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Abstract

It is now well established that complex economies with sophisticated export specialization experience higher income and economic growth levels. A group of countries, including those in Central and Eastern Europe (CEE), have pursued a distinctive and arguably successful economic development strategy, focusing on foreign direct investment and embedding in global value chains (GVCs) in manufacturing. However, while these countries now appear to have a high degree of economic sophistication after considerable modernization, they also face significant challenges in catching up with more developed economies in terms of prosperity. In this paper, we propose that considering the coordination of local and non-local capabilities in the same theoretical framework and empirical application helps to resolve this apparent complexity puzzle. Using a panel dataset covering 67 territories and 45 sectors from 1995 to 2018, we first show that measuring countries' economic complexity based on value-added trade adjusts the resulting country ranking and reduces the measured complexity gap favoring CEE countries. Second, we argue that value-added-based economic complexity needs to be complemented by measures of positions in GVCs to account for access to non-local capabilities. Our results from benchmark regression analyses show that economic complexity and positions in GVCs together offer improved predictive power for income and economic growth. Finally, we show that GVC positions in services are particularly important for economic development but that a related pattern of diversification, whereby CEE countries and factory economies more broadly strengthen their GVC positions in manufacturing activities, is likely to limit their future opportunities for functional upgrading and for achieving highly complex economic structures that would be rooted in local capabilities.

Keywords: capability base, economic complexity, global value chains, upstreamness, downstreamness, economic development.

1 Introduction

The literature on economic complexity documents that the ability to carry out sophisticated economic activities is at the core of the long-term economic development of countries and regions (Hidalgo and Hausmann, 2009; Balland et al., 2022). Successful development paths in this framework involve moving towards more complex and valuable specializations in production or technologies (Petralia et al., 2017; O'Clery et al., 2021; Pinheiro et al., 2022). Singapore, South Korea, or Hungary represent cases where economic complexity has been substantially upgraded over the recent half-century (Pinheiro et al., 2022). Indeed, the economic complexity of export portfolios of selected Central and Eastern European (CEE) countries improved significantly between 1995 and 2020, surpassing a number of developed economies in the rankings (Figure 1).

While transitioning from a planned to a market economy in the 1990s, CEE countries observed substantial increases in their per capita gross domestic product (GDP) accompanying the climb in economic complexity (Califano and Gasperin, 2019; Cieślik and Wciślik, 2020; Pinheiro et al., 2022; Petrović and Matić, 2023). That being said, there is also mounting evidence in the literature concerning the challenges these countries are facing in further upgrading and potentially being stuck in their ability to catch up (Nölke and Vliegenthart, 2009; Bohle, 2018; Gál and Gábor, 2022). This makes these countries an instructive case of economic development with broader relevance to so-called "factory economies". This paper argues that the two sides of this tension represent a complexity puzzle: how can countries ranking high in economic complexity struggle to close the gap in income with more developed economies that are exhibiting lower levels of economic complexity in comparison?

Recently Stojkoski et al. (2023) provided pieces to solving this puzzle by showing that the sophistication of technological knowledge and research activities carried out in countries yields a different economic complexity ranking compared with that of exports. Czechia, for instance, ranked 6th in economic complexity of trade, but 22nd and 34th in complexity of technology and research, respectively. This multidimensional economic complexity offered improved predictive power on economic growth compared with just the economic complexity of trade. The reason, they argue, is that information about the spatial distribution of trade alone may miss out on capability endowments that are necessary for the production of technological and scientific knowledge that nonetheless influence economic growth and development.

Another piece of the complexity puzzle is the role of services. Information on export product sophistication does not take into account the ability and underlying capabilities to carry out services that are increasingly characterizing developed economies. Indeed, Stojkoski et al. (2016) showed that the complexity of services tends to be higher than that of products, which in turn produces a tendency for countries with developed service sectors to rank higher in economic complexity compared with those that are specialized in manufactured goods.

This paper argues that another critical missing piece in the puzzle is the participation and position of countries in global value chains (GVCs). This is because economies are not complex in isolation but as part of a larger system of economic interactions. Thinking about economic complexity in terms of value chains relaxes the assumption that countries are endowed with all necessary capabilities required to carry out specific economic activities (Frenken et al., 2023). Examples like Mexico upgrading in economic complexity through integrating with the value chains of the US (Hidalgo, 2023), or CEE countries with German manufacturing value chains (Ambroziak, 2018; Califano and Gasperin, 2019) point to this direction. Indeed, measuring economic complexity through export already implicitly reflects a country's position in global trade.

Considering value chains and economic complexity jointly has at least two implications. First, a country's economic complexity is better measured by value-added trade sophistication, as it provides more information on the distribution of locally available and borrowed capabilities. Koch (2021) and Koch and Schwarzbauer (2021) showed that economic complexity based on value-added trade produces different rankings and improves the predictive performance of models on economic growth and diversification. And most recently Hernandez-Rodriguez et al. (2023) used domestic value-added content in conjunction with industry-occupation data to reveal patterns of functional upgrading

