This version was accepted for publication in the Review of International Political Economy
DOI linked to the published version: doi.org/10.1080/09692290.2022.2152074

Functional division of labour and value capture in global value chains: A new empirical assessment based on FDI data

Andrea Coveri
Department of Economics, Society and Politics, University of Urbino, Italy
Corresponding author; e-mail address: andrea.coveri@uniurb.it

Antonello Zanfei
Department of Economics, Society and Politics, University of Urbino, Italy
E-mail address: antonello.zanfei@uniurb.it

ABSTRACT

This work provides a new empirical assessment of global economic hierarchies and the associated unequal distribution of value between core and peripheral economies. This is accomplished by looking at the functional division of labour induced by the international fragmentation of production and the related value capture dynamics in global value chains (GVCs). To this aim, we introduce and compute an indicator of 'functional specialization' of economies based on their ability to attract Foreign Direct Investment, which allows us to detect the value adding activities in which more than 100 countries have specialized from 2003 to 2018. We show that the most intangible-intensive activities are concentrated in core capitalist economies, while production operations at the lower end of the value chain are mainly the prerogative of low- and middle-income countries. Although China and India have emerged as partial but significant outliers, a substantial persistence of this functional division of labour across world macro-regions is also observed over the period. Most notably, we find that a higher specialization in the most intangible-intensive functions allows countries to capture a greater amount of value from trade in GVCs, thus providing novel empirical support to the 'Smile curve' hypotheses and the underlying 'intellectual monopoly' perspective.

Keywords:
Global Value Chains; Foreign Direct Investment; Functional specialization; Intangible assets; Smile curve

JEL codes:
F14, F21, O19

Word count (all inclusive, except the title page):
11,909 words

1. Introduction

The international fragmentation of production and the rise of global value chains (GVCs) prompted firms to increasingly specialize in specific value chain functions – from those concerning the conception of goods to the ones relating to their fabrication and commercialization (Feenstra, 1998; Sturgeon & Gereffi, 2009). The result has been the emergence of an ever finer international division of labour that occurs mainly at the level of individual production stages within sectors, also called ‘tasks’ (Grossman & Rossi-Hansberg, 2008).

This transformation and the dynamics of value distribution along GVCs have been often associated with the ‘smile curve’ (Shih, 1996; Mudambi, 2008). The latter consists in a stylized representation of the value adding functions that make up the value chain of a product or service and the value capture opportunities that each function would provide to the actors performing them. According to this conception, firms in low- and middle-income countries tend to specialize in functions at the lower end of the value chain, namely production activities such as manufacturing and assembly operations, which would allow them to capture a relatively low amount of value added. Conversely, firms in high-income countries concentrate on pre-production functions such as headquarters, research, design and development activities, as well as post-production ones like branding, marketing, sales and after-sales services, and this would enable them to seize the largest share of value added from production in GVCs.

Durand and Milberg (2020) have recently provided a theoretical foundation to the smile curve hypothesis by extending the notion of ‘intellectual monopoly capitalism’ introduced by Pagano (2014) to the analysis of GVCs. According to these authors, companies that control the intangible assets needed to carry out activities at the upper ends of the value chain are in the position to reap monopoly rents at the expense of actors mainly performing tangible-intensive functions. To the extent that intangibles are largely controlled by transnational corporations located in core capitalist countries, this would lead the latter economies to specialize in functions that make more intensive use of these assets and capture most of the value produced in GVCs.

While we find this theoretical framework convincing and flexible enough to accommodate important developments in the field of International Political Economy, empirical research aimed at testing its predictions is, however, still limited. This state of affairs reflects the influence of standard product-based trade models that have long been prominent in economic research, as well as a lack of micro-data hindering empirical analyses at the functional level.

This work takes a step forward in the empirical assessment of countries’ functional specialization and value capture in GVCs by focusing on the geographical location of Foreign Direct Investment (FDI) in different value chain functions at the global level. By doing so, our empirical investigation adds to the extant literature in three ways.

First, we provide a contribution to the literature on the modern international division of labour by computing the functional specialization of countries in terms of inward FDI; we call this indicator 'functional specialization in FDI'. This metric represents a novel tool to assess global economic hierarchies and the prospects for upgrading of countries at different stages of development.

Second, we focus on the evolution of the FDI-based functional specialization patterns of macro-regions over the first two decades of the XXI century, hence overcoming the lack of longitudinal perspective in the current analyses of the internationalization of business activities. This allows us to analyze whether the international division of labour at the functional level has undergone major shifts before and after the Great Financial Crisis.

Third and finally, we investigate the link between the functional specialization in FDI of the economies and their capability to capture value in GVCs. In particular, we analyze whether the dynamics of functional specialization of economies are significantly associated with the amount of value added embodied in exports that is captured domestically by countries. Our study thus offers the first systematic test at the country level of the specialization-value capture nexus illustrated by the smile curve. Consistent with the monopoly capital perspective, the analysis of this nexus will shed light on the role played by intangible assets in shaping global asymmetries and value appropriation in GVCs.

The remainder of this work is organized as follows. Section 2 outlines the theoretical framework for our analysis. Section 3 reviews the empirical literature on the topic. Section 4 describes data and methods. Section 5 provides evidence on functional specialization in FDI across countries and macro-regions of the world. Section 6 addresses the link between functional specialization and value capture at the global level, and Section 7 discusses the results of our empirical analysis. Section 8 summarizes our main findings and draws some concluding remarks.

2. Intellectual monopoly, GVCs and the smile curve: in search for testable predictions

Building on the analysis of post-World War II Monopoly Capital provided by Braverman (1974), Pagano (2014) advanced the notion of 'Intellectual Monopoly Capitalism' to illustrate how giant corporations took advantage of the commodification of knowledge and its subsequent private concentration to consolidate their market power.[1] In particular, Pagano argued that the crucial aspect of modern monopoly capitalism lies in the inclusion of knowledge among the privately owned capital goods of firms and its direct transformation

[1] In a similar vein, a pioneering contribution by Susan Strange (1994) introduced the concept of 'knowledge structure' to highlight the mechanisms by which structural power can be exercised by those who possess, can limit and decide, at least in part, the conditions of access to knowledge.

into *intangible assets*.[2] As he wrote, '[w]hile the start of industrial capitalism was preceded by the enclosure of lands, Intellectual Monopoly Capitalism has been made possible by a parallel enclosure of ideas in privately owned fields' (Pagano, 2014, p. 8). According to Pagano and Rossi (2009), this enclosure was triggered by the increasingly strong protection of intellectual property rights (IPRs) at the global level and by the introduction of Trade Related Intellectual Property Rights (TRIPS) in particular, which prompted the monopolization of a huge slice of global knowledge, especially in the hands of giant transnational corporations.[3]

Schwartz (2019) argued that the monopoly power due to the increased protection of IPRs is a key factor in the astonishing concentration of profits and stagnating investment rates recorded in the last decades. In particular, Schwartz (2021) contended that the transition from the Fordist economy to what he dubbed the 'Franchise economy' lies in the shift in corporate strategies, from those centered on the search for oligopolistic power based on the control of physical capital organized in vertically integrated production structures, to corporate strategies aimed at the consolidation of monopolistic power based on the control of IPRs and articulated in legally disintegrated, but functionally integrated, production structures.

Durand and Milberg (2020) went beyond the analysis of IPRs as a source of monopoly power by extending the notion of intellectual monopoly capitalism to examine intangibles in GVCs. Their work placed intangible assets at centre stage and helps provide a stronger theoretical foundation for the smile curve hypothesis (Durand & Milberg, 2020, pp. 6-7). The latter was first proposed at the beginning of the Nineties by Stan Shih, the founder of the IT company Acer Inc. headquartered in Taiwan, based on his analysis of the personal computer industry (Shih, 1996). In his view, the more upstream value chain activities – mainly involving research, development and design activities – as well as the more downstream ones – such as branding, marketing, sales and post-sales services – represent the highest value adding stages of the value chain. Hence, firms performing either or both these activities can command a higher value than the ones specialized in the middle segment of the value chain, especially in manufacturing and assembly activities (Mudambi, 2008; Shin et al., 2012).

According to Durand and Milberg (2020), the uneven distribution of value (and hence the steepness of the smile curve) is largely determined by two major drivers which insist respectively on the central part and the higher ends of the curve.

[2] While classical examples of tangible assets are land, building and equipment, intangible assets are mainly constituted by patents, brands, customer data and software. More precisely, intangibles can be grouped in three broad categories, the first one being computerized information (such as software and databases); the second is made of innovative property (such as scientific and nonscientific R&D, copyrights, designs, trademarks); lastly, the third regards economic competencies, including brand equity, firm-specific human capital, networks joining people and institutions, organizational know-how that increases enterprise efficiency, and aspects of advertising and marketing (Corrado et al., 2005).

[3] See Sell & May (2001) for a critical reconstruction of the key 'moments' in the history of intellectual property rights that led to the TRIPS Agreement.

The first driver is the high and increasing global competition among actors performing fabrication activities. The slicing up of value chains across countries has indeed enabled wage arbitrage at the global level, making production offshoring a profitable strategy (Baldwin et al., 2014; Timmer et al., 2014; Bernard & Fort, 2015). Insofar as manufacturing and assembly operations can be carried out by a very large number of firms worldwide, the price of their output falls, and the amount of value they can reap is bound to shrink. These market forces thus generated a strong downward pressure on the middle segment of the curve (Baldwin & Evenett, 2015).[4]

The second driver concerns the key role played by intangibles in GVCs (Chen et al., 2018; UNCTAD, 2018). In particular, Durand and Milberg (2020) stress the strategic command that leading firms orchestrating global production networks – namely Multinational Corporations (MNCs) largely based in high-income countries – maintain over these distinctive assets. They identify four mechanisms through which control over intangibles enables these companies to consolidate their monopoly power. First, the strengthening and broadening of IPR regulations entails a legally enforced proprietary control over standards, technologies, and brands. Second, positive network externalities, strong scale economies (due to huge fixed costs and very low variable costs) and high sunk costs trigger increasing returns on intangibles, thus favoring natural monopoly conditions in knowledge production. Third, the differential rent that stems from the uneven distribution of intangibles assets along GVCs allows leading firms that control the intangible-intensive parts of the chain to receive a disproportionate amount of earnings from managing the production network. Fourth, the ability of giant tech corporations to generate, control and manage data further reinforces their orchestrating power over chain activities.

