WIDER Working Paper 2019/43

Digital technologies and 'value' capture in global value chains

Empirical evidence from Indian manufacturing firms

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May 2019

Abstract: This paper examines whether digitalization can be a driver of 'upgrading' in global value chains and help developing countries move into higher value-added activities. In particular, the paper provides empirical evidence on the impact of digital capabilities on product upgrading in Indian manufacturing firms participating in global value chains. Empirical analysis is undertaken on a panel of global value chain manufacturing firms in the period 2001–15, using the methodology of system generalized method-of-moments. Product upgrading is captured through a novel sales-weighted average product sophistication indicator at the firm level, while principal component analysis is used to construct a digital capability index that draws information on both 'hard' and 'soft' digital assets of the firm. Empirical results suggest that an increase in digital capability of the firm has a significant and positive impact on its product sophistication, other things being constant. Firms with both high levels of digital capability and share of skilled labour are observed to have roughly 4–5 per cent higher product sophistication than firms with low levels of digital capability and skills. In addition, lagged product sophistication, size, industry concentration, and to some extent R&D, are also found to have a positive and significant impact on product sophistication of Indian global value chain firms. The paper further attempts to tie these empirical results to the global value chain governance literature, and advances the nexus of governance and digitalization as a key area of global value chain research.

Keywords: digital technologies, global value chains, upgrading, Indian manufacturing
JEL classification: F1, F6, O1, O3, L1

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This study has been prepared within the UNU-WIDER project on Structural transformation—old and new paths to economic development.

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ISSN 1798-7237 ISBN 978-92-9256-677-7

Typescript prepared by Gary Smith.

1 Introduction

Digital technologies are rapidly changing the landscape of manufacturing and global value chains (GVCs). The majority of the existing literature at the nexus of manufacturing trade and digitalization has focused on the implications of digital technologies on magnitude of GVC participation and the changing structure of value chains. Digital technologies like big data, cloud computing, and artificial intelligence are likely to contribute to expansion of GVCs by creating efficiencies in production, planning, and product development, as well as in logistics. Technologies of digital communication and tracking (such as RFID (radio-frequency identification)) are also likely to create new opportunities for smaller firms to enter into GVCs, due to lower barriers to export in the digital era, and can facilitate monitoring of production by the lead firms, even in longer and more complex GVCs.

But developing countries are facing a two-pronged problem in the digital economy. Not only is the level of digitalization lower in these economies compared to their developed counterparts, but the impact of digitalization is also lower. Banga and te Velde (2018a), for instance, find a lower impact of doubling of internet penetration on manufacturing labour productivity in low-income countries and in sub-Saharan Africa (SSA) compared to the rest of the world. Using data on access to digital services, affordability, speed, reliability, and ease of use of these services along with skill level, Booz and Company (2012) also find that while a 10 per cent increase in a country's digitization index leads to 0.75 per cent growth in its gross domestic product (GDP) per capita, the impact is lowest in African and South Asian countries. A persistent divide in 'access' and 'use' of digital technologies is likely to increase risks of exclusion of developing country firms from GVCs. As the cost of capital falls in developed countries, there is likely to be an increase in re-shoring of manufacturing value-added, as well as limited future offshoring to developing countries (Banga and te Velde 2018a; Dachs et al. 2017; Rodrik 2018). The increase in 'on-demand' production brought forward by 3D printing and digital machinery is expected to further bring production closer to the end-markets, shortening the GVCs (De Backer and Flaig 2017).

While the literature on digitalization and GVCs is gradually developing, there is a lack of studies examining digitalization as a driver of upgrading in GVCs. A long-standing challenge for developing economies is that when they do link into GVCs, it is mostly at the lower ends, where they perform low-value-added manufacturing tasks. A four-fold categorization of upgrading strategies has been developed in the GVC literature: (a) process upgrading or improving efficiency of production; (b) product upgrading or moving to better and more sophisticated goods; (c) functional upgrading, which refers to moving from manufacturing tasks to pre- and post-manufacturing activities such as R&D, branding, and marketing; and (d) chain upgrading, that is moving into a completely new chain.

This paper focuses on digitalization as a driver of *product upgrading* in Indian manufacturing firms participating in GVCs. Empirical examination is undertaken using system generalized method-of-moments (GMM) on a panel of Indian manufacturing GVC firms in the period 2001–15. Data are drawn from the firm-level dataset Prowess. While 'functional upgrading' may be the end goal of many developing economies looking to upgrade in GVCs, this type of upgrading has higher barriers to entry compared to process and product upgrading. In Kaplinsky and Morris' (2000) upgrading trajectory, product upgrading precedes functional upgrading—it is a 'stepping-stone' strategy which is easier to achieve, and is also easier to measure with secondary data, as in Prowess.

India, in particular, presents an interesting case for analysing digitalization and upgrading in GVCs. In terms of digital technologies, many initiatives have been taken by the government to digitally transform India under the 'Digital India' programme. While India ranks high in terms of exports of digital services compared to other countries, it currently lags behind not only developed countries but many developing economies in terms of digital preparedness for global manufacturing trade, including in its traditional export sectors (Banga 2019). The value added by India's digital services in its manufacturing sectors is lower than many developing countries (Banga 2019). India has also been identified as an outlier in terms of GVC participation. Despite being one of the largest and fastest growing markets located in direct proximity to 'Factory Asia' (Baldwin 2006), India's GVC linkages are low compared to other Asian economies (Athukorala 2013; Baldwin 2011; Goldar et al. 2017). This is due to a number of contributing factors, including stagnant growth in manufacturing, which is not only less export-oriented in India (Banga and Das 2012) but is also experiencing a decline in value-added growth in output and exports (Banga 2014).

This paper makes three important contributions to the existing literature on global integration and development dimensions of digitalization. Firstly, the paper lends empirical evidence to the conceptual literature examining GVCs in the context of Industry 4.0. The majority of the literature on digitalization and development outcomes, in both developed and developing countries, has focused on labour market outcomes, such as employment, skill structure, and wages. There is very limited evidence, particularly empirical, on how digitalization is impacting the product basket of developing economies in GVCs, and no such study exists for India. Further, the paper conceptualizes the linkages between digitalization and GVC governance.

Second, barring Banga (2017), this is the only paper that takes a quantitative approach towards GVC analysis at the firm level in India. Most studies examining India in the GVC context are at the country or industry level (e.g. Banga 2014; Banga 2016; Goldar et al. 2017, 2018). The firm-level studies that do exist are largely qualitative in nature—that is, based on case studies or on firm surveys in selected industries (for instance, Ray and Miglani 2018). While qualitative studies may be useful in providing detailed analysis of specific cases and capturing the complexity and dynamics of relationships in a value chain, they suffer from 'selection bias' (Milberg and Winkler 2013) and lack generalizability, making causal inference difficult (Dicken et al. 2001). By taking a quantitative micro-perspective to GVC analysis, this paper is able to account for important heterogeneity in firm-level GVC participation, in terms of industry, depth and type of linkages, size, foreign ownership, etc.

Third, only a handful of studies have empirically examined drivers of product upgrading for the case of Indian firms, and barring Banga (2017) and Eck and Huber (2016), product upgrading has been mainly analysed as a rise in unit values (Bas and Strauss-Kahn 2015; Hallak 2006; Harding and Javorcik 2012; Manova and Zhang 2012). However, this definition of product upgrading is highly imperfect since, along with capturing product quality, it may also be capturing production costs, market power, and measurement errors (Javorcik et al. 2017).[1] In this paper, product upgrading is defined as a shift towards more sophisticated products, either by moving into new products (for example, moving from leather footwear to finished leather upholstery) or diverting existing production towards more sophisticated product lines. To capture product upgrading, a sales-weighted average product sophistication level is calculated for Indian firms using Hausmann et al.'s (2007) product sophistication index. This involves construction of a novel dataset which matches firm and product-level data in Prowess with gross trade data (at the Harmonized System (HS) four-digit level) in the World Integrated Trade Solutions (WITS) dataset.

[1] Important exceptions in the empirical work on product upgrading include Khandelwal (2010) and Khandelwal et al. (2013), which use both information on unit values and quantities to estimate product quality.

Section 2 provides an overview of the drivers of product upgrading, and discusses the different channels through which digitalization can impact product space. Section 3 presents the econometric model used to estimate the impact of digitalization on product upgrading, and the empirical strategy used for dealing with econometric issues. Section 4 discusses data used and explains construction of key variables. Section 5 presents empirical results and robustness checks. Section 6 discusses the linkages between digitalization and GVC governance, with Section 7 providing concluding remarks.