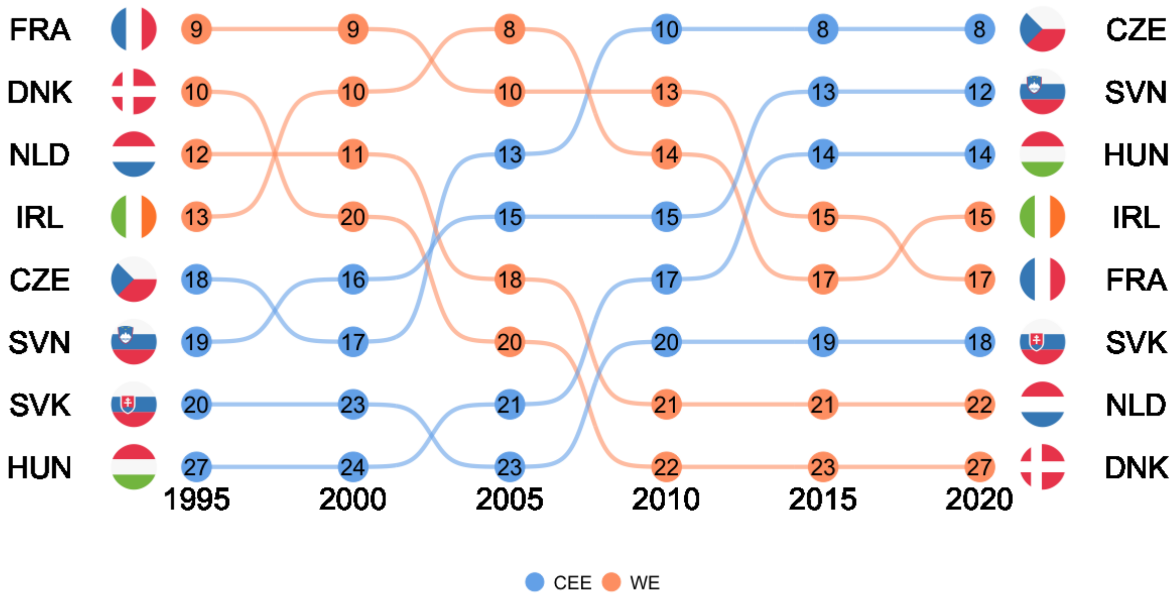

Figure 1: Ranking of select European countries by economic complexity index. Select countries are ordered by their ranking in the economic complexity index based on HS92 6-digit classification, while the numbers in points indicate their ranking considering the whole world. Developing Central-Eastern European countries are denoted by blue and more developed Western European countries by orange. Data source: the Observatory of Economic Complexity (Simoes and Hidalgo, 2011).

and downgrading in EU regions. Second, considering value chains refines the understanding of how economies develop through capability accumulation. Specifically, the development challenge becomes how to leverage existing local and borrowed capabilities to upgrade in value chain position and functions. In this sense, multidimensional economic complexity or the role of services gets us closer to solving the complexity puzzle by revealing bottlenecks in functional upgrading, like missing capabilities to carry out research and development (R&D) or to carry out high-value services. For these reasons, a number of calls have been made recently to bridge the gap between research on value chains and economic complexity (Yeung, 2021; Boschma, 2022; Frenken et al., 2023).

To this end, this paper aims to solve the complexity puzzle by considering, within the same framework, how upgrading in terms of economic complexity and changes in GVC position generate a particular path of economic development. Specifically, combining the literature on economic complexity, evolutionary economic geography, and GVCs (*Section 2*), we use the OECD Inter-Country Input-Output dataset that provides data on more than two decades of value-added trade (OECD, 2021) to measure the economic complexity of countries and industries, including services, as well as their position within GVCs (*Section 3*). Using growth models that are standard in the economic complexity literature, we test the joint impact of economic complexity and GVC position on short and long-term economic growth (*Section 4*). The paper concludes with a discussion of our findings for resolving the complexity puzzle, policy implications, limitations, and remaining open questions (*Section 5*).

In sum, we offer theoretical arguments and empirical application to simultaneously consider co-ordinating local and non-local capabilities when appraising economic development on the basis of economic complexity (Hidalgo and Hausmann, 2009; Balland et al., 2022; Hidalgo, 2023), thereby answering recent calls in the literatures on evolutionary economic geography and global value chains to cross-fertilize between the two (Yeung, 2021; Boschma, 2022; Frenken et al., 2023). We show that shifting from gross exports to value-added exports when measuring economic complexity changes the complexity ranking of countries and decreases the gap introduced above between CEE and WE countries in terms of economic complexity. In this respect, this work reinforces and complements the findings of Koch (2021) and Koch and Schwarzbauer (2021) by the use of a different dataset that covers a longer time period and a larger country sample. We extend this approach to argue that while value-added trade is more suited to capture locally available capabilities, it has to be complemented by considering the access to non-local capabilities through leveraging intermediate stages of production in global value chains. Our analysis of the upstreamness and downstreamness of local sectors shows that these GVC positions add further information to appraising the sophistication of productive specializations. Using benchmark regressions proposed by Hidalgo and Hausmann (2009) and Koch (2021), we show that value-added-based economic complexity and GVC positions together have an increased predictive power on income and economic growth in countries. Hence, we show how the capability base of countries reflected in their economic complexity and GVC positions co-create trajectories of economic development, and they are complementary dimensions in resolving the complexity puzzle. In doing so, our paper connects the literature on economic complexity and GVCs more tightly around the theoretical framework of capabilities.

2 The capability framework of economic development and global value chains

2.1 Economic complexity and economic development

Structural change is key to the economic development of territories over time, as growth rates tend to be unevenly distributed across broad sectors and individual economic activities (Fagerberg, 2000; Fagerberg and Verspagen, 2002). Evidence shows that as countries experience economic growth, there tends to be an increase in the number of economic activities in which they have a comparative advantage (Imbs and Wacziarg, 2003). At the same time, economies develop not just by doing more of the same but also by adding new kinds of activities (Jacobs, 2016). OECD countries, for instance, experienced a growing variety of products in their export basket between 1964 and 2003 (Saviotti and Frenken, 2008).

This unfolding structural change is not random but follows a related diversification pattern whereby countries and regions develop comparative advantage in economic activities that are related to their existing portfolio (Hidalgo et al., 2007; Neffke et al., 2011). This is because territories are endowed with complementary capabilities, *i.e.* a set of heterogeneous inputs and conditions that are combined in the production process into products (Hidalgo and Hausmann, 2009). Following this reasoning, the ability of a country to export a product depends on whether all the necessary capabilities are available in place. The flip side of complementarity in capabilities is the relatedness of products that require more or less overlapping capabilities (Hidalgo and Hausmann, 2009; Frenken et al., 2023). From this perspective, the economic development of places can be understood as the gradual accumulation of (complementary) capabilities that unlock the capacity to produce different products (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011; Neffke et al., 2018; O'Clery et al., 2021; Frenken et al., 2023), giving rise to the pattern of increasing product (related) variety over the course of economic development.

In this framework, products differ from one another in the number of capabilities that need to be combined in order to produce them, resulting in a ladder of complexity where development through capability accumulation unlocks more complex products (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009; Petralia et al., 2017). The economic complexity of a country or region is, in turn, the average complexity of products in this portfolio (Hidalgo and Hausmann, 2009; Frenken et al., 2023). Since the production of more complex products assumes a deeper division of labor to successfully combine complementary capabilities, complex products tend to represent higher value-added (Frenken et al., 2023). Higher economic returns to more complex specialization patterns are reflected in the higher level of income and economic growth of more complex economies (Hidalgo and Hausmann, 2009; Chávez et al., 2017).

2.2 Open questions on economic complexity

The assumption that each capability needs to be present in a country or region for a corresponding productive activity to emerge may be too restrictive. While capabilities are imperfectly mobile, there are ways to combine local with non-local capabilities. The internal networks of multi-location firms (Zhang and Rigby, 2022; Frigon and Rigby, 2022, 2023), collaborative inter-regional knowledge production (Hoekman et al., 2009; Sebestyén and Varga, 2013; Kogler et al., 2023), or the presence of foreign-owned firms (Javorcik et al., 2018; Elekes et al., 2019; Lo Turco and Maggioni, 2019) are examples of channels to access knowledge and capabilities from outside the region. Recently Frenken et al. (2023) argued that the presence of capabilities in a region is neither a necessary nor a sufficient condition for the production of complex products because economic agents can access capabilities outside their region by leveraging intermediate stages of production. Hence, the economic complexity of a territory reflects a capacity to coordinate complex value chains within and across places. The importance of this channel is evidenced by locations with high-complex neighbors that managed to upgrade in economic complexity by joining the value chains of their high-complex neighbor (Hidalgo, 2023).