According to Durand and Milberg (2020), these four mechanisms endogenously promote large asymmetries between high- and low- and middle-income countries in GVCs, allowing the former to increasingly reap monopoly rents while hindering the economic and social upgrading of the latter. Consistently, Rikap (2019) argued that asymmetric market structures along GVCs allow lead firms to derive a significant share of their profits from intellectual rents by leveraging their ability to centralize intangibles while decentralizing and geographically dispersing the most tangible-intensive functions. In other terms, the control of intangibles provides leading firms in GVCs with the opportunity to pursue a form of differential accumulation by capturing high returns while squeezing the profit margins of lower-tier suppliers, mostly based in low- and middle-income economies (Nitzan, 1998; Bair

[4] This phenomenon can also be interpreted as a modern version of the Prebisch-Singer hypothesis (Prebisch, 1949; Singer, 1950), whereby increased competition in fabrication functions, mainly performed by low- and middle-income countries, leads to a deterioration in the terms of trade of manufactures, thus reducing the amount of value captured by these economies from trade in GVCs (Kaplinsky, 2000; Milberg & Winkler, 2013). From this perspective, Gimet et al. (2010) talked of 'immiserizing specialization', which recalls the concept of 'immiserizing growth' proposed by Bhagwati (1958). In fact, while technology transfer from core to peripheral economies can trigger productivity gains in the latter, strong competitive pressure in these value chain segments leads these productivity gains to be capitalized especially by leading firms acting as global buyers (Kaplinsky et al., 2002).

et al., 2021). Moreover, capital income seized by affiliates of MNCs headquartered abroad can be easily moved away from the local economy and transferred to the residence of MNCs' shareholders or directly to offshore jurisdictions (assuming the two do not coincide), fueling the decoupling between the places where value is created and those where it is captured (Seabrook & Wigan, 2017). From this perspective, the legal allocation of intangibles across jurisdictions makes it easier for companies controlling such assets to reduce the tax burden and accumulate wealth, compared to traditional, tangible asset-intensive firms (Bryan et al., 2017).

In conclusion, by consistently integrating the two drivers just recalled – increasing competition in fabrication activities and the race to accumulate and control intangibles – Durand and Milberg's extension of the intellectual monopoly perspective to GVCs provides theoretical grounds for the specialization-value capture nexus illustrated by the smile curve. Two relatively straightforward predictions can be derived from this perspective. The *first prediction* is that high-income economies will specialize in the most intangible-intensive functions at the higher ends of the value chain, while low- and middle-income regions will specialize in performing production operations. The *second prediction* is that a higher specialization in the most intangible-intensive stages of the value chain compared to production functions is positively related to the amount of value that economies can seize domestically from participating in GVCs. However, as shown in the next section, the lack of data at the functional level prevented a systematic empirical testing of these predictions.

3. Review of the empirical literature

The prevalence of scattered empirical evidence on the smile curve led Baldwin and Evenett (2015, p. 34) to write that it is 'based mostly on casual empiricism'. Different approaches have indeed been adopted in the empirical literature.

A first stream of contributions, which provided findings consistent with the smile curve illustration of the specialization-value capture nexus, refers to *case studies* on the GVC of individual products. In 1996 the *Los Angeles Times* published an article showing that the amount of value accruing to China was about 35 cents out of a $9.99 retail price of a 'made in China' *Barbie doll* commercialized by the US-based Mattel Inc. (Tempest, 1996). Afterwards, most case studies focused on electronic products, especially smartphones, finding similar results. Well-known analyses in this regard are those concerning the Nokia N95 (Ali-Yrkkö et al., 2011), the iPod and laptops (Dedrick et al., 2010), the iPhone (Xing & Detert, 2010) and the iPad (Kraemer et al., 2011). Besides smartphones, case studies on other products were also provided – see Kenney (2012) and UNCTAD (2015) for reviews. For example, Kaplan and Kaplinsky (1999) provided a seminal contribution regarding South African peaches.

Another stream of literature made large use of input-output tables at the international level to provide measures on the positioning of countries and industries in GVCs. In particular, Fally (2011) and Antràs and Chor (2013) independently developed indicators of 'upstreamness' ('downstreamness') based on the distance of industries from final demand in terms of the number of stages their products go through (from the economy's primary factors of production). Meng et al. (2020) exploited the upstreamness measure provided by these authors to perform an empirical assessment of the smile curve at country-industry level for several world regions. Their findings show that for several GVCs (e.g., both Chinese and Mexican electrical and optical equipment, as well as German and Japanese automotive) the value added to gross output ratio is higher for the most upstream and downstream industries. Ito and Vézina (2016) found a quadratic fit between the upstreamness measure proposed by Antràs et al. (2012) and the value-added shares of final demand for a sample of 42 manufacturing industries belonging to nine Asian nations from 1990 to 2005, thus providing support to the smile curve illustration of the links between production stages and value appropriation. Similarly, Rungi and Del Prete (2018) matched data on about 2 million European firms with detailed information on the sectoral upstreamness of 4-digit industries they belong to and found a non-linear U-shaped relationship between the latter indicator and the value added to gross output ratio of firms.

Yet, while case studies can hardly provide generalizable results, sectoral measures based on input-output statistics disregard the value adding functions undertaken for the realization of products and services, thus failing to provide a proper test of the determinants of value distribution in GVCs. As stressed by Sturgeon and Gereffi (2009), it is in fact at the functional level that firms' offshoring decisions are taken. Even more important, value chain functions – rather than sectoral outputs positioned differently along the supply chain – differ substantially in their use of intangibles and thus in terms of competitive pressures, cost structure, technological content and skill intensity, giving rise to different opportunities for value capture.

An important advancement was recently accomplished by Timmer et al. (2019). These authors compute the revealed comparative advantage indicators (Balassa, 1965) at country level based on the value added which can be traced back to workers employed in different occupations for the production of exported goods and services. By so doing, they show that a positive correlation exists between the GDP per capita of economies and their specialization in R&D activities, while a negative relationship emerges between GDP per capita and the specialization of countries in fabrication tasks. In a subsequent work building on the same methodology, Buckley et al. (2020) show that the value captured by knowledge-intensive activities – which in their paper include both pre- and post-fabrication activities – has increased faster than that accruing to fabrication activities, with the former accounting for more than 60% of total income in GVCs since 2008, up from 54% in 1995. However, these results are based on a mapping of occupational categories to business activities, with the former only partially reflecting value chain functions.

Finally, Stöllinger (2021) used FDI data to compute the specialization of industries across business activities and investigate the relationship between this figure and the value added to gross output ratio. His empirical analysis – performed on an unbalanced sample of ten manufacturing industries belonging to a number (46 to 61) of countries – confirms that a negative relationship exists between the relative specialization of industries in production activities and his indicator of value capture. While interesting, this work comes with two shortcomings. First and foremost, it is purely cross-sectional, as the author used the average level of the functional specialization of industries over the whole period (2003-2015). This largely limits the analysis, not only because the econometric exercise is performed on a relatively low number of observations (223 to 461), but also because it does not allow to test whether an increasing (decreasing) specialization in functions at the higher ends of the value chain is associated with a growing (declining) capability to capture value in GVCs. Second, the econometric analysis does not account for any measure of participation of industries in GVCs and includes very few control variables, thus risking to amplify the omitted variables bias.

In the next section, we describe the empirical strategy we employ to take another step forward in the empirical assessment of the functional division of labour on a global scale and the associated uneven distribution of value in GVCs.

4. Empirical strategy

4.1 A two-step procedure

Our empirical strategy unfolds in two steps. The first step, carried out in the next section, aims to empirically verify the *first prediction* stemming from the smile curve as conceptualized by the intellectual monopoly perspective, namely that high-income economies specialize in most intangible-intensive functions at the higher ends of the value chain, while low- and middle-income regions are mainly specialized in performing production operations. In other terms, we expect that the functional specialization of high-income economies graphically results in a smiling curve when the former is measured on the vertical axis and functions are sorted from most upstream to most downstream on the horizontal axis. Conversely, we expect that the functional specialization of low- and middle-income countries draws a 'reverse-smile' curve.

In addition, we also provide evidence on the evolution of functional specialization in FDI of world macro-areas over time to assess whether *major shifts* in the functional division of labour at the international level occurred between 2003 and 2018. Observing the dynamics of functional specialization in FDI, therefore, allows us to provide some evidence regarding the persistence of global hierarchies at the functional level.

The second and most important step, carried out in Section 6, aims to empirically test the *second prediction* stemming from the intellectual monopoly perspective underlying the smile curve, namely that a higher specialization in the most intangible-intensive stages of the value chain compared to production functions is positively associated with the amount of value the economies can seize domestically from participating in GVCs.