2 Existing literature on drivers of product upgrading

2.1 Product upgrading and GVC integration

International trade can impact product upgrading through three channels; exporting, importing, and two-way trading. On the export side, it is observed that firms exporting to international markets are more likely to acquire new technology (Almeida and Fernandes 2008) and invest in innovation due to increased competition and exposure to foreign markets. Atkin et al. (2017), for example, analyse 'learning by exporting' for rug producers in Egypt and document knowledge and information flows between foreign buyers, intermediaries, and producers. On the import side, firms can access better and cheaper foreign inputs, and learn from the foreign technology and knowledge embodied in these imports (Paunov 2011). Empirical studies confirming the positive impact of 'learning-by-importing' on product scope and quality include Kugler and Verhoogen's study (2009) for Colombia and Goldberg et al.'s (2010) study for India.

Studies examining the impact of two-way trading, which refers most closely to GVC trade, on product upgrading are limited. Veugelers et al. (2013) find that GVC firms are significantly more likely to introduce new products and new processes solely or in combination. Lo Turco and Maggioni (2015) also find that the joint involvement of a firm in importing and exporting positively impacts product scope and new product introduction, which may contribute towards a more sophisticated product basket. Seker (2012) confirms that two-way traders are more innovative, in terms of product and process innovation, than any other group of firms. Most recently, Banga (2017) examines the case of Indian manufacturing and finds that the product sophistication in GVC firms is roughly 2 per cent higher than that in non-GVC firms, on average and *ceteris paribus*.

Simply linking into GVCs is not enough; prospects of upgrading in a GVC supplier firm are shaped by the type of governance structure the firm is operating under. As production becomes more fragmented and manufacturing activities get increasingly dispersed, the role of governance in GVCs emerges as a key issue in ensuring that there is an equitable distribution of gains between participants, and that developing countries are able to link and upgrade in GVCs (Gereffi et al. 2005; Humphrey & Schmitz 2001).

Standard economic theory identifies market-based linkages (based on trade) and vertically integrated governance structures (based on foreign direct investment (FDI)). Existing evidence suggests that investments made by multinational enterprises (MNEs) into local suppliers can lead to transfer of knowledge (Arnold and Javorcik 2009) and also increases the probability of the affiliate itself introducing new products (Brambilla 2009; Guadalupe et al. 2012). Furthermore, MNEs may provide local producers with better inputs, technical know-how, and support, lowering the cost of production and enabling product innovation. Examining the impact of foreign ownership on product sophistication in Indian firms, Eck and Huber (2016) find that vertical backward FDI spill-overs from downstream MNEs to upstream local Indian suppliers have a positive and significant impact on the supplier firm's sophistication.

Compared to standard economic theory, the GVC literature defines governance more broadly, as 'inter-firm relationships through which non-market coordination of activities is achieved' (Humphrey and Schmitz 2001: 5). Gereffi et al. (2005) identify three types of 'network' governance:—modular, relational, and captive—existing between market-based linkages and vertical integration. These network chains exhibit different power symmetries between the supplier and the lead firm, depending on three key factors. The first factor is the *complexity of information transfer*, with higher complexity requiring more coordination in production. The second is *codifiability of transactions* or the degree to which knowledge can be transmitted (for instance, through contracts and standards) between various actors. The third *is supplier competence*, that is the ability of the supplier to deal with complex information in transactions and to meet the requirements of orders placed by the buyers. Combinations of these key factors can result in different governance structures (see Figure 1).

Figure 1: Factors affecting GVC governance structure

	Market	Modular	Relational	Captive	Hierarchy
Complexity of transactions	Low	High	High	High	High
Ability to codify transactions	High	High	Low	High	Low
Supplier competence	High	High	High	Low	Low
Lead firm control over production	Low ⟷				High

Source: author, adapted from Gereffi et al. (2005).

An extensive literature review of case studies conducted by Morrison et al. (2008) and Pietrobelli and Rabellotti (2011) suggest that in governance structures with high lead firm control, it is easier for supplier firms to upgrade processes and products but more difficult to upgrade functions performed by them in the value chain. From Figure 1, this indicates that as a firm moves away from market-based GVCs towards hierarchical governance structures, the opportunities for the supplier to upgrade products and process increase, but at the expense of functional upgrading. Relational chains, which exhibit most power symmetries, tend to offer favourable opportunities to the supplier across all upgrading strategies (Pietrobelli and Rabellotti 2011). It is important to note that while several qualitative studies document high opportunities for captive suppliers to upgrade products through lead firm support (Pietrobelli and Rabellotti 2011), it is widely accepted in the GVC literature that production in captive chains is tightly monitored by the lead firms and knowledge flows are at the complete discretion of lead firms. Often these remain confined to a narrow range of activities, such as production of standard consumer goods (Strasser 2015) or mere assembly (Pietrobelli and Rabellotti 2008).

2.2 Product upgrading and firm-level capabilities

While GVC participation can boost firm-level product sophistication, gains from linking are neither automatic nor uniform. Even within the same governance structure, some firms manage to upgrade while other do not, as evidenced in the case of market-based chains in the study by Schmitz (2006). Research shows that local firms in fact have heterogeneous technological capabilities and very distinctive firm-specific learning strategies (Bell and Pavitt 1993; Giuliani and Bell 2005; Lall 1992, 2001; Nelson and Winter 1982), which may prevent them from taking advantage of the foreign knowledge in the same way. There is consensus in the literature on the importance of organizational learning, building R&D capacity and having a well-trained educated labour force for exploiting external knowledge and innovating successfully (Figueiredo 2001). Lall

(2001) describes these internal efforts as 'technological capabilities'—the organizational, technical, and managerial skills necessary to utilize technology efficiently and to generate any form of technical change or innovation. Digital capabilities of a firm can be thought of as a subset of its wider capabilities of acquiring, absorbing, and adapting technology.

In many cases, firms have been able to leverage facets of the digital economy—such as electronic commerce, blockchain, digital trade, robotics, and fin-tech—to significantly reduce production and transaction costs. The potential productivity gains from these technologies have been discussed in several studies,[2] but product sophistication gains remain less researched. On the production side, digital technologies can increase efficiencies and costs savings, which can be reinvested into more sophisticated product lines. Banga and Velde (2018b) highlight the case of Funkidz, a local furniture manufacturing SME (small or medium enterprise) in Kenya, that has heavily invested in computer-aided design and manufacturing technologies, and as a result has diversified into new furniture lines that are completely flat, packable, and of better quality. Another firm in Kenya, Megh Cushion Industries, has also moved into more sophisticated production, realized through heavy investments in multipurpose digital technology such CNC auto-cut and laser technology and 3D scanning (Banga and Velde 2018b). From supplying automotive parts (such as foam pads and car door panels), the firm has moved into production of complete transport seating, van conversions, and after-market accessories.

Digital technologies in pre- and post-manufacturing can also impact the product basket of firms. Digital engineering, for example, is shrinking product development timelines and costs (Bain and Company 2017), while e-commerce is opening up new opportunities for product diversification and higher market access. For example, in Bangladesh, the apparel and clothing sector dominates the offline trade, but the country has diversified its online trade into agriculture, food and beverages, and consumer electronic products (ITC 2018). In Cambodia, too, e-commerce has enabled the shift of production from cereals towards higher value-added products such as fresh mangoes and cashew nuts (ITC 2018). Taking the case of German manufacturing firms, Kroll et al. (2018) confirm that even after controlling for export orientation, value chain position, and R&D activity of firms, the effect of digital technologies on product innovation remains significant.

In the case of India, Ray and Miglani (2018) bring focus to automotive firms in India which have heavily invested in digital technologies to realize productivity and product sophistication gains. The authors point to examples of Hyundai Motors India Limited and Mahindra and Mahindra, which initially specialized in manufacturing commercial and utility vehicles but later developed capabilities to serve the passenger car segment as well. The authors propose that compared to traditional auto manufacturing plants, factories using digital technologies are likely to have higher output without major changeover costs, with faster delivery time, and higher quality (Ray and Miglani 2018).

Modern technologies, such as big data analytics, additive printing, and automation that allow for development of new and complex products often require higher skills (de Groen et al. 2017). Focusing on digitalized manufacturing, Mayer (2018) points out that in addition to digital capabilities, suppliers' managerial capabilities also matter for reaping benefits in the digital economy. Digitalized products tend to involve very complex knowledge that is highly tacit in nature and difficult to codify into standards and blueprints (Andrews et al. 2016). When knowledge is tacit, passive learning by suppliers (i.e. using capital goods or through technology embedded in

[2] Dauth et al. (2017) for Germany, Graetz and Michaels (2017) for 17 developed countries, Rodrik (2018) for developing economies, UNCTAD-TDR (2017) for Asian and Latin American countries, and Banga and te Velde (2018a, 2018b) for African countries.