Putting value chains at the core of thinking about organizing and producing economic complexity has at least two implications. First, the value-added created through combining a set of capabilities will be distributed along the value chain. Since capabilities are indirectly observed through the production portfolios of places, there is a need to consider this when measuring economic complexity through the spatial distribution of productive activities. Indeed, Koch (2021); Koch and Schwarzbauer (2021) showed that measuring economic complexity through the value-added trade of countries improves its predictive power of economic growth and also substantially changes the economic complexity ranking of countries.

Second, the existing capabilities of countries do not necessarily cover the entire value chain required for a product but instead allow for specializing in different functions along this value chain. Value creation through strategic management, R&D, marketing, production, logistics, or distribution functions likely requires different sets of capabilities ranging from research labs and universities to ports and airfields. These different functions capture different shares of the total value created along the chain. From this perspective, economic development in a capability framework entails the functional upgrading into more complex functions along the value chain. Empirical evidence on functions in global value chains in relation to diversification, however, is lacking (Yeung, 2021; Boschma, 2022). A recent study showed for European regions that these tend to diversify into more complex functions in global value chains that are also related to their existing functional specializations (Hernandez-Rodriguez et al., 2023). An important implication is that specializing along the value chain to assembling activities may bottleneck diversification towards higher complexity activities and functions in services that are, on average, more complex than the production of goods (Stojkoski et al., 2016). Next, we turn to the literature on global value chains to develop the connection with economic complexity further.

2.3 Global value chains

In recent decades, several studies emphasized the growing importance of GVCs or global production networks (Gereffi, 1995; Dicken et al., 2001; Gereffi et al., 2001; Henderson et al., 2002; Yeung and Coe, 2015; Coe and Yeung, 2019), and the increasing role of intermediate goods within trade (Feenstra and Hanson, 1996; Hummels et al., 2001; Yeats, 2001; Grossman and Rossi-Hansberg, 2008; Amador and Cabral, 2009; Johnson and Noguera, 2012; Baldwin and Lopez-Gonzalez, 2015). Thereby, the fragmentation of production, or in other words, the vertical specialization, has become more pronounced, and we cannot capture the precise degree of specialization by trade statistics based on gross exports that do not identify where the value-added is created in the production process (Lall, 2000; Johnson and Noguera, 2012; Johnson, 2014). For this reason, value-added-based measurements are needed, which show how much of the gross export was produced domestically and what proportion was produced abroad (Johnson and Noguera, 2012; Johnson, 2014; Koopman et al., 2014; Los and Timmer, 2018). Indeed, the literature revealed that the domestic value-added content of gross export is considerably lower than gross export itself and has decreased in recent decades, especially in emerging economies (Johnson and Noguera, 2012; Timmer et al., 2015; Johnson and Noguera, 2017; Pahl and Timmer, 2019). Furthermore, above a certain level, the strengthening of specialization results in limited growth (Pahl and Timmer, 2019).

A set of recent studies focused on the position of firms, sectors, or countries in GVCs. In addition to identifying the origin of value-added along the value chains, these attempts also analyze the location of firms, sectors, or countries between the starting- and endpoints of the production processes (Antràs et al., 2012; Fally, 2012; Antràs and Chor, 2013; Johnson, 2018). In this respect, the *upstreamness* of a production stage shows its overall distance from the final products or users, while its *downstreamness* shows its distance from the initial stage or raw materials. Using these metrics, the literature shows that the main driving force behind globalization was the fragmentation of production processes into different locations that led to many cross-border transactions in intermediate goods (Wang et al., 2022) and longer production chains (Wang et al., 2017; Fally and Hillberry, 2018).

Another line of the GVC literature focuses on the stages of production where value-added comes from. This approach intertwines the analysis of the domestic value-added content with the upstreamness position in global value chains. The concept of the *GVC smile* (Shih, 1996) emphasizes that in its initial stages (upstream), the production mainly consists of R&D activities, design, and commercialization. The middle stages include fabrication and basic services, while related services, such as marketing, sales, and after-sales services, play a role at the end of the process, i.e. downstream (Mudambi, 2008). While the early and final stages can generate high value-added, the middle phase (mainly fabrication) creates less value-added (Shih, 1996; Mudambi, 2007, 2008). This pattern emerged from a shift in trade in the last half-century, including the relocation of manufacturing to developing countries, while higher value-added activities, such as R&D or marketing, were left in advanced economies (Gereffi et al., 2005). Several studies in recent years have found empirical evidence of the existence of the GVC smile curve (Shin et al., 2012; Ito and Vézina, 2016; Meng et al., 2020; Stöllinger, 2021; Meng and Ye, 2022).

Hence, the literature on GVCs, similarly to the literature on economic complexity, suggests that there is a connection between the productive and functional specialization of places and their economic development. Moreover, this connection may be found at the intersection of the (upstreamness and downstreamness) position of countries and sectors within value chains and the value-added of specific value chain stages. As a more integrative approach to GVCs and economic complexity is still missing, we now turn to forging a more explicit connection between the two.

2.4 Complexity along value chains: placing GVC position in the capability framework

Building on Hidalgo (2023)'s approach to dimensions of economic complexity, specializations in gross export show *what* a given economy produces and exports. Several papers argue that product complexity can be used as a proxy for the technological sophistication of products or activities (Felipe et al., 2012; Javorcik et al., 2018; Poncet and De Waldemar, 2013), which is a valid interpretation as long as only domestically available capabilities are considered. Relaxing the Leontief-type assumption that each place needs to have all the necessary capabilities before being able to produce a specific product shifts the focus instead to *where* the value in export products is created and how places form chains of value creation. As economic complexity arises from combining diverse, rare, and complementary capabilities, this shift implies that complexity is organized and produced by combining locally available capabilities with intermediate stages of production, reflecting complementary capabilities in other places. Hence, the economic complexity embodied in an export product specialization (based on gross export values) has a local and a non-local component. As argued earlier, the local component is evidenced by the value-added export specializations of places, taking into account the distribution of value creation along the value chain. The non-local component is, in turn, evidenced by the complexity of the value chains in which the productive specializations of a territory are embedded. In this way, economic complexity and the underlying building blocks of capabilities would be simultaneously considered geographically (complexity of the productive activity itself) and relationally (complexity of the division of labor between intermediate value chain stages and the distribution of corresponding sets of complementary capabilities). We argue that this is precisely where the literature on GVCs, in general, and on upstreamness and downstreamness, in particular, has much to offer.