4.2 Measuring functional specialization in FDI

The empirical investigation outlined shall rely mainly on the fDi Markets database, which collects detailed information on cross-border greenfield investments (i.e., new wholly owned subsidiaries, including joint ventures whenever they lead to a new physical operation) covering all sectors and countries worldwide from 2003 onwards.[5]

A distinctive feature of the fDi Markets database consists in providing information on the value chain function each FDI project is aimed to carry out, together with information on the economic sector targeted by cross-border investments (e.g., automotive, electronics, publishing services, computer programming industries, etc.). It is worth clarifying that value chain functions represent the value adding activities – from headquarters activities, R&D, design and testing to fabrication and assembly operations, up to logistics, branding and sale services – needed to bring an industry product to market and beyond (as functions also include after-sales services).[6]

We exploit this key feature of the dataset and measure the functional specialization of the economies by computing Balassa's (1965) index of revealed comparative advantage based on inward FDI projects related to different value adding functions. We call this 'functional specialization in FDI' (*FS*). This indicator is therefore an inward FDI-based specialization index which captures for the *i*-th country in a given year the relative attractiveness of investments in the *a*-th value chain function. In formal terms, it is calculated as follows:

$$FS_i^a = \frac{\frac{FDI_i^a}{\sum_a FDI_i^a}}{\frac{\sum_i FDI_i^a}{\sum_i \sum_a FDI_i^a}} \tag{1}$$

where the share of inward FDI related to a given function over total inward FDI received by a given economy (the numerator) is normalized according to the share of inward FDI related to the same function over total inward FDI all over the world, namely the global average (the denominator). This indicator takes a value greater than one when the economy shows a relative specialization in (attracting FDI in) a given function, i.e., when the share of FDI aimed to perform a given value adding function for the economy exceeds the average weight of this function for the world as a whole.

This metric can provide a good proxy for the position occupied by countries in the modern international division of labour, which largely occurs at the functional level. Cross-border capital flows have indeed represented a key driver of GVC expansion and contributed to the growing involvement of low- and middle-income countries in global capitalism (Gereffi, 1994). In this context, MNCs' competitive strategies regarding both the location as well as

[5] A short description of the fDi Markets database, including a brief discussion of the nature of the data, can be found in the Online Appendix. Further details on this dataset are reported in Coveri & Zanfei (2022).
[6] The list of value chain functions included in the fDi Markets database is reported by Table A.1 in the Online Appendix.

the quality and amount of direct investment inflows have assumed a growingly crucial role in shaping the global economic landscape in general and the countries' prospects for social and economic upgrading (or downgrading) in particular (Humphrey & Schmitz, 2002; Gereffi et al., 2005; Milberg & Winkler, 2011). At the same time, an important limitation of our approach should also be acknowledged. By relying on FDI data, our measure of functional specialization mainly captures forms of countries' involvement in GVCs in which MNCs exercise control on the offshore production by retaining the ownership of foreign affiliates, while it formally neglects GVCs in which lead firms do not orchestrate transactions through equity participation (Gereffi et al., 2005). It follows that our indicator allows us to draw only a partial picture of the complex involvement of economies in GVCs.[7] Nonetheless, by revealing the ability of countries to attract foreign capital in specific functions relative to others, functional specialization in FDI may at least partially reflect more generally the actual competitive advantages of economies as defined by their current technological capabilities and factor endowments (Nachum et al., 2000; Hausmann & Rodrik, 2003; Waldkirch, 2011). Accordingly, in the next section we use functional specialization in FDI to provide, to the best of our knowledge, the first empirical assessment of the functional division of labour on a global scale.

5. First step: assessing the functional division of labour on a global scale

5.1 Functional specialization in FDI: cross-sectional evidence

To address the first step of our empirical strategy, we break down the world economy into thirteen macro-regions belonging to both high- and low- and middle-income economic areas. High-income economies are EU28, North America, Japan, the Four Asian Tigers, and Australia & New Zealand.[8] Low- and middle-income countries are Non-EU Europe, Russia, the Rest of Asia, the Middle East & North Africa (MENA), Sub-Saharan Africa and Latin America.[9] To account graphically for major outliers like China and India, these countries are considered separately from other economies belonging to the Asian region.

Moreover, we pool data on FDI received by each macro-economic region over the whole period under investigation (2003-2018). In doing this, we classify value adding functions in the three canonical stages of the value chain, i.e., the upstream, production and downstream

[7] FDI and pure market-based exchanges are conceptually at the two opposite poles of GVC governance types, the former being typical of hierarchical GVCs and the latter of GVCs in which exchanges take place primarily through inter-firm arm's length transactions. Between the two, hybrid forms of GVC governance exist (Gereffi et al., 2005; Buckley & Strange, 2015; Strange & Humphrey, 2019). Focusing on FDI, our analysis mostly concerns GVCs of the former type.

[8] The EU28 macro-region – being an aggregate of 28 formally independent high-income economies – shows a very high share of intra-region FDI, making comparisons with other world regions more difficult. Hence, for this macro-region we also compute the functional specialization net of intra-region FDI.

[9] The complete list of countries by macro-region that are included in our analysis is reported by Table A.8 in the Online Appendix.

segment, based on the classification of business functions provided by Sturgeon (2008) and adapted by Crescenzi et al. (2014).[10] Then, we compute the functional specialization in FDI of macro-regions across these three GVC stages using expression (1) illustrated above.[11]

Figures 1 and 2 report the results of this descriptive exercise. As expected, all high-income macro-regions exhibit a higher functional specialization in upstream and downstream functions compared to production activities (fig. 1, panel A), thereby yielding a standard smile curve in most cases. North America is the only partial exception in this regard. While it is highly specialized in upstream activities as expected, its functional specialization index is close to one both in production and downstream activities. Conversely, all low- and middle-income macro-regions – with the partial exception of Sub-Saharan Africa – emerge clearly (de-)specialized in (upstream and downstream) production functions, hence yielding 'reverse-smile' curves (fig. 1, panel B). Figure 2 reports the same statistics for India. This country shows a remarkably high specialization in attracting FDI in the upstream segment, while it is barely specialized (the FDI-based Balassa index is close to one) in production and downstream activities respectively. This descriptive result provides an important nuance in the international division of labour sketched by the smile curve but does not come really unexpected if an intellectual monopoly perspective is taken. In fact, since the turn of the century, India has indeed become an important hub for MNCs active especially in the chemical and pharmaceutical industries, as well as in the software development and ICT segment, mainly because of the country's growing investments in R&D and IT-related infrastructures combined with a large pool of highly skilled, low-wage workers (Lewin et al., 2009; Lema et al., 2015; Crescenzi & Rodríguez-Pose, 2017). One might thus suggest that the Indian case does indeed reflect a history of intellectual capital investment that may allow this country to benefit at least partially from the cumulative dynamics highlighted by Durand and Milberg (2020), hence allowing it to specialize in intangible-intensive activities more than other lower-middle-income countries.

[FIGURE 1 ABOUT HERE]

[FIGURE 2 ABOUT HERE]

[10] While we adopt the convention largely used in the GVC and smile curve literature according to which R&D is assumed to be an 'upstream' function, we are also aware that this is a simplistic way of articulating our discourse. Based on the seminal contribution by Landau and Rosenberg (1986) it has become apparent that in most circumstances innovative activities should be conceived a non-linear, chain-linked process wherein R&D often plays a key role in most if not all production and commercialisation stages along the whole value chain.

[11] The classification of value chain functions according to the GVC stage they can be allocated to is provided by Table A.1 in the Online Appendix, while Table A.2 reports the values of the specialization in FDI of macro-regions across GVC stages.

While suggestive, this descriptive analysis lends itself to two criticisms. First, our aggregation of countries into macro-regions might be seen as too arbitrary. Second, the functional specialization of macro-regions hides important differences across countries. Accordingly, we fully exploit the cross-sectional dimension of our dataset by also performing a simple econometric test using data at the country level. In particular, we estimate a between effects model with time fixed effects using country-level data on a yearly basis to assess whether the relationship between the functional specialization of countries across GVC stages and their development level (proxied by GDP per capita) mirrors the international division of labour predicted by the smile curve.[12]

The results provided in Table 1 seem to further confirm our expectations. Consistent with the interpretive framework discussed in Section 3, we show that a higher GDP per capita appears positively and statistically correlated with a greater functional specialization both in the upstream and downstream GVC segments (columns 1 and 3, respectively). Moreover, the coefficient of GDP per capita in column 3 is far lower than the one reported in column 1, suggesting that a weaker association exists between the former and functional specialization in downstream functions.[13] Conversely, the negative and significant coefficient of GDP per capita reported in column 2 shows that poorer countries are characterized by a greater specialization in attracting FDI into production functions.

[TABLE 1 ABOUT HERE]

It is not our intention to identify the various factors that may contribute to determining the FDI-based specialization of countries across GVC stages, nor to identify causal relationships between the variables of interest. Nonetheless, we think that the descriptive test provided illustrates quite neatly the functional division of labour at the global level, showing that the economic development level of economies is positively associated with their specialization

[12] Note that, as a further refinement of the dataset, we do not consider country-year observations for which the specialization indices are computed over a total number of inward FDI lower than three (this threshold is equal to the total number of inward FDI for the 25th percentile of the distribution of total inward FDI received by low- and middle-income economies, a large share of which draws very few or zero FDI per year). This is a fair adjustment in order to improve the reliability of the sample as it allows to avoid biases in the computation of the specialization indices; conversely, the latter would risk being driven by a very small number of total inward FDI for a series of country-year observations, with the result that some countries would report, in a given function, very large specialization indices in specific years and zeroes for all the remaining years. Also note that setting a higher, more ‘cautious’ threshold – as we will do in the econometric analysis reported in Section 6 – leaves our findings largely unchanged (results are available upon request).

[13] Similarly, Timmer et al. (2019) find a very low (positive) correlation between GDP per capita and functional specialization in marketing activities.

in the upstream and downstream stages of GVCs and negatively with their specialization in the production stages.[14]

In addition, we check our results at a higher level of functional disaggregation by selecting for each GVC stage the most relevant business activities in terms of total number of FDI projects and compute the specialization of countries in attracting FDI in these functions. The functions we focus on are the following: Headquarters (HQ), Research and Development (R&D), Design, Development and Testing (DDT), Manufacturing (Man), Logistics, Distribution and Transportation (LDT), and Sales, Marketing and Support (SMS).[15]

Table 2 shows that the results reported in Table 1 emerge even more clearly when using these more detailed specialization indices as dependent variables. The highest positive and significant coefficient for GDP per capita is found in columns 1 and 2, showing that the correlation is strongest with specialization in the most upstream functions, i.e., headquarters and R&D. Moving to column 3 (DDT), i.e., to the right along the smile curve, the coefficient remains significant and positive, while their magnitude sharply decreases. Column 4 concerns the relationship between GDP per capita and the specialization in manufacturing activities and is the only one reporting a negative and significant coefficient. Finally, columns 5 and 6 again report positive and significant coefficients of GDP per capita, with the magnitude of the former being slightly lower than the latter. Overall, the resulting picture therefore seems to confirm the first prediction stemming from the smile curve on the functional division of labour at the international level.