FDI) may not be enough to acquire technical knowledge (Bell and Albu 1999), and in such cases, suppliers will need to make increased investments in skills development. This can be done through hiring of more skilled workers and managers, or more investment in R&D (Bell and Pavitt 1993).

Chiarvesio et al. (2010) confirm that for Italian firms both international presence and innovation efforts are important for global competitiveness. Firms that gain, in terms of profit and growth, are those that invest in R&D, codified knowledge, design, and innovative ICT solutions. Focusing on East Asian firms involved in GVCs of tea, tourism, and business process outsourcing (BPO), Foster et al. (2018) find that internet connectivity has resulted in 'thin integration' in East African firms; barring those that have developed market niches, firms have only made small productivity gains without more substantial upgrading (Foster et al. 2018). The authors conclude that internet connectivity activity in itself does not generate many gains, but acts as a complement to creativity and local knowledge.

3 Econometric model and empirical strategy

Overall, the review of the literature in Section 2 suggests that linking into GVCs can be an important driver of product sophistication. However, gains from linking are neither automatic nor uniform. The internal efforts made by the firm to upgrade products, particularly in terms of building digital capabilities and skills development, are important for upgrading, along with other firm-level characteristics such as foreign ownership and R&D intensity.

Drawing from the literature review, the baseline specification used in the paper to model the impact of digital capability on average product sophistication of GVC firm i at time t is as follows:

$$\begin{aligned}\log(PSI_{it}) = \alpha_0 + \alpha_1 \log(PSI_{it})_{t-1} + \alpha_2 \log(PSI_{it})_{t-2} + \beta_1 \log(\textit{digital capability})_{it} \\ + \beta_2 \log(\textit{skilled labour share})_{it} \\ + \beta_3 \log(R\,\&\,D\,\textit{intensity})_{it} \\ + \beta_4 HHI_{jt} + \beta_5 X_{it} + a_i + a_t + a_j + e_{ijt} \ldots\end{aligned} \tag{1}$$

where an increase in PSI_{it} captures product upgrading at the firm level, which can occur either through introduction of new and more sophisticated products, such as moving from production of bicycles (HS 1706) to, say, automobiles (HS 1704) or diversion of sales towards more sophisticated goods.

Several studies have noted persistency in product sophistication of a country's export basket (e.g. Kočenda and Poghosyan 2017). Firm-level product sophistication is also expected to be highly persistent in nature due to path dependencies in systems of production, and costs associated with market exploration and changes in the production basket of the firm (Kočenda and Poghosyan 2017). The study therefore controls for lagged values of firm-level sophistication by adding $PSI_{it\,t-1}$ and $PSI_{it\,t-2}$ in the models.

It is expected that the impact of lagged sophistication variables, digital capability, skilled labour share, and R&D intensity on product sophistication will be significant and positive. HHI (Herfindahl–Hirschman Index) captures the impact of industry concentration, but this remain ambiguous. A positive sign on HHI may indicate that firms in more concentrated industries are earning higher profits which are being reinvested into more sophisticated lines. A negative sign implies that firms in highly concentrated industries face lower competition and thus lower incentives to innovate.

X_{ijt} refers to a set of variables controlling for firm characteristics such as age, size, foreign shares, labour productivity, and product scope (single-product firms or multiple-product firms). A positive sign on age suggests that older firms have had more experience in 'learning by doing' and may have already established marker power, allowing them to focus on innovation. However, younger firms may have more incentives to innovate and remain competitive in the market, in which case the sign on age will be negative. It is expected that bigger firms produce more sophisticated products. The coefficient on foreign shares is expected to be positive since spill-overs from foreign firms can lead to transfer of knowledge, technology, and skill flow. The expected sign on product scope remains ambiguous; introduction of new products or product innovation can increase the sophistication of products on one hand, but on the other firms may choose economies of scale for rent generation and may produce new but less-sophisticated goods. Firm, industry, and time fixed effects are captured by *a*(*i*), *a*(*j*), and *a*(*t*) terms, respectively.

To understand how product sophistication gains differ with digital competence—characterized by both digital capabilities and skills—the following model is also estimated:

$$\begin{aligned}\log(PSI_{it}) = {} & \alpha_0 + \alpha_1 \log(PSI_{it})_{t-1} + \alpha_2 \log(PSI_{it})_{t-2} + \beta_1 (\textit{low digital capability} - \textit{low skilled firm})_{it} \\ & + \beta_2 (\textit{low digital capability} - \textit{high skilled firm})_{it} \\ & + \beta_3 (\textit{high digital capability} - \textit{low skilled firm})_{it} \\ & + \beta_4 \log(\mathrm{R\&}D\, \textit{intensity})_{it} \\ & + \beta_5 HHI_{jt} \\ & + \beta_6 X_{it} + a_i + a_t + a_j + e_{ijt}\end{aligned} \tag{2}$$

where the dummy variable $\textit{low digital capability} - \textit{low skilled}$ firm = 1 for all GVC firms in which both digital capability and the share of skilled labour is below the median level in the industry. These are firms with overall low digital competence. Similarly, $\textit{low digital capability} - \textit{high skilled}$ is indicative of suppliers with digital capability below the industry median but share of skilled labour above the median level, and $\textit{high digital capability} - \textit{low skilled}$ = 1 for firms in which digital capability is higher than the industry median but share of skilled labour is relatively lower. These two categories represent firms with medium digital competence. The reference category is $\textit{high digital capability} - \textit{high skilled}$ firms, which represents firms with overall high digital competence.

In empirically investigating the impact of digital capability on product upgrading in GVCs, a number of econometric issues arise. Unobserved firm characteristics, such as unobserved productivity, may affect both firm sophistication and the digital capability of the firm, leading to spurious correlation between the two. Endogeneity and biased results may also arise when unobservable time-invariant firm effects are correlated with regressors in the empirical model. Moreover, reverse causality can bias the results if an increase in firm-level sophistication in turn impacts firm-level investment into digital capability. Similarly, increasing product sophistication may impact foreign investment, expenditure R&D, and size of the firm, making these variables also potentially endogenous.

To deal with such econometric problems of reverse causality and endogeneity, the study employs the system GMM methodology. The system GMM estimator[3] deals with the problem of

[3] This estimator uses extra moment conditions that rely on certain stationarity conditions. If these conditions are satisfied, the system GMM estimator has much better finite sample properties in terms of bias (Blundell and Bond 1998, 2000). It also assumes that differences are not correlated to firm-specific effects compared to levels. System GMM estimators are specifically designed for cases with; 'small T large N panels', a linear functional relationship, a

endogeneity by simultaneously running the econometric model in levels and differences, using lagged values of levels as instruments for first differences and lagged values of first differences as instruments for levels. It allows the inclusion of lagged values of firm sophistication as explanatory variables, which further deals with: (1) autocorrelation of disturbances in the panel estimation; and (2) time-invariant firm characteristics correlated with explanatory variables.

Two-step system GMM estimation is conducted using the Xtabond2 command by Roodman (2009). Standard errors are robust to heteroscedasticity and autocorrelation, and clustered at the firm level, since the main variable of interest—digital capability—varies across firms. The 'orthog' option[4] (Arellano and Bover 1995) is also used to preserve sample size in the unbalanced panel of Indian manufacturing firms. Following the rule of thumb, the instrument count is kept below the number of groups and the instrument set is collapsed when there are too many instruments.

To check against misspecification of instruments, Arellano and Bond's autocorrelation test is carried out to ensure that there is no autocorrelation in the first-differenced residuals. A *p*-value greater than 0.05 indicates that there is no autocorrelation at the second order lag at 5 per cent. The validity of results is also checked using the standard Sargan–Hansen J-test of over-identifying restrictions. A *p*-value lower than 0.05 on this test casts suspicion on the exogeneity of the instrument set.

4 Data sources and construction of variables

The study primarily uses Prowess, a database of the financial performance of Indian companies, created by the Centre for Monitoring Indian Economy Pvt Ltd (CMIE). Information in Prowess is compiled from firm-level annual reports and balance sheets of listed companies. The total income of all companies in Prowess covers about 80 per cent of India's GDP; for international trade, Prowess covers about 50 per cent of India's exports and nearly 60 per cent of imports.[5]

dynamic dependent variable, fixed individual effects, and presence of heteroscedasticity (variance of the errors is not constant across observations) and autocorrelation (correlation within time-series observations—that is the present value being correlated with the past and future value) within individuals but not across them (Roodman 2009).