Downstreamness is based on the Leontief-inverse of an input-output matrix that describes the structure of the global production network (see formal definitions in section 3.3.2). The inverse matrix offers a way to take into account both direct and indirect input connections between local export sectors with a focus on final demand. By representing the distance between a particular local production stage and the initial inputs, downstreamness captures the multifaceted ways in which earlier stages of production exert influence on a particular local sector. Reframing in terms of local capabilities, on the one hand, complex economic activities are considered to rely on combining a diverse set of complementary capabilities. On the other hand, sectors with high average downstreamness represent a high level of coordination between sets of complementary capabilities distributed across places and stages of production. Places with high economic complexity, in turn, are able to create value-added in a diverse set of rare economic activities that also rely on longer value chains reflected in higher average downstreamness. For these reasons we expect first that sectors with high average downstreamness are more complex. Second, as complex economic activities tend to be more valuable, we expect that countries with higher value-added-based economic complexity and with higher average downstreamness have a higher growth rate.

Upstreamness is based on the Gosh-inverse of the same input-output matrix (see formal definition in section 3.3.2). This inverse matrix offers information on the direct and indirect effects of changes in the supply of a local input sector. Upstreamness is then the distance of a local sector from final demand, and the more upstream a local sector is, the more its output is used by many other local sectors and through many different steps along the value chains, meaning that the local sector in question has an important or influential position in GVCs. In terms of capabilities, this would mean that while an upstream local sector may not in itself be complex (requiring many complementary capabilities), the capabilities it presupposes would be important building blocks throughout value chains. Hence, such upstream local sectors would be critical in building complexity downstream. Based on these arguments, we expect sectors with high average upstreamness not to be complex but expect places with high average upstreamness to have higher returns to the value of their local capabilities in organizing complex value chains and hence a higher growth rate.

2.5 Limits to development in factory economies

While testing these expectations, we pay particular attention to the economic complexity and development of CEE countries as they represent a specific economic development strategy built on foreign direct investment (FDI) (Pavlínek, 2004; Rugraff, 2006; Nölke and Vliegenthart, 2009; Kalotay et al., 2010; Bohle and Greskovits, 2019; Kalotay and Sass, 2021). This strategy brought about an upgrading in economic complexity, at least in the export portfolio of these countries, through integration into GVCs (Gurgul and Lach, 2014; Bohle, 2018). These countries are attractive destinations for multinational companies and foreign capital due to cheap but qualified labor (Nölke and Vliegenthart, 2009; Pavlínek, 2020; Gräbner et al., 2020), favorable labor laws and environmental protection regulations, infrastructural subsidies, and various tax breaks (O'dwyer and Kovalčík, 2007; Drahokoupil, 2008; Bohle, 2009). FDI entered mainly into manufacturing, especially the electronics and vehicle industries (Rugraff, 2006; Nölke and Vliegenthart, 2009; Greskovits, 2014), leading to the relocation of labor-intensive production processes from the core to the periphery in Europe in search for cost reductions (Frigant and Layan, 2009; Jürgens and Krzywdzinski, 2009; Pavlínek, 2020, 2022).

Although this development strategy led to higher growth and convergence in CEE countries

(Awokuse, 2007; Nannicini and Billmeier, 2011; Iyke, 2017; Bohle, 2018), it also contributed to an economic structure dependent on foreign investments and supplier relations (Nölke and Vliegenthart, 2009; Bohle, 2018; Gál and Gábor, 2022). Domestic firms were less able to serve the multinationals, domestic supplier networks did not develop, and the integration of the multinational companies into the CEE countries' economies was less realized (Pavlínek, 2004, 2018). On the other hand, activities such as marketing, financial, strategic decision making, and research and development, in other words, the services are kept in the home countries (Pavlínek, 2018; Gräbner et al., 2020; Pavlínek, 2022). The CEE countries' position in GVCs also reveals that the domestic value-added content of their gross export is small (Johnson and Noguera, 2012; Timmer et al., 2015; Cieślik, 2022) and includes manufacturing rather than related service or R&D activities (Timmer et al., 2019; Buckley et al., 2020; Kordalska and Oliczyk, 2023).

Taken together, these factors limit the possibilities of CEE countries in catching up further with leading European economies, despite the fact that they are able to export highly complex products and are ranked high in economic complexity rankings. We argue that this complexity puzzle can be resolved by disentangling the economic complexity of domestic value-added sector specializations and the GVC positions of these countries and their sectors, thereby accounting for their actual capability bases, as well as the spatial division of labor in how different local capability bases are brought together to organize complex value chains. While CEE countries represent a significant and geographically concentrated example of this development path and the resulting challenges, they are part of a broader class of economic development trajectories, namely "factory economies" like Mexico in the Americas or Malaysia, Thailand, and Vietnam in Asia.

3 Methods and Data

3.1 Data

The primary database used in this study is the OECD Inter-Country Input-Output (ICIO) Data, which provides sector-level supply and use linkages between 67 different territories, including 38 OECD, 28 non-OECD countries, and one "rest of the world" area (OECD, 2021).[1] This data is available annually from 1995 to 2018 and shows the interconnectedness of the countries, broken down into 45 different sectors. For purposes of measuring GVC positions, we also classified these 45 sectors into larger, more aggregated groups, distinguishing the agriculture and raw material sectors (A), the manufacturing and other industry sectors (M), and the service sectors (S). The detailed list of countries, sectors, and their classifications can be found in .

This data is used to calculate the domestic value-added content of exports. Also, the economic complexity of countries and the activity complexity of sectors are built on the input-output data. Both the gross export-based, and the value-added-based (domestic value-added content) versions of the latter indicators are used. Finally, the indicators that reflect countries' and sectors' position in global value chains are based on this data. The methodological details of these calculations are given in the following sections.

In addition to this input-output data, we also use macroeconomic indicators in our empirical analysis, like population, GDP per capita at chained PPPs, capital stock at current PPPs, and human capital index. This macroeconomic data was collected from Penn World Tables (Feenstra et al., 2015).

3.2 Measuring economic complexity

Economic complexity captures a country's available skills, capabilities, and knowledge through its export structure, and it is associated with economic development and growth (Hidalgo and

[1]The database contains input-output data separately for special export zones and the other territories for Mexico and China. We aggregated these into one single area in both cases.