[TABLE 2 ABOUT HERE]

5.2 Evidence on the functional specialization in FDI over time

The previous cross-sectional analyses do not allow us to account for fluctuations in the functional specialization of the economies that can be occurred over time, especially before and after the Great Financial Crisis. On the one side, the latter hit the high-income countries

---

[14] According to the smile curve hypothesis, the functional specialization of economies is largely associated with their level of economic development. GDP per capita generally shows indeed a strong correlation with several aspects related to the skill intensity, technological capabilities and labour market conditions of economies, thus representing a good proxy for their overall position in the global economic hierarchy. However, GDP per capita of countries is certainly not the only aspect that explains their functional specialization and identifying all determinants of specialization of economies across GVC stages goes beyond the scope of this work. The different factors associated with value capture in GVCs are instead considered in the empirical model introduced in Section 6.

[15] The selected functions, together with a brief description, are reported by Table A.3 in the Online Appendix, while Table A.4 shows the values of the specialization of macro-regions in these functions. Note that we avoid focusing on activities which go under the head of 'ICT & Internet infrastructure' and 'Business services' notwithstanding the high share of FDI related to these functions. The reason is that they constitute rather broad and heterogeneous classes of activities aimed to provide a very large series of telecommunications and business support functions (Sturgeon, 2008).

the hardest, especially the United States and the European Union, paving the way to an even greater role of low- and middle-income economies as recipients of global investment flows across functions (UNCTAD, 2013). On the other side, the crisis was followed by a considerable slowdown in the expansion of production in GVCs for most goods (UNCTAD, 2020), thus reducing the size of the cake to be sliced up at a global scale. The evolution of the functional specialization of macro-regions is thus worth exploring. We illustrate such patterns by computing on a year-per-year basis our indicator of functional specialization for the whole group of high-income economies, the whole group of low- and middle-income economies, as well as for China and India alone.

Figure 3 shows that high-income countries have proceeded to de-specialize in production activities, with an acceleration in the years of deep crisis. This pattern corresponds quite symmetrically to a higher involvement of lower-income world areas as fabrication hubs (Figure 5). Among the most intangible-intensive FDI, the greater increase in specialization can be observed for upstream functions in the case of high-income countries, mainly driven by FDI in HQ, R&D and DDT activities (see Fig. A.1 in the Online Appendix); conversely, low- and middle-income economies are characterized by rather stable de-specialization patterns in upstream activities and constantly show even lower values when considering the HQ, R&D and DDT functions (Fig. A.3 in the Online Appendix). Even in the case of the most dynamic middle-income Asian economies, i.e., China and India, what is remarkably increasing is only the specialization in production operations (Figure 4). In particular, China confirms and consolidates its profile as the largest attractor of FDI in production, showing an increasing specialization in these activities up to 2014, which settles in the following years around a value of 1.5 (Panel A). Nonetheless, since 2006 this country also reports a value of the specialization index in upstream functions which fluctuates around one. Amid the great financial crisis, India appears to have significantly diminished its once remarkable capability to attract FDI in upstream activities, although in 2018 this country still reports a specialization in these high value-added functions greater than in production ones (Panel B).[16]

With the partial exception of China and India, global economic hierarchies thus appear to largely persist and even strengthen over time. In this respect, the Great Financial Crisis seems to have further consolidated the deep functional division of labour between core and peripheral areas of the world.

[FIGURE 3 ABOUT HERE]

[FIGURE 4 ABOUR HERE]

[16] As regards the index of specialization in logistic functions, a decreasing trend is found for China (Fig. A.2 in the Online Appendix, Panel A) while India shows fluctuating values but always well below one.

[FIGURE 5 ABOUT HERE]

6. Second step: assessing the link between functional specialization in FDI and value capture in GVCs

In this section we test whether, in line with the intellectual monopoly perspective, a higher specialization of countries in the most intangible-intensive segments of the value chain is positively related to value capturing in GVCs.

Several different measures have been employed by the empirical literature to assess value capture in GVCs. They span from total value added (Kummritz et al., 2017) and labour productivity of industries and countries (Kummritz, 2016) to the value added to gross output ratio at both firm (Rungi & Del Prete, 2018) and industry level (Stöllinger, 2021), from the labour productivity in exports (Pahl & Timmer, 2020) to the forward to backward linkages ratio of industries (Jona-Lasinio et al., 2019).

We follow Kowalski et al. (2015) and measure value capture in GVCs by using the domestic value added embodied in exports (DVA) per capita. This indicator stems from the decomposition of countries' gross exports in their domestic and foreign value adding components and its calculation derives from matrix manipulations applied to Inter-Country Input-Output (ICIO) tables (Koopman et al., 2014).

The reasons which lead us to employ this indicator are the following. First, the domestic value-added content of exports can be regarded as a measure of the gains that countries capture domestically from trade in GVCs. In fact, and differently from total value added, this indicator focuses on the amount of value added (encompassing both gross profits and employee wages) that is retained by domestic actors involved in export chains. More precisely, this indicator allows to capture the economic results of exporting for domestic agents, since it includes the value added captured by domestic firms directly exporting, together with value added generated by all other domestic firms indirectly contributing to exports of the former; by the same token, it excludes value added imported from abroad, i.e., the value added content coming from foreign producers which is embodied in imported intermediates used by domestic, direct and indirect, exporting firms. In this sense, the domestic value added in exports measures the value added captured by domestic firms participating to the country's export chains. Given that our analysis is mainly concerned with value capture in GVCs, we regard domestic value added in exports as the most suitable dependent variable to be used in our empirical investigation.

Second, data on domestic value-added content of exports are available for a wide range of world economies, thus allowing us to include in our sample a very large number of low-income countries together with high-income ones; consequently, this indicator perfectly fits our objective of studying value capture in GVCs in a truly global perspective.

Formally, we estimate the following regression equation:

$$DVA\ per\ capita_{i,t} = \beta_0 + \beta_1 RFS_{i,t} + \beta_2 X_{i,t} + \beta_3 GVC_{i,t} + \beta_4 Institutions_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

The dependent variable (*DVA per capita*$_{i,t}$) is the domestic value added embodied in exports divided by the population size for country *i* in year *t*. Data on DVA are drawn from the UNCTAD-Eora GVC Database (Casella et al., 2019), which also offers a 1990-2018 time series for the other GVC indicators employed in our analysis (see below).

Our key regressor is what we call the Relative Functional Specialization (*RFS*) index, namely a composite indicator which jointly accounts for the level of functional specialization of the economies in both upstream, production and downstream stages of the value chain. The *RFS* index is computed as follows:

$$RFS_{i,t} = \frac{FS_{i,t}^{production}}{FS_{i,t}^{upstream} + FS_{i,t}^{downstream}} \quad (3)$$

where $FS_{i,t}^{a}$ is the index of functional specialization in FDI as computed by expression (1) reported in Section 4.3 and related to the *a*-th GVC stage (see Table A.1 in the Online Appendix).[17]

Although we do not identify causal relationships among the variables under investigation, we make use of a series of precautions to better detect the association between the magnitudes of interest. First, we estimate our empirical model in log terms to mitigate heteroskedasticity and increase the efficiency of the fixed effects estimator. We hence take the natural logarithm of the *RFS* index, so that it may be written as:

$$ln(RFS_{i,t}) = ln\left(FS_{i,t}^{production}\right) - ln\left(FS_{i,t}^{upstream} + FS_{i,t}^{downstream}\right) \quad (4)$$

As a robustness check, we also compute a second version of the *RFS* index by introducing a correction which consists in adding a constant equal to one to both the numerator and denominator. This correction, which can be found quite usually in the literature, is aimed to allow the calculation of the *RFS* index also for those observations reporting zeroes at the denominator (i.e., showing an *FS* equal to zero in both upstream and downstream stages of the value chain). This corrected version of the *RFS* index, which we label *RFSc*, is computed as follows:

$$RFSc_{i,t} = \frac{1 + FS_{i,t}^{production}}{1 + FS_{i,t}^{upstream} + FS_{i,t}^{downstream}} \quad (5)$$

and is likewise included in our empirical model in logarithmic terms.

[17] The *RFS* index differs from the production specialization index used by Stöllinger (2021) since the latter indicator does not account for the evolution of functional specialization, i.e., it does not vary over time.

Moreover, $X_{i,t}$ includes country-year variables controlling for: (i) the (logarithm of) the total number of inward FDI projects, which measures the overall attractiveness of economies in terms of foreign investments; (ii) the (logarithm of) GDP per capita in constant 2011 PPP$, which proxies the economic development level of countries; (iii) the percentage share of value added from industry over total GDP, which accounts for the economic structure of the economies; (iv) the number of fixed broadband subscriptions per 100 inhabitants, that is a proxy for ICT-based technology. Data for these variables are taken from the World Bank's World Development Indicators (WDI) database, except for the number of FDI projects that is drawn from fDi Markets.