[4] This option subtracts the average of all available future observations, rather than subtracting the previous observation from the current one.

[5] These statistics are for the year 2013–14.

The study restricts analysis to manufacturing firms[6] in the period 2000/01 to 2014/15,[7] and collects firm-level data on total sales, exports, imports, software and technology expenses, wages and salaries, R&D expenses, and more. Construction of key variables is explained below.[8]

4.1 Identifying Indian manufacturing firms participating in GVCs

Following Baldwin and Yan (2014) and Banga (2017), the study identifies GVC firms as those that are simultaneously importing intermediate goods (raw materials, stores and spares, and capital goods) and exporting intermediate or final goods.[9] As argued by Baldwin and Yan (2014), this approach captures the sequential integration of production processes across countries. This definition is also consistent with the indicator used by the Organisation for Economic Co-operation and Development (OECD), which describes GVC participation as intermediates produced in one country which are included in another country's exports. Since there are some firms that report a positive but very low value on exports, only those two-way traders that export at least 1 per cent of their total sales are considered in the study. All other firms—that is firms that do not trade at all or undertake very little, as well as one-way traders that either import or export—are considered as non-GVC firms in the study, and therefore excluded from analysis.

4.2 Construction of firm-level product sophistication

By the 1956 Indian Companies Act, Indian firms are required to report information on product-level sales (data on exports are available at the product level), capacities, and quantities produced; however, they are not required to report product information using any particular classification or governing rule. Therefore, the CMIE uses its own internal product classification, loosely based on National Industrial Classification (NIC) and HS schedules. In order to calculate sophistication level of each product in Prowess, the study matches products in Prowess to the HS product classification. This is done by assigning correspondences between the two by hand, and exploiting the fact that both Prowess' classification and HS classification are closely related to the International Standard Industrial Classification (ISIC).[10] The study is able to match around 80 per cent of products in Prowess to four-digit HS products (1996 classification). While matching to six-digit would be ideal, Indian firms do not report detailed product names and therefore are best matched to HS at the four-digit level. Matching to the six-digit level would lead to loss of accuracy, and is therefore avoided.

Once Prowess products are matched to HS products, the study calculates sales-weighted average firm-level sophistication:

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[6] The two-digit NIC industries considered in the study are given in Section A1 in the Appendix.

[7] Prowess data do not allow one to analyse entry and exit. However, the database has been extensively used in a variety of economics and business literature, and there is no evidence that there is any systematic way in which firm attrition takes place. The following reasons increase confidence in non-random attrition: (1) data in Prowess mostly come from medium to large firms, therefore missing data for a firm is most likely due to the fact that the firm has not reported the data rather than it having exited the industry; (2) entry of a firm into the Prowess database does not mean that a new firm was formed at the time of the entry but that Prowess received information for the first time about the firm; (3) Prowess does not drop any firm from its database even if it exits; and (4) the paper uses an unbalanced panel in which sample size varies from year to year, with only data availability and purging of outliers guiding our sample selection.

[8] Construction of other firm-level controls is given in Section A2.

[9] Prowess reports on total exports of the firm; it does not distinguish between intermediate and final exports.

[10] This matching process is explained in detail in Section A3.

$$PSI_{it} = \sum_{k} \frac{Sales_{it}^{k}}{\sum_{k}^{K} Sales_{it}^{k}} PRODY^{k}$$

where $Sales_{it}^{k}$ is the sales of product k by firm i at time t and $\sum_{k}^{K} Sales_{it}^{k}$ is the total sales of firm i across all products at time t.

$PRODY^{k}$ is Hausmann et al.'s (2007) product-specific sophistication level, calculated as

$$PRODY^{k} = \sum_{c} \underbrace{\left(\frac{X_{c}^{k} / X_{c}^{\bullet}}{\Sigma_{c}(X_{c}^{k} / X_{c}^{\bullet})} \right)}_{\varphi_{c}^{k}} Y_{c}$$

where Y_{c} is the per capita income of country *c*, X_{c}^{k} denotes country *c*'s export volume of good *k*, and $X_{c}^{\bullet}$ is the sum of exports of country *c*. The weights φ_{c}^{k} add up to 1 for each good. $PRODY^{k}$ avoids normalization or any sort of grouping of countries and measures the income per capita associated with each product, weighted by a variant of Balassa's revealed comparative advantage (RCA). Hausmann et al. (2007) emphasize that the adjusted weight ensures 'that country size does not distort the ranking of goods'. Data on GDP per capita (PPP) in constant 2011 US dollars are collected for 267 countries/regions from the World Development Indicators database.[11] Product (at the four-digit level) export data are collected (in thousands of US dollars) from WITS in UNCOMTRADE.[12] This index is calculated using the PRODY command developed by Huber (2017).

4.3 Construction of firm-level digital capability

At the country level, the existing literature has proxied the extent of digitalization through different indicators, including robot density (Acemoglu and Restrepo 2017; Autor and Dorn 2013; Berg et al. 2018; Donou-Adonsou et al. 2016), e-commerce growth, digital servicification of manufacturing (Banga 2019), and internet penetration (Banga and te Velde 2018a).

At the firm level, particularly for Indian manufacturing firms, data on the use of digital technologies, robotics, and e-commerce are not available. It is therefore more useful to estimate digital capability at the firm level, which captures the underlying potential of the firm to exploit modern technologies such as cloud computing and robotics. This also implies that analysis in the paper is not limited to any specific technological development.

To measure digital capability, a firm-level index is constructed that uses information on (1) communication and transport infrastructure; (2) technology assets, which refers to gross plant,

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[11] Using GDP per capita PPP allows for correction of differences across time (inflation) and across countries (deviations from PPP). This means that the product sophistication indicators can be compared across time and countries

[12] Since the exporting countries and comparative advantages can change over time, calculating product sophistication using different countries in different years can create biases in the indicator (Hausmann et al. 2007). Therefore, it is important to create sophistication indices using data from a consistent sample of countries that report trade data in the period 2001–15. This means exclusion of those countries for which trade data are missing for even one period in 2001–15. Consistent data are obtained for 113 countries, reporting both export flows and GDP in the period considered. The list of countries taken into the analysis is given in Section A4 in the Appendix.

machinery, computers, and electrical installations; and (3) software assets of the firm. This index is constructed using principal component analysis (PCA; a statistical technique to reduce dimensionality of multivariate data) on the share of software, technology, and communication assets in total sales of the firm.[13] To check the validity of the PCA, studies have used the Kaiser–Meyer–Olkin (KMO) test statistic, and Bartlett's test of sphericity (see Jolliffe 2002). A KMO statistic of 0.67 and a *p*-value of 0.000 on the Bartlett's test of sphericity confirm the validity of the digital capability index.

5 Impact of digitalization on product upgrading in Indian GVC firms

5.1 Summary statistics and preliminary analysis

The analysis in this paper pertains to a panel of Indian GVC manufacturing firms in the period 2001–15. As part of data cleaning, firm–year observations with missing or negative values for sales and observations with export intensity greater than 100 are removed from the analysis. Summary statistics of the panel are presented in Section A5 in the Appendix. There are 22,274 firm–year observations in the panel, with 14 per cent of firms being foreign-owned (defined as more than 10 per cent foreign shares). The average value of the product sophistication index is 36.68, and the digital capability index ranges between 0 to 12. Share of skilled labour refers to share of managerial compensation in total labour compensation, and is observed to vary between 5 and 8 per cent, with an average share of 7.8 per cent.

Table 1 presents sectoral averages of product sophistication and digital capability index for the period 2010–15. It also reports on the estimates of the value added by digital services (software, information, consultancy, and telecommunication services) in the exports of the manufacturing sectors in the year 2014, obtained from Banga (2019).

The ranking of Indian manufacturing sectors on product sophistication in Table 1 is consistent with that in Banga (2017) and Eck and Huber (2016); sectors of pharmaceuticals; computers, electronics, and optical products; machinery and equipment; other transport equipment; and rubber and plastics rank high in terms of industry-level product sophistication. Within these sectors, computer and electronics rank high on both digitalization indicators; pharmaceuticals and the rubber and plastic sectors rank relatively higher on the digital capability index; other transport equipment and machinery and equipment sectors rank higher on value added by digital services in sectoral exports. On the opposite spectrum, sectors of furniture, food, beverages and tobacco rank low on product sophistication, and on the two digitalization indicators.