Hausmann, 2009). If a country can produce and export more unique goods in the sense that few other countries can also export them, it signals a more complex economy with higher potential GDP and growth. In their seminal paper, Hidalgo and Hausmann (2009) use the "method of reflection" and the binary form of Balassa's revealed comparative advantage (RCA) (Balassa, 1965) to quantify economic complexity and construct the Economic Complexity Index (ECI). A potential drawback of this method is that the binary RCA may be too sensitive to small changes around unity and does not consider relative distances from this threshold (Davies and Maré, 2021).[2] This study aims to compare economic complexity rankings using different methods to compute them, which calls for a solution that is more sensitive to small changes in relative shares of different activities. For these reasons, we follow Davies and Maré (2021) to calculate economic complexity, which is an extended version of Caldarelli et al. (2012)'s eigenvector approximation method and is referred to as the "fitness" indicator in the literature.

3.2.1 Activity complexity

We follow the method described in Davies and Maré (2021) to calculate economic and activity complexities using the fitness method. This method starts from a locations times activities matrix (the activity matrix) which collects information on the volume of every activity at every location. In our context, the set of locations (C) contains countries, and the set of activities (A) contains export volumes of economic sectors as defined by the global input-output tables (OECD, 2021). Activity a of country c is measured by export volume E_c^a. Country-level and activity-level export volumes are written as $E_c = \sum_{a \in A} E_c^a$ and $E^a = \sum_{a \in A} E_c^a$, respectively. Total global exports are $E = \sum_{a \in A} \sum_{c \in C} E_c^a$. The local share of activity a in country c is

$$LS_c^a = \frac{E_c^a}{\sum_{a \in A} E_c^a}. \tag{1}$$

Relatedness between activities a_i and a_j are calculated as the correlation between these local export shares across locations/countries. Formally, we compute the weighted covariance between the elements of the corresponding vectors $(LS_1^{a_i}, LS_2^{a_i}, ..., LS_{|C|}^{a_i})$ and $(LS_1^{a_j}, LS_2^{a_j}, ..., LS_{|C|}^{a_j})$, where the weights are quantified by the countries' export shares in global export (E_c/E):

$$\begin{aligned}\Omega_{a_i,a_j} &= \sum_{c \in C} \frac{E_c}{E}(LS_c^{a_i} - \sum_{c \in C} \frac{E_c}{E} LS_c^{a_i})(LS_c^{a_j} - \sum_{c \in C} \frac{E_c}{E} LS_c^{a_j}) \\ &= \sum_{c \in C} \frac{E_c}{E}(\frac{E_c^{a_i}}{E_c} - \frac{E^{a_i}}{E})(\frac{E_c^{a_j}}{E_c} - \frac{E^{a_j}}{E}).\end{aligned} \tag{2}$$

Then, covariance is transformed to the $[0, 1]$ interval to write activity relatedness as

$$R_{a_i,a_j} = \frac{1}{2}(\frac{\Omega_{a_i,a_j}}{\sqrt{\Omega_{a_i,a_i}\Omega_{a_j,a_j}}} + 1). \tag{3}$$

$R_{a_i,a_j} = 1$ indicates identical local export shares of activities a_i and a_j for all countries. $R_{a_i,a_j} = 0$ shows that the difference between local and global export shares is the same but with an opposite sign in the case of activities a_i and a_j.[3]

Pairwise activity relatedness values (R_{a_i,a_j}) can be rendered in a relatedness matrix, the row-standardized version of which is defined as follows:

[2]Imagine that the local share of a given activity in a country is above the global share by a little. The RCA of this activity in this country will be 1, but if this share is under the global share by a little, the RCA switches to zero even if the local share changes only slightly. In addition, there is no difference in the RCA if the local activity share is slightly or much above the global share. It is similarly 1 in both cases.

[3]For computational convenience, we need $\Omega_{a_i,a_i} > 0$ to hold for every $a \in A$. Consequently, the sector D97T98 "Activities of households as employers" was omitted from the calculations as this sector has no export for all countries and years.

$$\bar{R}_{a_i,a_j} = \frac{R_{a_i,a_j}}{\sum_{a \in A} R_{a_i,a}}. \tag{4}$$

This defines a Markov chain on activities with transition probabilities determined by the relatedness of different activities. Activity complexity of activity a_i (ACI_{a_i}) is then given by the ith element of the second eigenvector of the row-standardized activity relatedness matrix $\bar{R}$. Finally, the signs of the resulting indicators are adjusted so that activity complexity correlates positively with the weighted mean size ($\sum_{c \in C} E^a_c / E^a E_c$).

3.2.2 Economic complexity

We quantify countries' economic complexity symmetrically to activity complexity. We measure the similarity between countries' export portfolios ($LS^1_{c_i}, LS^2_{c_i}, ..., LS^{|A|}_{c_i}$) by the weighted covariance:

$$\begin{aligned} \Omega_{c_k,c_l} &= \sum_{a \in A} \frac{E^a}{E} (LS^a_{c_k} - \sum_{a \in A} \frac{E^a}{E} LS^a_{c_k})(LS^a_{c_l} - \sum_{a \in A} \frac{E^a}{E} LS^a_{c_l}) \\ &= \sum_{a \in A} \frac{E^a}{E} (\frac{E^a_{c_k}}{E^a} - \frac{E_{c_k}}{E})(\frac{E^a_{c_l}}{E^a} - \frac{E_{c_l}}{E}), \end{aligned} \tag{5}$$

which is then converted to the $[0, 1]$ interval in the same way as activity relatedness in Equation 3. This measures how similar the export portfolios of the countries are relative to a random distribution of export activities. Then, a row-standardized country relatedness matrix is created in line with Equation 4, and the elements of the second eigenvector of this matrix quantify the countries' economic complexity (ECI_c). The signs of the eigenvector elements are adjusted so that economic complexity correlates positively with share-weighted mean activity complexity ($\sum_{a \in A} (E^a_c / E^a) ACI_a$). In order to keep the interpretation intuitive throughout the paper, we refer to the values calculated with this method as the economic complexity of countries and use the shorthand ECI for the sake of brevity.

3.3 Measuring GVC position

Countries' position in global value chains (GVCs) can be measured on the basis of sector-level input-output data, which offers information about supply and use transactions between every sector across countries. In this paper, we quantify these positions in two different ways. First, following Johnson and Noguera (2012), we filter out the domestic value-added content of gross exports. As argued earlier, this is useful because countries use more and more imported inputs as intermediaries in production processes due to globalization, rendering statistics calculated on the basis of gross exports less reliable (Lall, 2000; Johnson and Noguera, 2012; Johnson, 2014). Second, we extend the interpretation of economic complexity by capturing the countries' role in GVCs with respect to their upstream and downstream position in production (Antràs et al., 2012; Fally, 2012; Antràs and Chor, 2013; Johnson, 2018).

