopes were severely impacted by the COVID-19 pandemic. However, to push the economy back on its path, GoI announced in May 2020 several key economic reforms around the much-hyped *Aatma Nirbhar Bharat Abhiyan* package. In fact, the Prime Minister in his address to the nation on Independence Day (2020) has harped on the idea of 'Make for World' alongside 'Make in India'; GoI (2020b). Even in his last address to the nation, PM Modi has called for Indian manufacturers to adopt 'Zero Effect, Zero Defect' policy; GoI (2020c). Altogether, these policies look to increase India's export share through participation in GVCs and also move up the quality ladder. A study of India's IIT in the context of such policies seems to be worth considering for future research.

Appendix A

See Tables 12 and 13.

Table 12 Average share of the magnitude of horizontal and vertical IIT

Time period	Types of IIT	Industry groups					
		I	II	III	IV	V	VI
1990–95	H-IIT	11.28	9.32	5.03	9.66	3.37	5.74
	V-IIT	88.72	90.68	94.97	90.34	96.63	94.26
	I-VIIT	61.52	79.51	91.43	82.76	88.93	85.11
	h-VIIT	38.48	20.49	8.57	17.24	11.07	14.89
1996–01	H-IIT	12.05	13.12	9.63	13.26	5.25	7.56
	V-IIT	87.95	86.88	90.37	86.74	94.75	92.44
	I-VIIT	52.07	56.10	60.79	50.88	72.88	57.07
	h-VIIT	47.93	43.90	39.21	49.12	27.12	42.93
2002–07	H-IIT	15.58	18.59	12.53	16.61	7.78	9.45
	V-IIT	84.42	81.41	87.47	83.39	92.22	90.55
	I-VIIT	57.46	81.16	79.43	75.31	74.20	79.05
	h-VIIT	42.54	18.84	20.45	24.69	25.80	20.95
2008–13	H-IIT	17.51	21.84	12.79	23.68	7.81	7.20
	V-IIT	82.49	78.16	87.21	76.32	92.19	92.80
	I-VIIT	55.14	61.38	63.48	60.70	55.81	63.96
	h-VIIT	44.86	38.62	36.33	39.30	44.19	36.64

Data source: UN Comtrade

I, Chemical; II, Plastics and rubber; III, Stone, cement and glass; IV, Base metals; V, Machinery and mechanical appliances and VI, Transport equipment

Note: The average share of the magnitude of H-IIT and V-IIT were computed over total IIT; while that of I-VIIT and h-VIIT were calculated on V-IIT

Table 13 Construction of explanatory variables

Variable name	Definitions
Product differentiation	MKT = Ratio of Marketing Expenditure to Total Expenditure ADVT = Ratio of Advertising Expenditure to Net Sales RDE = Ratio of Research and Development Expenditure to Total Expenditure
Market structure	HHI = Sum of squares of share of firm's sales to total industry sales CR ₄ = Four firm (sales) concentration ratio (i.e., percentage of sales of four largest firms in industry)
Scale economies	MES = Share of sales of the median sized firm in total industry sales
Industry aggregation (IA)	No. of commodity groups engaged in IIT/V-IIT/H-IIT at the HS- 6 digit level in the <i>i</i> th industry
Scale economies × Mkt. structure	MES × HHI MES × CR ₄
Mkt. structure × product differentiation	HHI × ADVT HHI × MKT HHI × RDE CR ₄ × ADVT CR ₄ × MKT CR ₄ × RDE
Product differentiation × scale economies	ADVT × MES MKT × MES RDE × MES

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Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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