[13] Kaiser's rule—retaining components with eigenvector greater than 1—is followed and component 1 is chosen, which explains about 56 per cent of variation in the variables. Weights obtained from component 1 (0.55 for software assets, 0.65 for communication and transport infrastructure assets, and 0.54 for technology assets) are then used to construct the weighted digital capability index for every firm.

Table 1: Product sophistication and digitalization across Indian manufacturing sectors

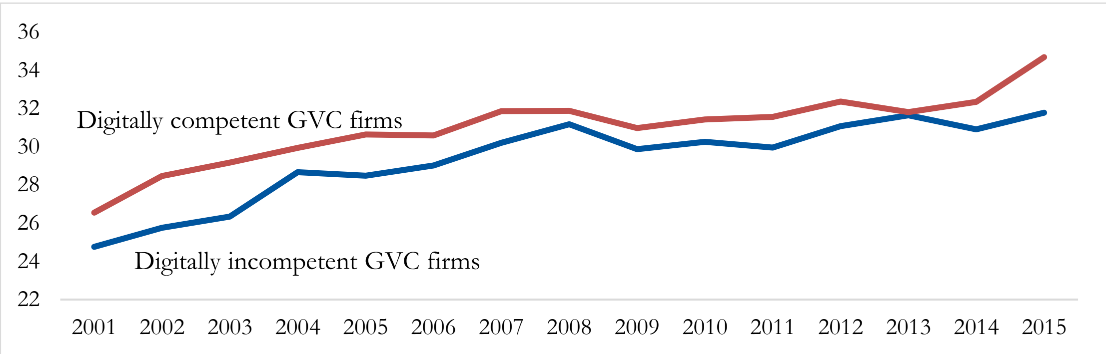
Sector	Product sophistication index	Digital capability index	Value added by digital services in manufacturing exports (%)
Manufacture of pharmaceuticals, medicinal, chemical, and botanical products	39.86	18.41	1.80
Manufacture of machinery and equipment	37.24	15.53	3.40
Manufacture of computer, electronic, and optical products	36.31	22.92	10.10
Manufacture of other transport equipment	33.27	16.94	3.50
Manufacture of rubber and plastics products	32.92	17.23	1.70
Manufacture of fabricated metal products, except machinery and equipment	32.61	19.40	3.30
Manufacture of motor vehicles, trailers	31.79	16.66	2.40
Manufacture of chemicals and products	31.74	15.26	1.90
Manufacture of furniture	30.15	15.50	2.60
Manufacture of basic metals	28.05	21.57	1.10
Food, beverages, and tobacco	21.59	14.33	1.50
Textiles, wearing apparel, leather	19.74	15.75	2.30

Note: data on product sophistication and digital capability index is from the GVC panel of Indian manufacturing firms, and is presented as the 2010–15 average. For the purpose of presentation, the digital capability index values are multiplied by 100. Data on value added by digital services in sector-level exports is for the year 2014 from Banga (2019). Some sectors have been aggregated to allow comparison across different sources.

Source: author, based on Prowess data.

Given the discussion on the importance of both digital capability and skills for boosting product sophistication, the study analyses product sophistication across *digital competence* of firms. Digitally competent firms are identified as those firms in which both digital capability and share of skilled labour is above the median level in the industry. Figure 2 reveals that product sophistication in digitally competent GVC firms has remained consistently higher than that in digitally incompetent GVC firms, in which both digital capability and skill level are below the median level. Both series witness a similar trend; firm sophistication increased in the period 2001–07, declined during the financial crisis, and recovered post-2009.

Figure 2: Product sophistication, by firm type



Source: author, based on Prowess data.

5.2 Empirical results: impact of digital capability on product sophistication

To examine the causal relationship between product sophistication and digital capability, Table 2 employs system GMM estimations. Model 1 regresses current firm sophistication on lagged values of firm sophistication to control for persistency. It also adds foreign shares and share of skilled labour as controls. To this, Model 2 adds HHI as a control for industry concentration. Model 3 adds R&D intensity to control for a firm's internal efforts to innovate its products. Models 4 and 5 add controls for firm size and age, respectively. Time dummies are included in all models to account for time-specific shocks—for instance, the economic boom of 2003–04 in India and the financial crisis of 2008–09.

Table 2: Dependent variable: firm-level product sophistication (PS_{it})

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
L. (PS_{it})	0.823***	0.822***	0.825***	0.784***	0.795***
	(0.0418)	(0.0418)	(0.0419)	(0.0460)	(0.0447)
L2. (PS_{it})	0.0884	0.0870	0.0850	0.0956	0.101*
	(0.0576)	(0.0573)	(0.0590)	(0.0583)	(0.0576)
Digital capability	0.0101*	0.00997*	0.0102*	0.0108*	0.0116**
	(0.00599)	(0.00593)	(0.00583)	(0.00570)	(0.00567)
Skilled labour share	0.00706***	0.00715***	0.00771***	0.0202***	0.0169***
	(0.00178)	(0.00179)	(0.00180)	(0.00479)	(0.00361)
Foreign shares	2.95e–05	2.82e–05	4.06e–06	–0.000227	–0.000187
	(0.000204)	(0.000204)	(0.000200)	(0.000205)	(0.00020)
HHI		0.0197**	0.0185**	0.0212**	0.0208**
		(0.00825)	(0.00842)	(0.00957)	(0.00970)
R&D intensity			0.000705	0.000239	0.000336
			(0.000758)	(0.000816)	(0.00081)
Firm size				0.0218***	0.0189***
				(0.00727)	(0.00605)
Firm age					–0.012***
					(0.00457)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Hansen *p*-value	0.11	0.12	0.16	0.39	0.46
AR(2)	0.10	0.09	0.10	0.17	0.18
Observations	9,208	9,208	9,208	9,206	9,186
Number of firms	1,744	1,744	1,744	1,744	1,736

Notes: dependent variable, lagged PS variables, digital capability, skilled labour share, R&D intensity, firm size, and age are in natural logs. Firm size is captured by number of workers employed. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are robust, clustered on firms. Constant is included in all models but coefficient is not reported.

Source: author, based on Prowess data.

The *p*-value on the AR(2) statistic is greater than 0.05 across all models, indicating that there is no problem of serial correlation. Similarly, the *p*-value on Hansen's test statistic is also consistently greater than 0.05, indicating that the set of instruments used in the estimations is exogenous, and therefore GMM estimations are valid. Across the models, it is clear that lagged firm sophistication is affecting the current period's sophistication positively and significantly, rendering support for the choice of system GMM estimator.

The positive and significant coefficient on the HHI index suggests that as the concentration of industry to which the firm belongs increases by one unit, the firm's PS rises by roughly 2 per cent on average, *ceteris paribus*. Industries which are more concentrated generate larger profits for firms, which may be getting reinvested in the creation of more sophisticated product lines. This result is in line with the findings of Banga (2017) but differs from the findings of Eck and Huber's (2016) study. While R&D intensity does not seem to be significantly impacting firm sophistication, bigger firms tend to produce more sophisticated goods. It is further observed that younger firms are more sophisticated, a finding also corroborated in the studies by Eck and Huber (2016) and Banga (2017). While older Indian firms are more likely to hold greater market power and the ability to innovate, it is the younger firms who have more incentives to innovate and remain competitive. The survival and growth of younger firms may depend more heavily on product innovation and manufacturing of more sophisticated goods. Larger firms are observed to be producing more sophisticated goods.

Similar to Eck and Huber (2016) and Banga (2017), no significant impact of foreign shares or foreign acquisition is found on firm-level product sophistication. As mentioned by the authors, one possible reason for this could be cost-saving strategies pursued by the foreign firms. Foreign firms could be investing in India to produce less-sophisticated low-cost goods, which are then exported to the home country of the foreign investor. Focusing on the impact of FDI, Eck and Huber (2016) note that while FDI does not directly impact product sophistication in Indian firms, vertical backward FDI spill-overs have a positive and significant impact. These vertical backward linkages measure the intensity of contact between Indian suppliers and their customers in downstream industries to which they supply, and capture the higher incentives of foreign buyers to transfer their knowledge and technology to upstream Indian suppliers.

Coming to the main variables of interest—firm-level digital capability and share of skilled labour—it is observed that the sign on the digital capability index is positive and significant (at 10 per cent) across all models, implying that as firms spend a larger share of their sales on software, technology, and communication assets, their product sophistication rises. This indicates that by investing in digital capabilities, firms can upgrade to more sophisticated product lines that capture higher value-added in GVCs. The share of skilled labour also impacts firm sophistication positively and significantly, suggesting the important role of a well-skilled manufacturing workforce in producing more sophisticated products.