3.3.1 Vale-added in trade

Economic activities around the world are increasingly using imported intermediate goods in their production, resulting in a significant share of foreign value-added in their output and exports. This means that an accurate measure of the contribution of domestic skills, capabilities, and knowledge to countries' exports requires a shift in focus from gross exports to their domestic value-added content (Koch and Schwarzbauer, 2021; Koch, 2021). We need to use sector-level global input-output data to filter out foreign-origin value-added from gross export. The input-output matrix W denotes the collection of this data, where the element $W^{a,b}_{c,d}$ is the value of products and services that is transported from sector a of country c to sector b of country d, and $b \in A$, $d \in C$. The gross export of sectors is denoted by E_c^a and calculated as the sum of exported intermediate goods and final consumption. The total output of sector a of country c is denoted by X_c^a, the value-added by V_c^a. Following Johnson and Noguera (2012), the Leontief-inverse (L) is defined first to get domestic value-added content of gross export:

$$L = (I - A)^{-1}, \tag{6}$$

where A is the Leontief-coefficient matrix with elements $A_{c,d}^{a,b} = W_{c,d}^{a,b}/X_c^a$ and I is the identity matrix. An element $L_{c,d}^{a,b}$ of the Leontief-inverse reflects the strength of direct and indirect input flows of different lengths (production stages) from sector a of country c to sector b of country d. Using the Leontief-inverse in Equation 6, the domestic value-added content in gross export ($\hat{E}$) can be written as

$$\hat{E}_c^a = V_c L_c^{a,b} G_c, \tag{7}$$

where V_c is a $1 \times |A|$ vector containing the value-added of all sectors in a given country c, $L_c^{a,b}$ is an $|A| \times |A|$ submatrix of L containing only the domestic elements for country c, and G_c is an $|A| \times 1$ vector with zero elements, expect $G_c^a = E_c^a$. Equation 7 determines the value of the export of a country-sector (c, a), which was produced in that country, with the contribution of domestic production factors.

Finally, we quantify the ratio of domestic value-added content in gross export by

$$DVAC_c^a = \frac{\hat{E}_c^a}{E_c^a}. \tag{8}$$

In the empirical analysis, we calculate economic complexity based on both types of export value (E_c^a and $\hat{E}_c^a$), and use the ratio of domestic value-added content ($DVAC_c^a$) in gross export as a control variable in regressions later on.

3.3.2 Upstreamness and downstreamness

We use the interpretation of GVC position proposed by Johnson (2018), which builds on previous approaches in the literature (Antràs et al., 2012; Fally, 2012; Antràs and Chor, 2013). To give intuition to this measure, assume that all output of a given sector goes to final use. This sector does not contribute to producing other goods and is one step away from final consumption. If all products of the sector are sold to another sector that only produces for final use, then the former sector is two steps away from final consumption. The process can be further continued, and as the production chain grows in this way, the initial sector is found more upstream in the value chains. Considering all possible production stages and their length, weighted by the sales ratio, the total distance between a given sector's production and final consumption can be determined. Johnson (2018) shows that the upstreamness index for all country-sector pairs (c, a) can be written as

$$U = (I - B)^{-1} l, \tag{9}$$

where B is a coefficient matrix with elements $B_{c,d}^{a,b} = W_{c,d}^{a,b}/X_d^b$, and l is a vector of ones (summing vector). The values of U are referred to as the strength of forward linkages in the input-output literature, and $(I - B)^{-1}$ is the Ghosh inverse. In other words, the upstreamness index sums the rows of the Ghosh inverse. We calculate country-level upstreamness indices as a weighted average of sector-level indices for a given country from Equation 9 where the weights are the sectors' size in the domestic economy (X_c/X_c^a).[4]

Similarly to the upstreamness index, we can quantify each sector's downstreamness index. This index measures the average number of steps through which the inputs reach a given industry along

[4]In the case of the breakdown of country-level upstreamness indices to the broad sectors defined earlier (Raw materials and agriculture, Manufacturing and Services) only the weighted values belonging to the given brad sector were added.

the value chains. Following Johnson (2018), the downstreamness index for all country-sector pairs (c, a) is given by

$$D = l'(I - A)^{-1}, \tag{10}$$

where l is a vector of ones, and $(I - A)^{-1}$ is the Leontief inverse from Equation 6. The input-output literature refers to these values as the strength of backward linkages. We quantify the country-level downstreamness indices and those for the broad sectors similar to the upstreamness indices.

As shown in Equations 9 and 10, the upstreamness and downstreamness indicators describing positions in GVCs build on the Leontief- and Gosh-inverses, that provide a sophisticated description of connections within the production network. An element of these matrices reflects how two activities or sectors are connected through direct and indirect transactions or input-output connections. It follows that these elements can be interpreted as a form of pairwise relatedness of activities. While activity relatedness in Equation 3 reflects the latent similarity of capability bases of economic activities, the matrix inverses in Equations 9 and 10 show relatedness through input-output connections. Disentangling the direction of connections towards downstream and upstream activities, this method is able to point out where a given economic activity is located along production processes relative to the location where complexity is dominantly arising within these processes.

Although it seems straightforward to think about U and D as perfect complements, this is not generally the case. Imagine a completely linear production process from raw inputs to final users: in that case, U is the highest at the raw inputs and lowest at the activity that directly serves final demand. On the contrary, D is highest at the final demand serving activity and lowest at the raw inputs. In other terms, one input-output connection is counted either upstream or downstream for a given activity. Once feedback or loops show up in the production network, this clarity disappears as these feedback connections are going to be counted both in the downstream and in the upstream (indirect) connections of specific sectors. This blurs the complementarity between U and D, and the more feedback is found in the network, i.e. the more complex its structure, the higher correlation is going to be observed between U and D.

4 Empirical findings

4.1 Economic complexity in value-added

The development of global value chains has resulted in countries specializing in a limited set of production processes. Consequently, the domestic content of value-added has decreased in overall exports due to the distribution of value-added in the final product along extended value chains.

Figure 2 reflects this process, where the evolution of domestic value-added content (DVAC) of gross exports is shown between 1995 and 2018. The main observation is that the majority of these observations (all three panels) are above the diagonal lines, showing that, on average, the share of domestic value-added in exports has fallen between 1995 and 2018. This is particularly true for CEE countries (see panel B) and the two dominant industries in these countries' export portfolios (see panel C). These findings reinforce that value chains have indeed become longer over time. As a result, countries' and industries' positions within these value chains are expected to be associated with economic development.