Further, we account for the GVC participation of economies by including in our model selected trade-in-value-added variables. The first indicator, which we refer to as *GVC position index*, was proposed by Koopman et al. (2010) and identifies the relative magnitude of forward and backward GVC linkages of countries as measured by the share of domestic value added in foreign exports – also known as indirect value-added in exports (DVX) – and the share of foreign value added in domestic exports (FVA), respectively.[18] Formally, this indicator is computed as follows:

$$GVC\ position\ index_{i,t} = ln\left(1 + \frac{DVX_{i,t}}{EXP_{i,t}}\right) - ln\left(1 + \frac{FVA_{i,t}}{EXP_{i,t}}\right) \quad (6)$$

where $EXP_{i,t}$ is the value-added content of domestic gross exports (net of double-counting) of country *i* at time *t*. Similarly, the second indicator that we employ in our model, which we refer to as *GVC ratio*, is defined as the logarithm of the simple ratio between forward and backward linkages in GVCs, that is:

$$GVC\ ratio_{i,t} = ln(DVX_{i,t}) - ln(FVA_{i,t}) \quad (7)$$

This second indicator is a non-corrected version of the first one and, more importantly, it is built according to the absolute value of forward and backward GVC linkages instead of their intensity. These indicators capture whether a country is predominantly a net exporter or a net importer of value added, i.e., whether the domestic added value embodied in exports of intermediate goods and services (forward participation) is higher or lower than the foreign added value embodied in country's exports (backward participation). Although these GVC variables are not of focal interest in our investigation, we expect to find a positive relationship between them and the domestic value added embodied in a given country's exports (i.e., our dependent variable) (Jona-Lasinio et al., 2019). In fact, forward linkages measure the amount of domestic value added embodied in a given country's exports which is further re-exported by importing countries. It follows that exports by importing countries constitute a source of demand for the country under observation. Conversely, backward linkages measure the foreign value added embodied in a given country's exports, namely the non-domestically captured value added in a given country's exports. Moreover, since a sort of mechanical

[18] These indicators are built by exploiting the EORA Multi-Region Input-Output tables and details on the methodology and comparisons with other value-added trade databases are reported in Casella et al. (2019).

endogeneity exists between our dependent variable and our GVC indicators, we follow Kowalski et al. (2015) and estimate our model introducing the latter with a one-year lag. To further check the robustness of our results, we also provide estimates which include the absolute (per capita) value of forward and backward GVC linkages and the GVC ratio of the economies with a two-year lag. Notably, by including these variables alongside those on FDI, we strive to jointly consider both forms of involvement of economies in GVCs, namely through both arm's length relationships (the result of firms' international outsourcing strategies) and more hierarchical or captive forms of offshoring (Gereffi et al., 2005).

As further controls, we introduce a set of variables accounting for several institutional factors that capture a country's business climate, as the latter has been shown to influence a country's location attractiveness for foreign investors (Kummritz et al., 2017). In particular, we include all Worldwide Governance Indicators (WGI) provided by the World Bank, covering the following institutional dimensions: corruption control, government effectiveness, political stability, regulatory quality, rule of law, and voice and accountability.

Finally, our model includes both country- (γ_i) and time- (δ_t) fixed effects, with the former allowing us to account for all unobserved time-invariant country-specific characteristics (e.g., geographical location), and the latter for the business cycle (otherwise, time-specific effects that impact on all observed variables would be captured by the error term, giving rise to endogeneity concerns). As usual, $\varepsilon_{i,t}$ is the error term and β_0 stands for the intercept.

The estimates are performed on a sample including 102 countries over the period 2003-2018. This is the number of economies that received at least one FDI per year and that we can therefore observe over the whole period under investigation. This sample selection procedure gives us the possibility to work on a remarkably large and balanced panel dataset while avoiding losing much information, as countries that did not receive at least one FDI per year suffer in any case from missing data for most of the other variables included in our model.

The summary statistics for all variables included in the estimates and the full list of countries are reported in Table A.5 and Table A.8 in the Online Appendix, respectively.

7. Results

Before showing the findings related to the estimate of our main model, Table 3 reports the results of a specification which includes as key regressors the share of inward FDI in the three GVC stages (i.e., upstream, production and downstream functions). More precisely, we use as a baseline the share of FDI in production activities (excluding it from the estimates) and explore the incremental effect of incoming FDI in upstream and downstream functions on our proxy of value capture, i.e., DVA per capita. As expected, we find that FDI shares in these GVC stages report positive and statistically significant coefficients, showing that larger shares of inward FDI in upstream and downstream functions are associated with greater value captured in export chains than FDI in production operations. This is especially true for FDI in upstream activities, whose coefficients are always higher than those for the share of FDI in downstream functions.

Moreover, the total number of FDI projects always reports a negative and significant coefficient, revealing that it is not inward FDI *per se*, i.e., regardless of their composition, that increase value capture capabilities. As expected, variables proxying the development level of countries (GDP per capita), the relative prominence of industry and technological progress are all positively associated with domestic value added in exports. Lastly, both variables proxying the GVC position of economies appear positively and significantly associated with value capture in GVCs, showing that greater forward relative to backward GVC linkages help countries to increase the value-added gains from production in GVCs.

[TABLE 3 ABOUT HERE]

Table 4 reports the results of our preferred model, namely the one including the relative functional specialization (*RFS*) index. Except for column (1), all estimates show a negative and statistically significant coefficient related to this regressor, confirming that a higher specialization in production compared to upstream and downstream functions is associated with a lower amount of value captured domestically in export chains. All other variables confirm both their sign and significance.

Table 5 reports the estimate results for a model which includes among regressors the (per capita) absolute value of both the indirect value added (DVX) and the foreign value added in exports (FVA), as well as the GVC ratio, with all these variables introduced with a two-year lag. Our main findings are largely confirmed, although the GVC ratio turns out still positive but not significant. The coefficients of the two-year lagged variables capturing the (per capita) absolute value of forward and backward GVC linkages emerge to be positive and strongly significant, suggesting that larger indirect exports and imports-to-export are associated with greater domestic value added in exports. In addition, we note that when we account for these GVC variables in absolute terms, the coefficient of total inward FDI loses significance while maintaining a negative sign.

[TABLE 4 ABOUT HERE]

Finally, Table A.6 in the Online Appendix shows the estimate results that we find when including the corrected version of the relative functional specialization index, i.e., *RFSc*, which reduces the variance of our indicator but allows us to perform the estimates on a greater number of observations. Again, all but the first columns report negative and (slightly less) significant coefficients for our key regressor, which are also slightly higher in magnitude than those reported in the previous tables. The coefficients of the other explanatory variables substantially confirm both their sign and their statistical significance. Notably, our findings are largely unchanged also when estimating a model including the *RFSc* index along with the two-year lagged value of forward and backward GVC linkages and of the GVC ratio (Table A.7 in the Online Appendix). The coefficient of the *RFSc* index is found both negative and significant in almost all specifications, while the coefficients related to the forward and backward GVC linkages of the economies remain positive and significant; as before, the GVC ratio reports a positive sign but is not significant.

Overall, our findings thus appear robust to different specifications of the model and the inclusion of different indicators of GVC participation, confirming the greater value capture opportunities associated with stronger specialization in the intangible-intensive segments of the value chain.

[TABLE 5 ABOUT HERE]

8. Conclusions

The notion of 'intellectual monopoly capitalism' refers to a stage of capitalism in which great monopoly power is enjoyed by leading firms that maintain control over pieces of commodified knowledge as intangible assets, and leverage them to seize intellectual rents (Zeller, 2008; Pagano, 2014). This framework has recently been extended by Durand & Milberg (2020) to explain the mechanisms that would lead high-income economies to specialize in the most intangible-intensive functions and capture larger shares of value in GVCs.

We have suggested that the intellectual monopoly perspective provides a sound theoretical foundation for the specialization-value capture nexus illustrated by the smile curve. Using data on over 100 countries for the 2003-2018 period, we have provided a new empirical assessment of the main predictions arising from the intellectual monopoly perspective applied to the analysis of GVCs. This has been done by introducing and computing a measure of functional specialization of world economies based on inward FDI distinguished according to the value chain activities they are aimed to perform.

We have shown that the functional division of labour on a global scale sees the most intangible-intensive activities to be concentrated in core capitalist economies, while production operations at the lower end of the value chain are mainly the prerogative of low- and middle-income macro-regions. Moreover, we have observed that this global economic hierarchy has been consolidating from the turn of the century to date, although China and India have emerged as partial but significant outliers during this period. Notably, this phenomenon is likely to reflect major developments in their national innovation systems, upon which the power of indigenous intellectual monopolies is growing (Xing & Huang, 2021; Rikap, 2022). Finally, and most importantly, we have shown that the volume of value added captured domestically by countries in export chains is strongly associated with their position in the functional division of labour. In particular, we found that higher FDI-based specialization in production compared to the most intangible-intensive value chain stages is negatively related to the amount of value-added economies are able to seize domestically from trade in GVCs.

Although inward FDI draws an incomplete albeit important picture of countries' involvement in GVCs, the evidence provided on the existence of persisting global hierarchies and the associated unequal potential for countries to capturing value raises major concerns about the upgrading opportunities that low- and middle-income economies may derive from participation in GVCs. In this regard, fast-growing countries such as China and India seem to represent more of an exception than a rule, and the developmental policies they have pursued to escape the threat of 'value added erosion' (Caraballo & Jiang, 2016; Kee & Tang, 2016) asks for major attention and should be the object of further research.

References

Ali-Yrkkö, J., Rouvinen, P., Seppälä, T., Ylä-Anttila, P. (2011) Who captures value in global supply chains? Case Nokia N95 smartphone. *Journal of Industry, Competition and Trade*, 11: 263–278.

Antràs, P., Chor, D. (2013) Organizing the Global Value Chain. *Econometrica*, 81(6): 2127-2204.

Bair, J., Mahutga, M., Werner, M., Campling, L. (2021) Capitalist crisis in the "age of global value chains". *Environment and Planning A: Economy and Space*, 53(6): 1253-1272.

Balassa, B. (1965) Trade Liberalisation and "Revealed" Comparative Advantage. *The Manchester School*, 33(2): 99–123.

Baldwin, R. E., Evenett, S. J. (2015) Value creation and trade in 21st century manufacturing. *Journal of Regional Science*, 55: 31-50.

Baldwin, R. E., Ito, T., Sato, H. (2014), "Portrait of Factory Asia: Production networks in Asia and its implications for growth – the 'smile curve'", IDE-JETRO Joint Research Program Series, No. 159, http://www.ide.go.jp/English/Publish/Download/Jrp/pdf/159_cover.pdf

Bernard, A.B., Fort T.C. (2015) Factoryless goods producing firms. *American Economic Review*, 105: 518–523.