A number of robustness checks are conducted in Section A6 in the Appendix to ensure validity and non-sensitivity of the empirical results in Table 2. Model 1 in Section A6 adds a control for labour productivity in the firm, while Model 2 controls for the impact of magnitude of GVC participation on product sophistication by adding the import content of exports (ICE) as an explanatory variable. This measures the ratio of imported intermediates to total exports, also used by Tucci (2005) and Banga (2017). It further controls for single- versus multi-product firms. These additional controls are, however, not found to be significant. Models 3 and 4 check for sensitivity of results to lag and variable specification respectively. Model 3 uses an alternate lag specification than that used in Table 2, while Model 4 changes the set of endogenous variables by assuming that the share of skilled labour is also endogenous to product sophistication. It is observed that the sign on share of skilled labour is still positive and significant. Models 5–7 check sensitivity of results to measurement. Model 5 uses the natural log of sales as a control for firm size rather than employment; Model 6 uses an alternate dependent variable (PS_{it}_mdgp) that calculates firm-level product sophistication using Hausmann's PRODY index but uses average GDP values of countries in the period 2001–15 instead of yearly GDP. Model 7 uses an alternate measurement for digital capability—instead of the index constructed using PCA, digital capability is measured simply as the share of gross plant, machinery, computers and IT, and electrical systems in gross fixed assets.

Across the different specifications, results obtained are similar to those in Section 5.2. Robustness checks confirm that lagged firm sophistication, digital capability, share of skilled labour, firm size, and HHI impact firm-level product sophistication positively and significantly, while age is observed to have a negative impact.

5.3 Empirical results: product sophistication gains across digital competence categories

Table 3: Dependent variable: firm-level product sophistication (PS_{it})

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
L. (PS)	0.786***	0.792***	0.787***	0.795***	0.791***	0.794***
	(0.0450)	(0.0443)	(0.0461)	(0.0427)	(0.0434)	(0.0456)
L2. (PS)	0.0891*	0.0932*	0.0891*	0.0726	0.0780	0.0904*
	(0.0509)	(0.0522)	(0.0486)	(0.0539)	(0.0536)	(0.0544)
Firm size	0.0169***	0.0163***	0.0127**	0.017***	0.0179***	0.0170***
	(0.00599)	(0.00599)	(0.00579)	(0.0059)	(0.00601)	(0.0065)
Low digital capability–low skill	–0.0451*	–0.0484**	–0.0479**	–0.0527**	–0.0552**	–0.0518**
	(0.0238)	(0.0242)	(0.0241)	(0.0246)	(0.0247)	(0.0257)
Low digital capability–high skill	–0.00369	–0.00654	–0.00856	–0.0141	–0.0210	–0.0173
	(0.0175)	(0.0173)	(0.0178)	(0.0180)	(0.0177)	(0.0184)
High digital capability–low skill	–0.00981	–0.0139	–0.0110	–0.0155	–0.0188	–0.0196
	(0.0203)	(0.0198)	(0.0192)	(0.0198)	(0.0197)	(0.0197)
Age	–0.0166**	–0.019***	–0.0153**	–0.015***	–0.015***	–0.0141**
	(0.00670)	(0.00659)	(0.00645)	(0.0059)	(0.00594)	(0.00621)
R&D intensity		0.00154*	0.00178**	0.000810	0.000553	0.000642
		(0.00086)	(0.00089)	(0.0009)	(0.00094)	(0.00093)
Labour productivity			0.0114	–0.00063	–0.000837	–0.000214
			(0.00952)	(0.0125)	(0.0124)	(0.0130)
Multi-product firm				–0.00347	–0.00423	–0.00409
				(0.0040)	(0.00406)	(0.00426)
HHI				0.029***	0.0294***	0.0263**
				(0.0101)	(0.0102)	(0.0107)
Foreign shares					–0.000115	–0.000117
					(0.00207)	(0.00020)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	Yes	Yes	Yes
Observations	9,383	9,383	9,383	9,097	9,047	9,047
Number of firms	1,757	1,757	1,757	1,701	1,684	1,684
Instruments	41	44	49	70	73	64
AR(2)	0.11	0.138	0.114	0.081	0.100	0.132
Hansen's *p*-value	0.51	0.540	0.574	0.522	0.527	0.170

Note: dependent variable, lagged PS variables, digital capability, skilled labour share, R&D intensity, firm size, age, and labour productivity are in natural logs. Time fixed effects are included in all models but coefficients are not reported. Firm sophistication is calculated using $PRODY^k$. Firm size is captured using employment. Standard errors are two-step robust, clustered on firms. Constant is included but coefficient is not reported. AR(1) = 0 for all models.

Source: author, based on Prowess data.

Table 3 presents system GMM results for Equation 2, which regresses average product sophistication on dummy variables for firms with relatively low digital capability and skilled labour;

high digital capability but low skilled labour; and low digital capability but high skilled labour. The results in Table 3 indicate that firms with low digital competence produce significantly less-sophisticated goods than firms with high digital competence. In low digital capability–low skilled firms, the average product sophistication level is roughly 4.5–5.5 per cent lower than that in high digital capability–highly skilled firms.

Similar to the results obtained in Table 2, the models in Table 3 show that the lagged values of firm sophistication, size, and HHI have a positive and significant impact on average product sophistication of Indian GVC firms, while age has a negative impact. Some evidence of R&D intensity boosting product sophistication is also found, albeit weak.

6 Linking digital competence with GVC governance structures

As discussed in Section 2, governance can play a key role in shaping upgrading prospects for supplier firms. Other than linkages based on trade and FDI, Gereffi et al. (2005) identify network governance, namely modular, relational, and captive governance structures. It can be argued that the GMM estimations in Section 5 do not control for such network governance structures that the Indian supplier firms may be operating under. Identifying GVC governance structures is a complex issue, often requiring qualitative information obtained through case studies. Some existing empirical studies have tried to identify and quantify governance by exploiting survey-based information on inter-firm relationships (see, for instance, Brancati et al. 2015 on Italian firms; Saliola and Zanfei 2009 on Thailand), while a few have also used transaction-level data (see Dallas 2015 on Chinese firms). However, such data are not publicly available for Indian firms. Also, firm-level datasets for India, such as Prowess, do not report locations from which intermediates are sourced or where they are exported to. With no data on buyers available, it is difficult to use buyer–supplier information (such as the stability of relationships with foreign firms, involvement of buyers in the production process, number of buyers, etc.) to examine inter-firm relations in India.

An alternative approach is to take a supplier-firm perspective in analysing the type of chain a supplier firm is likely to be a part of. Here, concepts of relative digital capability and share of skilled labour (used in Section 5.2) play a key role. These variables are closely related to the variables used by Gereffi et al. (2005) to identify governance structures, complexity of transactions, codifiability of information, and supplier competence.

Lakhani et al.'s (2013) employment systems framework for GVCs argues that skill and knowledge of employees in the supplier firm is strongly related to the nature of task requirements. For example, complex tasks will be associated with highly skilled workers while relatively simple tasks can be performed by less skilled workers. Similarly, if codifiability of transactions is low (i.e. it is difficult for the lead firm to codify product specifications into contracts or standards), then the supplier base will need to have a more skilled labour force in order to de-codify the transactions and to understand the order requirements. Thus, the average skill level in a firm can be used as an inverse proxy for codifiability of transactions faced by the firm. By this reasoning, relational and hierarchical chains are expected to have a higher share of skilled labour compared to modular and captive chains, since they engage with transactions that are less codifiable.

The other key factor in determining governance is supplier competence or the ability of the supplier to interact with foreign buyers, to receive orders, and to fulfil requirements, which is likely to be positively correlated with the digital capability index that used information on a range of infrastructure assets (communication, plant and machinery, electrical installations, computers, and software assets). This implies that suppliers with relatively higher digital capability indices are more likely being governed under modular or relational linkages.

From the supplier side, this indicates that firms with high digital competence—higher share of both skilled labour and digital capability—are best placed to deal with complex, less codifiable transactions, and are therefore more likely to enter into relational linkages with the lead firm. Mayer (2018) also argues that as transactions become increasingly complex in the digital economy and codifiability decreases, governance structures are more likely to be relational in nature. This would indicate production shifting to suppliers that are more ICT-enabled and have more skilled workforces. With the same reasoning, suppliers with low digital competence—lower share of both skilled labour and digital capability—are likely to be engaged in captive linkages. Similarly, firms with low skilled labour but high digital capability are more likely to participate in modular GVCs, and firms with high skills but low digital capability in hierarchical linkages.