As a first step in the empirical analysis, we follow the logic of Koch and Schwarzbauer (2021) and use the value-added content approach to calculate economic complexity. In this case, the revealed comparative advantage (RCA) is based on the domestic value-added content of exports rather than on gross exports per se. We expect that this approach better reflects countries' positions in global value chains and contributes to solving the complexity puzzle.

We calculate economic complexity using the method described in section 3.2. The empirical data behind these calculations is the ICIO input-output table, which means that the elementary unit of observation is a country-sector (c, a), which is a much higher level of aggregation than detailed

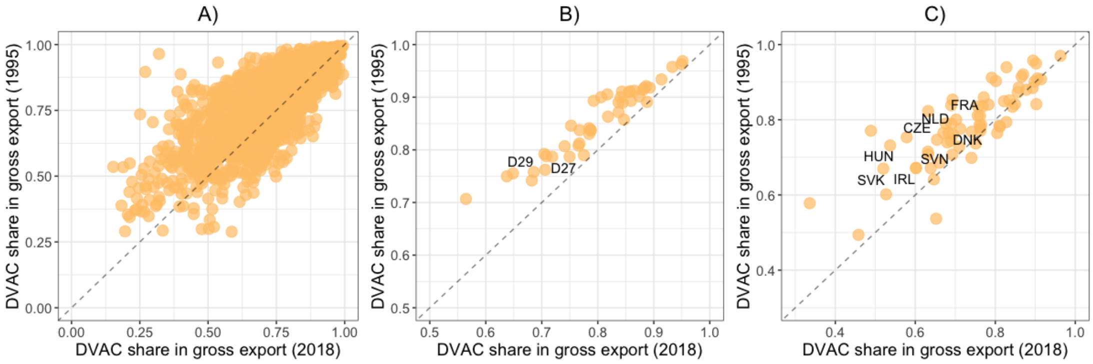

Figure 2: Dynamics of DVAC share in exports. Panel A) shows every country-sector as a single dot, and their position reflects the relative change in their DVAC share between 1995 (vertical axes) and 2018 (horizontal axes). The dashed black lines indicate identical values in the two periods. Code D29 denotes motor vehicles and (semi-)trailers, and D27 is the electrical equipment industry. Panel B) aggregates these DVAC shares in the two periods for sectors (across countries). Panel C) aggregates DVAC shares for countries (across sectors). Data source: own calculation based on ICIO database (OECD, 2021).

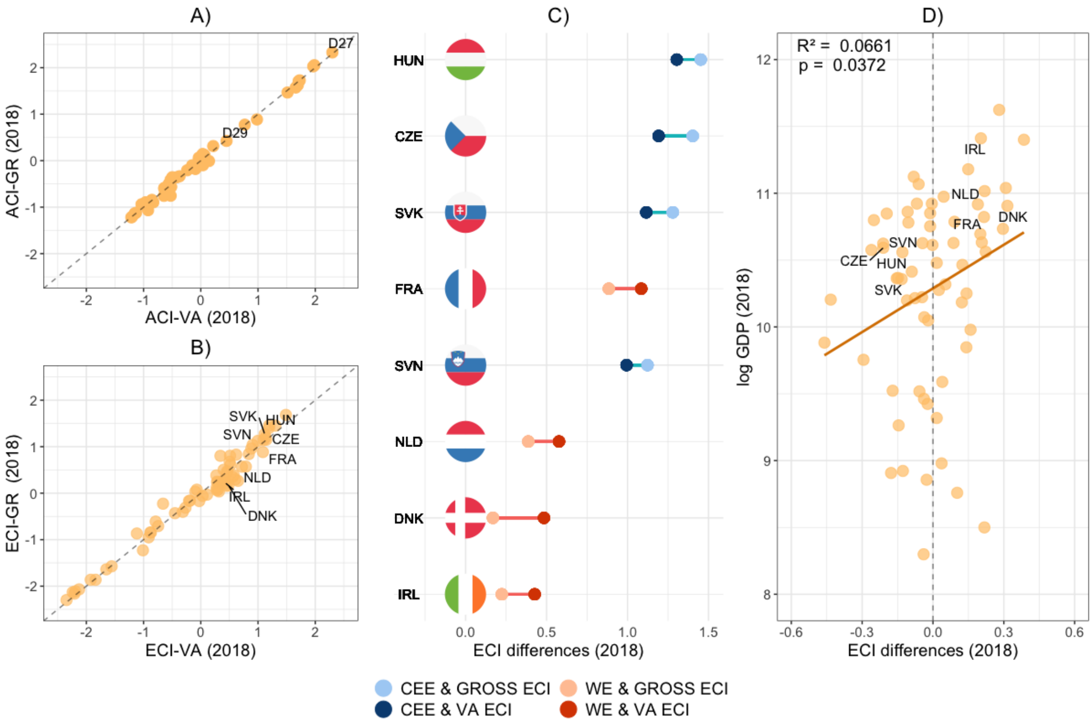

Figure 3: Economic complexity on the basis of value-added. Panel A) shows the difference between sector-level activity complexity indices based on gross (ACI-GR) and domestic value-added exports (ACI-VA) for 2018 (every point is a particular sector). Code D29 denotes motor vehicles and (semi-)trailers, and D27 is the electrical equipment industry. Panel B) shows the same difference for countries' economic complexity indices (every point is a particular country). The dashed black line on both panels indicates identical values for the two calculation methods. Panel C) shows the differences in economic complexity between the two methods for selected European countries. Central-Eastern European countries are denoted by blue, and more developed Western European countries by red colors. Panel D) reveals the general connection between the differences in the two methods and the log of GDP for 2018. The dashed black line indicates the same complexity indices. Data source: own calculation based on ICIO database (OECD, 2021) and GDP data from Penn World Tables (Feenstra et al., 2015).

product-level export data typically used to calculate economic complexity. It follows that the results here are not directly comparable with standard calculations of ECI.

Figure 3 summarizes the main findings by revealing the patterns behind the difference of gross export-based and value-added based calculations. The main observation from panels A) and B) is that in spite of minor differences, in general, the two calculation methods do not result in markedly different activity and economic complexity indices. Countries with a high gross export based economic complexity score have similarly high scores based on value-added exports. However, some differences exist, and these are in line with intuition. In panel B, we labeled the countries that are highlighted in Figure 1 and on panel C) here. CEE countries are slightly above the diagonal, so their gross export based economic complexity score is somewhat higher than the value-added based version. On the contrary, Western European (WE) countries are slightly below the diagonal, meaning that they perform better in value-added based calculations. This means that CEE countries are overvalued, WE countries are undervalued by the gross export based method relative to the value-added method, although these differences are relatively minor.