Bhagwati, J. (1958) Immiserizing Growth: A Geometrical Note. *Review of Economic Studies*, 25: 201–205.

Braverman, H. (1974) *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. New York, Monthly Review Press.

Bryan, D., Rafferty, M., & Wigan, D. (2017) Capital unchained: finance, intangible assets and the double life of capital in the offshore world. *Review of International Political Economy*, 24(1): 56-86.

Buckley, P.J., Strange, R., Timmer, M.P., de Vries, G.J. (2020) Catching-up in the global factory: Analysis and policy implications. *Journal of International Business Policy*, 3: 79–106.

Caraballo, J.G., Jiang, X. (2016) Value-Added Erosion in Global Value Chains: An Empirical Assessment. *Journal of Economic Issues*, 50(1): 288-296.

Casella, B., Bolwijn, R., Moran, D., Kanemoto, K. (2019) Improving the analysis of global value chains: the UNCTAD-Eora Database. *Transnational Corporations*, 26(3): 115-142.

Chen, W., Los, B., & Timmer, M.P. (2018). Factor incomes in global value chains: The role of intangibles. NBER Working Paper, No. 25242.

Corrado, C., Hulten, C., Sichel, D. (2005) Measuring capital and technology: An expanded framework. In: Corrado, C., Haltiwanger, H., Sichel, D. (eds) *Measuring Capital in the New Economy*. Chicago, IL: University of Chicago Press, pp.11–46.

Coveri, A., Zanfei, A. (2022) Who wins the race for knowledge-based competitiveness? Comparing European and North American FDI patterns. *Journal of Technology Transfer*. DOI: doi.org/10.1007/s10961-021-09911-z

Crescenzi, R., Pietrobelli, C., Rabellotti, R. (2014) Innovation drivers, value chains and the geography of multinational corporations in Europe. *Journal of Economic Geography*, 14: 1053–1086.

Crescenzi, R., Rodríguez-Pose, A. (2017) The Geography of Innovation in China and India. *International Journal of Urban and Regional Research*, 41(6): 1010-1027.

Dedrick J., Kraemer K.L., Linden G. (2010) Who profits from innovation in global value chains? A study of the iPod and Notebook PCs. *Industrial and Corporate Change*, 19:81–116.

Durand, C., Milberg, W. (2020) Intellectual monopoly in global value chains. *Review of International Political Economy*, 27(2): 404–429.

Fally, T. (2011) On the Fragmentation of Production in the US. Mimeo, University of Colorado-Boulder, https://www.etsg.org/ETSG2011/Papers/Fally.pdf

Feenstra, R.C. (1998) Integration of trade and disintegration of production in the global economy. *Journal of Economic Perspectives*, 12: 31–50.

Gereffi, G., Humphrey, J., Sturgeon, T. (2005) The governance of global value chains. *Review of International Political Economy*, 12: 78–104.

Gereffi, G., Korzeniewicz, M. (1994) *Commodity Chains and Global Capitalism*. Westport, CT: Praeger.

Gimet, C., Guilhon, B., Roux, N. (2010). Fragmentation and immiserising specialisation: the case of the textile and clothing sector. Available at: https://halshs.archives-ouvertes.fr/halshs-00464393

Grossman, G.M., Rossi-Hansberg, E. (2008) Trading tasks: a simple theory of offshoring. *American Economic Review*, 98: 1978–1997.

Humphrey, J., Schmitz, H. (2002). How does insertion in global value chains affect upgrading in industrial clusters? *Regional Studies*, 36(9): 1017–1028.

Ito, T., Vézina, P.L. (2016) Production fragmentation, upstreamness, and value added: Evidence from Factory Asia 1990–2005. *Journal of the Japanese and International Economies*, 42: 1-9.

Jona-Lasinio, C., Manzocchi, S., Meliciani, V. (2019) Knowledge based capital and value creation in global supply chains. *Technological Forecasting and Social Change*, 148: 119709.

Kaplan, D., Kaplinsky, R. (1999) Trade and industrial policy on an uneven playing field: The case of the deciduous fruit canning industry in South Africa. *World Development*, 27(10): 1787–1801.

Kaplinsky, R. (2000) Globalisation and Unequalisation: What Can Be Learned from Value Chain Analysis? *Journal of Development Studies*, 37(2): 117-146.

Kaplinsky, R., Morris, M., Readman, J. (2002). The globalization of product markets and immiserizing growth: lessons from the South African furniture industry. *World Development*, 30(7): 1159–77.

Kee, H.L., Tang, H. (2016) Domestic Value Added in Exports: Theory and Firm Evidence from China, *American Economic Review*, 106(6): 1402-36.

Kenney, M. (2012) Where is value in value networks? In: Breznitz, D., Zysman, J. (eds) *21st century manufacturing*. United-Nations Industrial Development Organization (UNIDO), Vienna, pp. 13–36.

Koopman, R., Powers, W., Wang, Z., Wei, S.-J. (2010) Give Credit Where Credit Is Due: Tracing Value Added in Global Production Chains. NBER Working Paper, No. 16426.

Koopman, R., Wang, Z., Wei, S.-J. (2014) Tracing value-added and double counting in gross exports. *American Economic Review*, 104: 459–494.

Kowalski, P., López-Gonzalez, J., Ragoussis, A., Ugarte, C. (2015) Participation of Developing Countries in Global Value Chains. OECD Trade Policy Papers, No. 179, OECD Publishing, Paris.

Kraemer K.L., Linden G., Dedrick J. (2011) Capturing Value in Global Networks: Apple's iPad and iPhone. Unpublished work. Available at: http://economiadeservicos.com/wp-content/uploads/2017/04/value_ipad_iphone.pdf

Kummritz, V. (2016) Do Global Value Chains Cause Industrial Development? CTEI Working Papers, No. 01-2016, Centre for Trade and Economic Integration, The Graduate Institute.

Kummritz, V., Taglioni, D., Winkler, D. (2017) Economic upgrading through global value chain participation: Which policies increase the value added gains? World Bank Policy Research Working Paper, No. 8007. Washington, DC: The World Bank.

Landau, R., Rosenberg, N. (1986) *The Positive Sum Strategy: Harnessing Technology for Economic Growth*. Washington, DC: National Academy of Sciences.

Lema, R., Quadros, R., Schmitz, H. (2015) Reorganising global value chains and building innovation capabilities in Brazil and India. *Research Policy*, 44(7): 1376-1386.

Lewin, A.Y., Massini, S., Peeters, C. (2009) Why are companies offshoring innovation? The emerging global race for talent. *Journal of International Business Studies*, 40(6): 901-925.

Meng, B., Ye, M., & Wei, S.-J. (2020) Measuring Smile Curves in Global Value Chains. *Oxford Bulletin of Economics and Statistics*, 82(5): 988-1016.

Milberg, W., Winkler, D. (2011) Economic and social upgrading in global production networks: Problems of theory and measurement. *International Labour Review*, 150(3-4): 341–365.

Milberg, W., Winkler, D. (2013) *Outsourcing Economics. Global Value Chains in Capitalist Development*. Cambridge University Press, Cambridge.

Mudambi, R. (2008) Location, control and innovation in knowledge-intensive industries. *Journal of Economic Geography*, 8: 699-725.

Nitzan, J. (1998) Differential Accumulation: Towards a New Political Economy of Capital. *Review of International Political Economy*, 5(2): 169-216.

Pagano, U. (2014) The crisis of intellectual monopoly capitalism. *Cambridge Journal of Economics*, 38(6): 1409–1429.

Pagano, U., Rossi, M. A. (2009) The Crash of the Knowledge Economy. *Cambridge Journal of Economics*, 33(4): 665–683.

Pahl, S., Timmer, M.P. (2020) Do Global Value Chains Enhance Economic Upgrading? A Long View. *Journal of Development Studies*, 56(9): 1683-1705.

Prebisch, R. (1949) *Economic Survey of Latin America 1948*. New York, United Nations.

Rikap, C. (2019) Asymmetric Power of the Core: Technological Cooperation and Technological Competition in the Transnational Innovation Networks of Big Pharma. *Review of International Political Economy*, 26(5): 987-1021.

Rikap, C. (2022) Becoming an intellectual monopoly by relying on the national innovation system: the State Grid Corporation of China's experience. *Research Policy*, 51(4): 104472.

Rungi, A., Del Prete, D. (2018) The smile curve at the firm level: Where value is added along supply chains. *Economics Letters*, 164: 38–42.

Seabrooke, L., & Wigan, D. (2017) The governance of global wealth chains. *Review of International Political Economy*, 24(1): 1-29.

Sell, S., & May, C. (2001) Moments in Law: Contestation and Settlement in the History of Intellectual Property. *Review of International Political Economy*, 8(3): 467-500.

Shih, S. (1996). *Me-too is not my style: Challenge difficulties, break through bottlenecks, create values*. Taipei: The Acer Foundation.

Shin N., Kraemer K.L., Dedrick J. (2012) Value capture in the global electronics industry: Empirical evidence for the smiling curve concept. *Industry and Innovation*, 19(2): 89-107.

Singer, H.W. (1950) The Distribution of Gains between Investing and Borrowing Countries. *American Economic Review*, 40(2): 473–85.

Stöllinger, R. (2021) Testing the Smile Curve: Functional Specialisation and Value Creation in GVCs. *Structural Change and Economic Dynamics*, 56: 93-116.

Strange, S. (1994) *States and Markets*. London: Pinter, 2nd edition.

Sturgeon, T. (2008) Mapping integrative trade: conceptualising and measuring global value chains. *International Journal of Technological Learning, Innovation and Development*, 1:237–257.

Sturgeon, T., Gereffi, G. (2009) Measuring success in the global economy: international trade, industrial upgrading, and business function outsourcing in global value chains. *Transnational Corporations*, 18: 1–35.