From the governance perspective, the results in Table 3 indicate that Indian firms linked in captive-type GVC governance structures (suppliers with overall low digital competence) are producing significantly less-sophisticated goods than relational suppliers (suppliers with high digital competence). This result is observed to be in line with the empirical findings of Brancati et al. (2015). Using data for Italian manufacturing firms, the authors find that relational suppliers have a higher probability of innovating and introducing new products, whereas no significant impact of linking into other types of chains is found. In the case of the Taiwanese computer industry, Kishimoto (2004) documents product upgrading occurring in relational chains through learning activities; suppliers progressed from producing goods according to the buyer's specification into own-design manufacturing by learning from blueprints supplied by MNEs to local suppliers, and direct interactions with personnel, which enables transfer of tacit knowledge (Guerrieri and Pietrobelli 2006). Taking the case of the electronics industry, Chuang (2015) notes that most firms in captive chains are only able to pursue production capabilities and fail to venture into other areas of product technology (Bell 2009; Bell and Pavitt 1995).

It is worth noting that the average firm-level product sophistication estimated in this paper uses data on products at the HS four-digit level, and therefore records an increase only when firms shift production towards already existing but more sophisticated products or move into significantly new product lines—for example, moving from bicycle production (HS 8712) to motorcycle production (HS 8711) or from women's blouses (HS 6206) to women's overcoats (HS 6202). Moving to a new and significantly more sophisticated product line will require suppliers to develop competencies in product development and design, functions which are performed by the lead firm due to higher rents generated by such activities. Therefore, product upgrading in this paper may also be capturing aspects of functional upgrading. It is widely acknowledged in the GVC literature that opportunities for suppliers in captive chains to functionally upgrade are actively blocked by lead firms.

7 Conclusion and scope of future research

This paper analyses digitalization as a pathway for Indian manufacturing firms to undertake product upgrading and to capture higher value addition in GVCs. Most of the existing literature at the nexus of digitalization and GVCs exists at the macro level and focuses on implications of digital technologies on the extent of GVC participation. There is very limited evidence, particularly empirical, on how digitalization is impacting upgrading of developing countries in GVCs. Furthermore, no study yet has examined implications of digitalization on firm-level upgrading in the context of Indian firms.

Using system GMM estimations on a panel of Indian manufacturing GVC firms in the period 2001–15, the study finds that digital competence can boost product upgrading in Indian GVC firms, thereby helping them to capture higher value-added in GVCs. Digital competence at the firm level is determined by two key factors in the study: (1) digital capability, proxied by a firm-level index on the use of software, technology, and communications assets; and (2) the share of skilled labour. The average product sophistication level in firms with high digital competence is found to be 4.5–5.5 per cent higher than in firms with low digital competence. In addition to digital competence, the study finds empirical evidence of lagged product sophistication, size, HHI, and to some extent R&D having a positive and significant impact on product sophistication in Indian GVC firms, while age is found to have a negative impact.

Analysis in this study is subjected to caveats. First, in terms of measuring firm-level product sophistication, an important caveat is that Prowess only reports product-level data on sales, and not on exports. As a result, the study is only able to calculate the average extent of firm's total sales sophistication, without distinguishing export sophistication from the sophistication of a firm's domestic basket. Second, to construct firm sophistication, products in Prowess have to be matched to products in the HS trade classification. Since there is no existing concordance, a subjective decision has to be taken in some cases. However, the matching method used in this paper was validated by obtaining and comparing concordances used in other studies. Third, controlling for export destinations for firms in the product sophistication regressions could have presented novel insights. For instance, examining the textile industry, Ray et al. (2016) find that Indian textile GVC firms tend to supply a bulk of lower value-added garments to the USA, while exports to the EU tend to be in lower quantities but are more value-added in nature. However, this information is not available at the firm level in Prowess. Fourth, information on buyer–supplier relationships is not available in Prowess; as a result, the study cannot identify explicit governance structures that Indian GVC suppliers are operating under. However, the paper advances the argument that key explanatory variables used in the paper—digital capability and share of skilled labour—are closely linked to governance concepts and are capturing governance structures to some extent. The study also controls for foreign ownership in suppliers, and the use of system GMM further deals with any endogeneity bias resulting from omitted variables, such as those linked to lead firm governance.

Important policy implications emerge from the findings of this study. Currently, India lags behind not only developed countries but many developing economies in terms of digital preparedness for global manufacturing trade (Banga 2019). Digitalization and automation also tend to be concentrated in a few sectors; computers and electronics, metals, pharmaceuticals, and other transport equipment. This paper finds that increasing digital capability at the firm level can boost product sophistication in Indian firms, enabling them to climb the value chain ladder. Both firm-level efforts and national-level policies therefore need to focus on building hard and soft digital infrastructure in manufacturing. While hard digital infrastructure broadly refers to the use of ICT hardware such as computers, routers, sensors, etc., 'soft' infrastructure refers to cloud computing, data policies, intellectual property network capacity, etc. (Banga and te Velde 2018b). Policy interventions are needed to boost manufacturing firms' access to internet and cloud computing services, along with updated laws on technology transfer, data privacy, and source-code sharing. If supplier firms do not build their digital capability, they risk being excluded from future GVCs (Foster et al. 2018).

This paper also finds evidence of the importance of skills for upgrading in GVCs. In the context of digitalization, targeted skill development is key. As pointed out by Banga and te Velde (2018c), 'future' skills in the digital economy include job-neutral digital skills such as data analysis and digital marketing; job-specific digital skills such as coding and mobile app development; and soft skills such as management, communication, collaboration, and analytical thinking. Policy efforts need to explore options for delivering these skills to different audiences; for example, through employer-led training for the workforce and increasing access to both TVET and non-formal TVET for the youth.

Examining the impact of digitalization on other types of upgrading strategies in Indian firms, such as process and functional upgrading, remain key areas for future research, as well as exploring whether digital technologies are impacting upgrading strategies across lead firms and supplier firms differently. This may provide novel insights into whether digital technologies will reinforce/widen existing inequalities in value-added distribution (Szalavetz 2019) or reduce global inequalities.

Horner and Nadvi (2017) also document the growing importance of South–South trade; firms in developing economies are increasingly exporting to other large developing economies, and this has led to the emergence of lead firms in the global South. Digitalization may be a pathway for potential Indian lead firms to establish well-connected and efficient supplier–vendor networks. Empirically exploring the potential of digitalization as a driver of South–South trade thus forms a key topic for future work.

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Appendix

A1 Manufacturing industries for analysis

NIC industry code	NIC industry name
10	Food products
11	Beverages
12	Tobacco products
13	Textiles
14	Wearing apparel
15	Leather and leather products
16	Wood and wood products
17	Paper and paper products
18	Printing and reproduction of media
20	Chemical products
21	Pharmaceuticals
22	Rubber and plastics
23	Non-metallic minerals
24	Basic metals
25	Fabricated metal products
26	Computer, electronics, and optical products
27	Electrical equipment
28	Machinery and equipment
29	Motor vehicles, trailer, and semi-trailer
30	Other transport
31	Furniture
32	Other manufactures

Note: Prowess follows NIC 2008 classification.

Source: author.

A2 Construction of control variables used in regression analysis

Variable	Construction
Deflated sales	Sales value deflated using two-digit industry-specific wholesale price index (WPI). Data on the WPI was collected from the Office of Economic Advisor (OEA) and weighted WPI index series is calculated for two-digit industries (NIC 2008 classification) and spliced according to 2004–05 base year.
Deflated GVA	Nominal sales adjusted for change in inventory and purchase of finished goods to get nominal output. Then expenditure on raw materials and expenditure on stores and spares is subtracted from nominal output to get nominal GVA. Real GVA is obtained by deflating using two-digit industry-specific WPI, the same as for sales.
Export intensity	(Total exports/total sales) × 100
Size	ln (Deflated sales), ln(employment)
Age	Reporting year – incorporation year
Foreign firm	Firms with more than 10 per cent foreign ownership
Labour productivity	Deflated GVA/total persons engaged
Share of skilled labour	(Managerial compensation/total labour compensation) × 100
Import content of exports	(Import of raw materials, capital goods, stores and spares, services/exports) × 100

Source: author.

A3 Matching procedure

Each product in Prowess is defined by a unique 14-digit product code (PRID). Since firms do not adhere to any particular rule when reporting product information, it is observed that many firms report the same PRID but with different product names. Therefore, the first step is to standardize each PRID with a product name. This standardization process is extremely time-consuming, since the names of products reported by the firm can differ in spelling as well as in aggregation. Following Barrows and Ollivier (2016), standardization is done by considering the number of times a product name is reported for a particular code and the product names reported for the PRID code at a more disaggregated level. Standardization of product names is also checked against the PRID names as mapped by Barrows and Ollivier (2016).[14]

The data are then cleaned, whereby all the products that are not classified under the manufacturing sector in Prowess data are removed. This involves removing products classified by Prowess as animal products, agricultural products, services, construction, and irrigation. Products considered in this study are therefore restricted to the following sectors: minerals, fats, oils and derived products, food products, beverages, tobacco products, textiles, leather and leather products, wood and wood products, pulp and paper products, chemicals and chemical products, plastics and rubbers, non-metallic minerals, base metals, machinery, transport equipment and miscellaneous manufactured articles (optical instruments, furniture, toys., clocks, etc.). After data cleaning, 2,977 unique 14-digit product codes are obtained.

These product codes are then matched to the HS four-digit classification from WITS, using product names and numerical ordering. Both classifications have similar names and ordering, allowing 80 per cent of the products in Prowess to be matched with four-digit HS classification (HS 1996). For example, in Prowess the PRID 6070101000000 refers to 'Men's overcoats etc., knitted or crocheted', followed by the PRID 6070102000000—'Women's overcoats, knitted or crocheted'. These names are very easily matched to HS code 6101 'Men's or boys' overcoats, car-coats, etc. knitted or crocheted' and HS 6102 'Women's or girls' overcoats, car-coats, knitted or crocheted' respectively.

As Barrows and Ollivier (2016) point out, mapping Prowess to HS is not merely a matter of harmonizing names as it is not necessarily the case that a Prowess code maps to only one four-digit HS product. Consider the example of 'silk and silk textiles' provided by the authors. While HS distinguishes between three types of silk yarn, Prowess has only one category of silk yarn. Therefore, 'silk yarn' in Prowess is matched to three HS codes. On the other hand, Prowess distinguishes between woven and processed fabrics of silk, while HS lumps them under the same category 5007, 'woven fabrics of silk or of silk waste'. Therefore, both 'woven fabrics of silk' and 'silk fabrics processed' are matched to HS 5007. Having matched products in Prowess to HS products, the validity of the matching is checked using Barrows and Ollivier's (2016) PRID–HS concordance.

[14] PRID codes with standardized names have been obtained from Dr Geoffery Barrows, used in Barrows and Ollivier (2016).

A4 Countries with no missing data on exports or GDP per capita, 2001–14

Albania	Italy	Belize	Malaysia
Algeria	Jamaica	Benin	Maldives
Argentina	Japan	Bolivia	Malta
Armenia	Jordan	Botswana	Mauritius
Australia	Kazakhstan	Brazil	Mexico
Austria	Korea, Rep.	Bulgaria	Moldova
Azerbaijan	Latvia	Burundi	Morocco
Bahamas	Lebanon	Cambodia	Mozambique
Bahrain	Lithuania	Canada	Namibia
Barbados	Luxembourg	Central African Republic	Netherlands
Belarus	Madagascar	Chile	New Zealand
Belgium	Malawi	China	Nicaragua
Finland	Sao Tome & Principe	Colombia	Niger
France	Saudi Arabia	Cote d'Ivoire	Norway
Gambia, The	Senegal	Croatia	Oman
Georgia	Singapore	Cyprus	Paraguay
Germany	Slovak Republic	Czech Republic	Peru
Greece	Slovenia	Denmark	Philippines
Guatemala	South Africa	Dominican Republic	Poland
Guyana	Spain	Ecuador	Portugal
Hong Kong	Sri Lanka	Egypt, Arab Rep.	Romania
Hungary	Suriname	El Salvador	Russian Federation
Iceland	Sweden	Estonia	Rwanda
India	Switzerland	Ethiopia	Samoa
Indonesia	Tanzania	Ireland	Thailand
Israel	United States	Tonga	Uganda
United Arab Emirates	Uruguay	Turkey	Ukraine
United Kingdom	Vietnam	Zambia	

Source: author.

A5 Summary statistics for GVC panel, 2001–15

Variable	Observations	Mean	Std Dev.	Min.	Max.
Real sales	22,274.00	55.17	202.15	0.010	4,773.07
Real GVA	22,274.00	25.85	106.94	0	2,627.62
Digital capability	22,273.00	0.19	0.029	0.001	11.95
Age	22,167.00	27.85	18.82	1.000	136.00
GVC firm	22,274.00	1.00	0.00	1.000	1.00
Foreign firm	22,062.00	0.14	0.35	0.000	1.00

Product sophistication	19,488.00	36.68	11.23	0.001	100.00
Labour productivity	22,166.00	0.01	0.02	0.000	1.21
HHI	22,274.00	0.20	0.21	0.014	1.00
Share of skilled labour	22,274.00	7.82	0.90	5.710	8.83
Total persons engaged	22,166.00	2,523	10,483	1	504,601

Note: real sales and GVA is in Rs. millions.

Source: author, based on Prowess data.

A6 Robustness checks for Table 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. variable	PS_{it}	PS_{it}	PS_{it}	PS_{it}	PS_{it}	$PS_{it} - mgdp$	PS_{it}
L. (PS_{it})	0.795***	0.800***	0.816***	0.775***	0.810***		0.805***
	(0.0446)	(0.0402)	(0.0433)	(0.0458)	(0.0430)		(0.0449)
L.2 (PS_{it})	0.100*	0.0911*	0.0789	0.127**	0.113**		0.0873
	(0.0574)	(0.0504)	(0.0587)	(0.0532)	(0.0566)		(0.0570)
L. ($PS_{it} - mgdp$)						0.797***	
						(0.0466)	
L2. ($PS_{it} - mgdp$)						0.0924	
						(0.0603)	
R&D intensity	0.000375	0.000272	0.000315	0.000116	0.000693	0.000331	0.000414
	(0.000830)	(0.000861)	(0.000818)	(0.000825)	(0.000776)	(0.000817)	(0.000792)
Digital capability	0.0128**	0.0106*	0.0112**	0.0107*	0.0141**	0.0116**	0.0159*
	(0.00623)	(0.00614)	(0.00561)	(0.00588)	(0.00656)	(0.00579)	(0.00962)
Share skilled labour.	0.0168***	0.0168***	0.0169***	0.00955*	0.00872***	0.0153***	0.0147***
	(0.00355)	(0.00365)	(0.00357)	(0.00575)	(0.00254)	(0.00367)	(0.00320)
Firm size	0.0189***	0.0180***	0.0191***	0.0210***		0.0153**	0.0152**
	(0.00605)	(0.00606)	(0.00605)	(0.00623)		(0.00597)	(0.00589)
Foreign shares	–0.000189	–0.000156	–0.000161	–0.000183	–6.22e–05	–0.000167	–0.000129
	(0.000209)	(0.000206)	(0.000200)	(0.000214)	(0.000206)	(0.000207)	(0.000201)
Firm age	–0.0122***	–0.0121***	–0.0122***	–0.0159***	–0.00285	–0.0102**	–0.0100**
	(0.00451)	(0.00439)	(0.00455)	(0.00612)	(0.00318)	(0.00454)	(0.00430)
HHI	0.0216**	0.0215**	0.0214**	0.0196*	0.0193*	0.0243***	0.0221**
	(0.00987)	(0.00902)	(0.00936)	(0.0109)	(0.0101)	(0.00916)	(0.00932)
Labour productivity	0.00228						
	(0.00224)						
Firm sales					0.00386		
					(0.00345)		
ICE		0.00597					
		(0.00580)					
Multi-product firm		–0.000838					
		(0.00364)					
Constant	0.267**	0.278**	0	0.237	0.263*	0	0
	(0.134)	(0.119)	(0)	(0.165)	(0.141)	(0)	(0)

Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR(2)	0.17	0.12	0.09	0.42	0.21	0.09	0.11
Hansen *p*-value	0.47	0.70	0.21	0.21	0.12	0.37	0.42
Observations	9,186	8,903	9,186	9,186	9,188	9,186	9,178
Number of firms	1,736	1,680	1,736	1,736	1,736	1,736	1,735

Notes: dependent variable, lagged PS variables, digital capability, skilled labour share, R&D intensity, firm size, and age are in natural logs. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are robust, clustered on firms. ICE refers to import content of exports and captures magnitude of GVC participation.

Source: author, based on Prowess data.