Schwartz, H. M. (2019) American Hegemony: Intellectual Property Rights, Money, and Infrastructural Power. *Review of International Political Economy*, 26(3): 490–519.

Schwartz, H. M. (2021) Global secular stagnation and the rise of intellectual property monopoly. *Review of International Political Economy*. DOI: 10.1080/09692290.2021.1918745

Tempest, R. (1996) Barbie and the world economy. Los Angeles Times, September 22. https://www.latimes.com/archives/la-xpm-1996-09-22-mn-46610-story.html

Timmer, M.P., Erumban, A.A., Los, B., Stehrer, R., de Vries, G.J. (2014) Slicing up global value chains. *Journal of Economic Perspectives*, 28: 99–118.

Timmer, M.P., Miroudot, S., de Vries, G.J. (2019) Functional specialisation in trade. *Journal of Economic Geography*, 19(1): 1–30.

UNCTAD (2013) *World Investment Report 2013. Global Value Chains: Investment and Trade for Development.* United Nations.

UNCTAD (2015) *Tracing the value added in global value chains: product-level case studies in China*. United Nations.

UNCTAD (2018) *Trade and Development Report 2018. Power, platforms and the free trade delusion*. United Nations.

UNCTAD (2020). *World Investment Report 2020. International Production Beyond the Pandemic.* United Nations.

Xing, Y., Detert, N. (2010) How the iPhone Widens the United States Trade Deficit with the People's Republic of China. ADBI Working Paper 257. Tokyo: Asian Development Bank Institute.

Xing, Y., Huang, S. (2021) Value captured by China in the smartphone GVC– A tale of three smartphone handsets. *Structural Change and Economic Dynamics*, 58: 256-266.

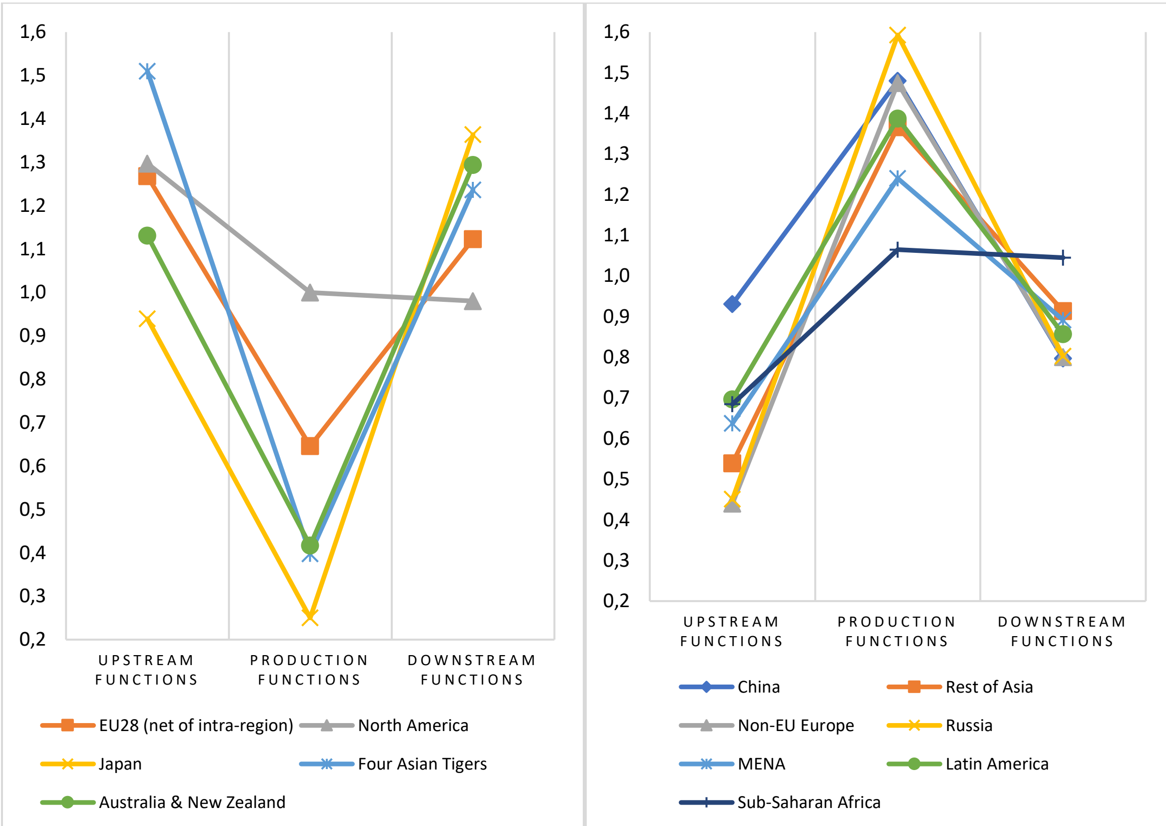
Zeller, C. (2008) From the Gene to the Globe: Extracting Rents Based on Intellectual Property Monopolies. *Review of International Political Economy*, 15(1), 86-115.

Figures and Tables in the Main Text

Figures

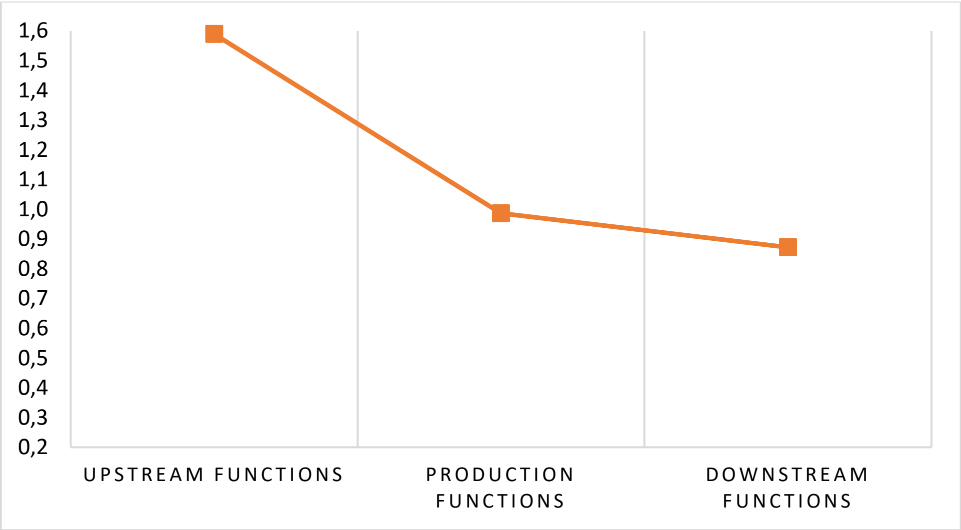
Figure 1. Functional specialization in FDI of high-income (Panel A) and low- and middle-income macro-regions (Panel B)

Panel A Panel B



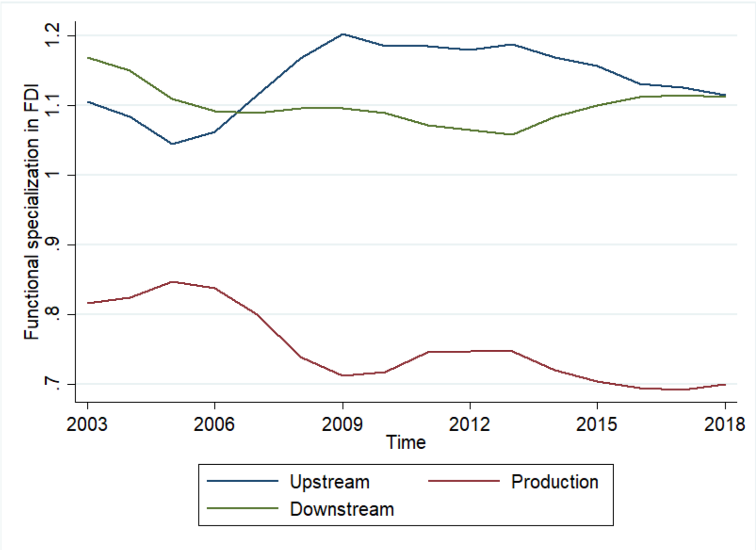
Source: authors' elaboration on data from fDi Markets.

Figure 2. Functional specialization in FDI of India



Source: authors' elaboration on data from fDi Markets.

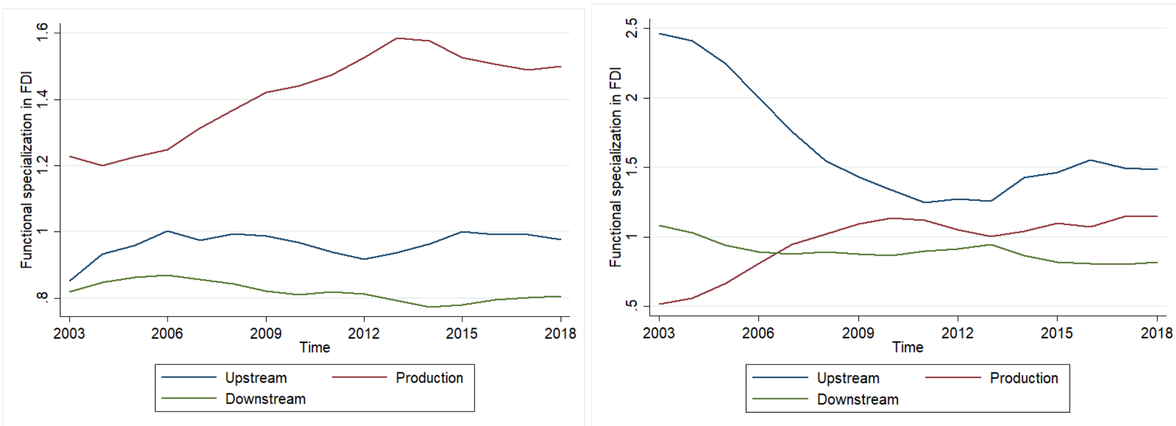
Figure 3. Specialization in FDI across GVC stages of high-income economies, 2003-2018 (3-year moving average)



Source: authors' elaboration on data from fDi Markets.

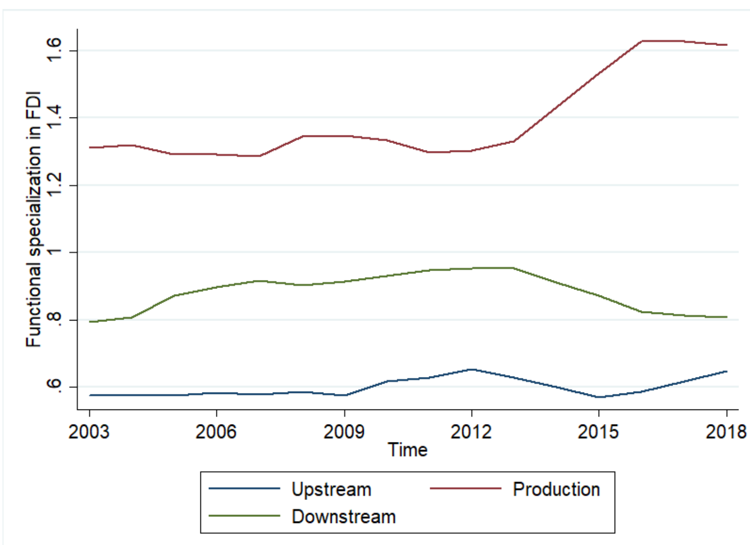
Figure 4. Specialization in FDI across GVC stages of China (Panel A) and India (Panel B), 2003-2018 (3-year moving average)

Panel A. China Panel B. India



Source: authors' elaboration on data from fDi Markets.

Figure 5. Specialization in FDI across GVC stages of low- and middle-income economies, 2003-2018 (3-year moving average)



Source: authors' elaboration on data from fDi Markets.

Tables

Table 1. The relationship between GDP per capita and specialization in FDI of countries across GVC stages

	(1) Upstream	(2) Production	(3) Downstream
GDP per capita	0.0145***	-0.0153***	0.00601***
	(0.00217)	(0.00240)	(0.00135)
Time FE	YES	YES	YES
Observations	1,950	1,950	1,950
R-squared	0.439	0.470	0.411
No. of countries	153	153	153

Note: dependent variables are the functional specialization in FDI of countries in the upstream (column 1), production (column 2) and downstream GVC stage (column 3). GDP per capita is expressed in constant 2011 thousand PPP$ (World Bank data). A constant is included but not reported. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. The relationship between GDP per capita and specialization in FDI of countries across selected functions

	(1) HQ	(2) R&D	(3) DDT	(4) MAN	(5) LDT	(6) SMS
GDP per capita	0.0284***	0.0222***	0.0148***	-0.0103***	0.00895***	0.00978***
	(0.00255)	(0.00385)	(0.00304)	(0.00288)	(0.00317)	(0.00169)
Time FE	YES	YES	YES	YES	YES	YES
Observations	1,950	1,950	1,950	1,950	1,950	1,950
R-squared	0.541	0.260	0.242	0.320	0.274	0.435
No. of countries	153	153	153	153	153	153

Source: authors' elaboration on data from fDi Markets and World Bank.

Note: dependent variables are the functional specialization in FDI of countries in headquarters (column 1), R&D (column 2), design, development and testing (column 3), manufacturing (column 4), logistics, distribution and transportation (column 6) and sales, marketing and support function (column 7). GDP per capita is expressed in constant 2011 thousand PPP$. A constant is included but not reported. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Share of FDI across GVC stages and value capture in GVCs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Base level				*Share of FDI in production functions*			
Share of FDI in upstream func.	0.0985**	0.0876*	0.0862*	0.0875*	0.0825*	0.0839*	0.0806*
	(0.0496)	(0.0503)	(0.0488)	(0.0467)	(0.0455)	(0.0451)	(0.0440)
Share of FDI in downstream func.	0.0512	0.0677**	0.0733**	0.0618*	0.0613**	0.0620**	0.0626**
	(0.0352)	(0.0337)	(0.0314)	(0.0315)	(0.0298)	(0.0304)	(0.0286)
Total inward FDI (log)	-0.0413***	-0.0417***	-0.0452***	-0.0327***	-0.0346***	-0.0368***	-0.0386***
	(0.0138)	(0.00971)	(0.00963)	(0.00959)	(0.00856)	(0.00921)	(0.00848)
GDP per capita (log)	0.826***	0.792***	0.707***	0.730***	0.711***	0.638***	0.622***
	(0.0792)	(0.0857)	(0.0944)	(0.0906)	(0.0940)	(0.0946)	(0.0959)
Industry share (% of GDP)		0.00781***	0.00848***	0.00811***	0.00765***	0.00878***	0.00830***
		(0.00282)	(0.00271)	(0.00279)	(0.00253)	(0.00263)	(0.00242)
Fixed broadband subs. (%)		0.00533***	0.00478**	0.00619***	0.00617***	0.00561***	0.00554***
		(0.00197)	(0.00188)	(0.00202)	(0.00200)	(0.00191)	(0.00186)
GVC position index (lagged)				1.103*		1.153*	
				(0.613)		(0.588)	
GVC ratio (lagged)					0.207*		0.212**
					(0.111)		(0.105)
Constant	-3.494***	-3.368***	-2.614***	-2.722***	-2.537***	-1.901**	-1.750**
	(0.734)	(0.778)	(0.856)	(0.831)	(0.850)	(0.860)	(0.864)
Quality of institutions vars.	NO	NO	YES	NO	NO	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,625	1,529	1,529	1,450	1,450	1,450	1,450
R-squared	0.892	0.896	0.899	0.880	0.880	0.884	0.884
Number of countries	102	102	102	102	102	102	102

Note: The dependent variable is the log of DVA per capita. Robust standard errors clustered at country level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Relative functional specialization (*RFS*) index and value capture in GVCs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RFS index (log)	-0.00944	-0.0107*	-0.0107**	-0.0154***	-0.0152***	-0.0149***	-0.0148***
	(0.00658)	(0.00606)	(0.00518)	(0.00515)	(0.00493)	(0.00458)	(0.00441)
Total inward FDI (log)	-0.0512***	-0.0446***	-0.0487***	-0.0373***	-0.0373***	-0.0419***	-0.0417***
	(0.0141)	(0.0107)	(0.0101)	(0.0107)	(0.0101)	(0.0101)	(0.00978)
GDP per capita (log)	0.800***	0.788***	0.696***	0.712***	0.705***	0.626***	0.623***
	(0.0817)	(0.0886)	(0.0950)	(0.0937)	(0.0962)	(0.0967)	(0.0968)
Industry share (% of GDP)		0.00645**	0.00702***	0.00732***	0.00733***	0.00800***	0.00796***
		(0.00267)	(0.00251)	(0.00267)	(0.00258)	(0.00250)	(0.00244)
Fixed broadband subs. (%)		0.00571***	0.00498***	0.00645***	0.00641***	0.00570***	0.00565***
		(0.00198)	(0.00188)	(0.00211)	(0.00209)	(0.00196)	(0.00192)
GVC position index (lagged)				1.131*		1.197**	
				(0.585)		(0.564)	
GVC ratio (lagged)					0.206*		0.214**
					(0.111)		(0.106)
Constant	-3.139***	-3.200***	-2.383***	-2.446***	-2.401***	-1.686*	-1.676*
	(0.754)	(0.803)	(0.861)	(0.857)	(0.869)	(0.880)	(0.874)
Quality of institutions vars.	NO	NO	YES	NO	NO	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,495	1,412	1,412	1,340	1,340	1,340	1,340
R-squared	0.894	0.899	0.902	0.884	0.883	0.888	0.887
Number of countries	102	102	102	102	102	102	102

Note: The dependent variable is the log of DVA per capita. Robust standard errors clustered at country level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Relative functional specialization (*RFS*) index and value capture in GVCs including two-year lagged GVC variables

	(1)	(2)	(3)	(4)	(5)	(6)
RFS index (log)	-0.0125***	-0.0148***	-0.0151***	-0.0120***	-0.0142***	-0.0148***
	(0.00368)	(0.00523)	(0.00518)	(0.00362)	(0.00452)	(0.00459)
Total inward FDI (log)	-0.00715	-0.0133	-0.0303***	-0.0112	-0.0200*	-0.0359***
	(0.00709)	(0.0105)	(0.0106)	(0.00724)	(0.0102)	(0.00984)
GDP per capita (log)	0.324***	0.550***	0.668***	0.285***	0.474***	0.585***
	(0.0702)	(0.0769)	(0.0905)	(0.0736)	(0.0810)	(0.0920)
Industry share (% of GDP)	0.00740***	0.00384*	0.00664***	0.00743***	0.00414**	0.00691***
	(0.00156)	(0.00204)	(0.00240)	(0.00157)	(0.00196)	(0.00230)
Fixed broadband subs. (%)	0.00416***	0.00689***	0.00818***	0.00385***	0.00640***	0.00726***
	(0.00129)	(0.00246)	(0.00222)	(0.00127)	(0.00234)	(0.00202)
DVX per capita (log) $^{\varphi}$	0.512***			0.501***		
	(0.0632)			(0.0631)		
FVA per capita (log) $^{\varphi}$		0.279***			0.274***	
		(0.0574)			(0.0594)	
GVC ratio $^{\varphi}$			0.165			0.170
			(0.111)			(0.107)
Constant	-0.371	-1.607**	-1.975**	0.0185	-0.881	-1.218
	(0.550)	(0.635)	(0.819)	(0.573)	(0.706)	(0.828)
Quality of institutions vars.	NO	NO	NO	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	1,262	1,262	1,262	1,262	1,262	1,262
R-squared	0.899	0.861	0.853	0.901	0.865	0.858
Number of countries	102	102	102	102	102	102

Note: The dependent variable is the log of DVA per capita. $^{\varphi}$ These variables are two-year lagged. Robust standard errors clustered at country level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.