This impression is reinforced by panel C) which highlights the countries used as examples in the paper's motivation (see Figure 1). There is a slight difference between the economic complexity scores calculated along the two different methods, and the direction of this difference is in line with intuition. CEE countries have slightly lower complexity scores if we base the calculation on value-added content instead of gross exports. Although their gross export values contain many sophisticated manufactured products, relatively minor value-added is created within their borders, and export is based on importing already sophisticated products. On the other hand, the picture is the opposite for more developed countries, which build their export more on domestic value-added. Although the differences between the two methods are visible, a striking result from this picture is that while the change in the method modifies ECI values along the intuition, it does not modify the ranking of the countries. Even with the value-added-based method, CEE countries typically end up above WE countries in the complexity ranking.

Panel C) projects the findings of these highlighted European countries on the whole sample: the difference between the two calculation methods per country is associated with the (log) GDP. While the highlighted countries seem to nicely follow the pattern that more developed countries are under, while less developed ones are over-valued by the gross export based method, this does not seem to be generally true for the whole sample. Indeed, countries with the lowest GDP level typically have positive complexity differences, meaning that their economic complexity is higher on the value-added basis than on the gross export basis.

Our main conclusion from this analysis is that basing the calculation of economic complexity on value-added content rather than gross exports adds something to understanding the complexity puzzle, correcting the economic complexity scores of the countries in the expected direction. However, CEE countries that are ranked high in economic complexity based on gross exports are still ranked high when we use value-added content to calculate economic complexity. This means that the solution to the puzzle has to be looked for elsewhere than simply in the value-added content of exports. This paper argues that considering the position in global value chains can be a more relevant factor in explaining the surprisingly high ranking of these countries in terms of economic complexity.

4.2 Upstream and downstream positions

Panels A)-C) of Figure 4 reveal that downstreamness and upstreamness indicators are strongly correlated at the country level. However, the overall strength of these upstream and downstream positions has significant differences across countries, revealing that these countries have very different positions along global value chains. While panels A)-C) help in locating the highlighted countries within the whole sample. Asian and Middle Eastern countries have strong positions in raw materials and agriculture, while manufacturing is dominant for countries known for their heavy manufacturing exports. Finally, the most developed countries have strong positions in services rather than in manufacturing or raw materials. Panels D)-I) show a more detailed picture of the highlighted countries. They are equally weak in raw materials and agriculture (shown by their low scores and lack of pattern in their ranking). However, there is a clear pattern in their position with respect to manufacturing and services. CEE countries have relatively stronger positions in manufacturing, while the order switches with WE countries on top in services. The overall impression from Figure 4 shows that this disaggregation of global supply networks according to the three broad sectors captures the differences of countries' specializations in global value chains relatively well.

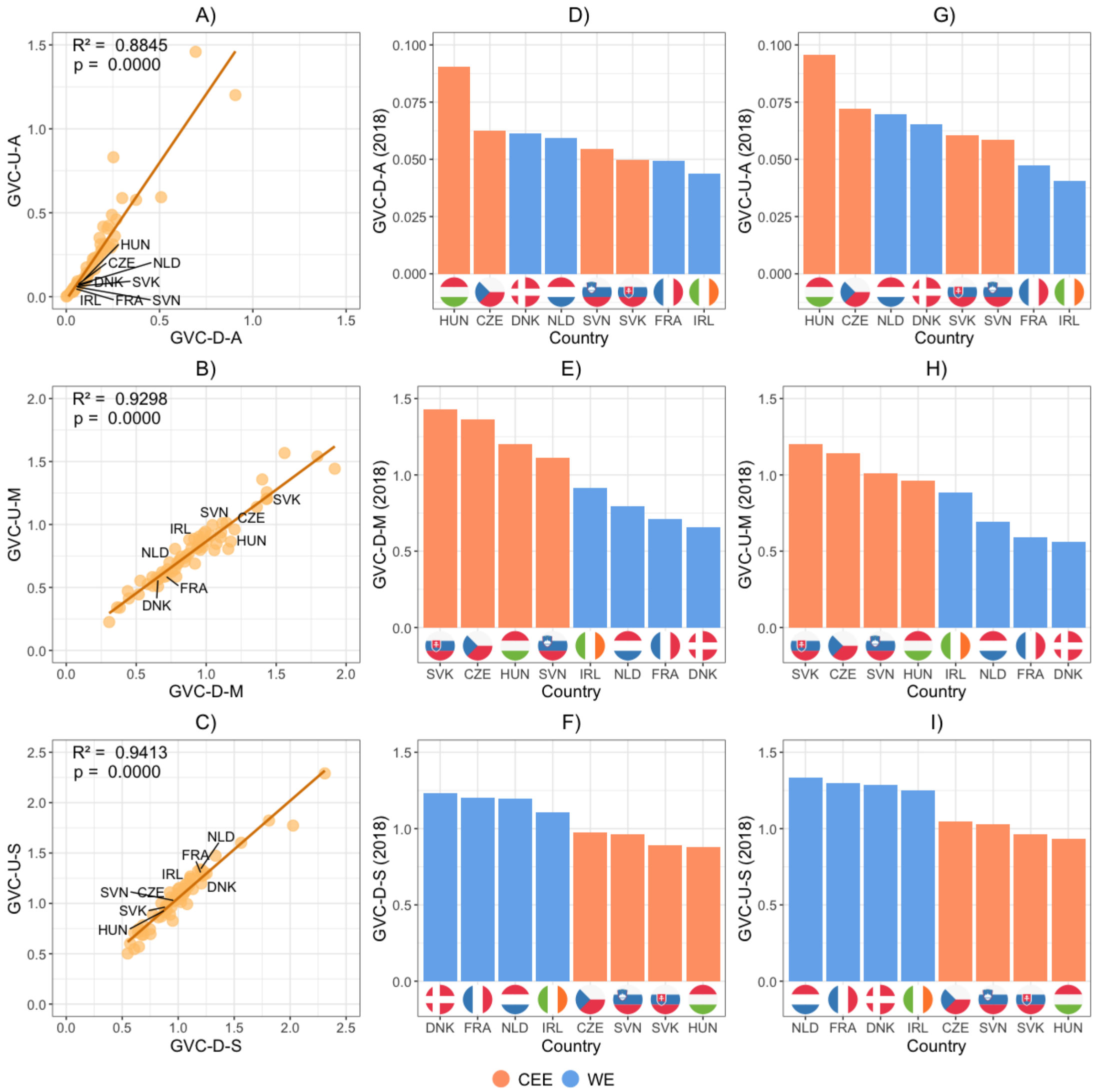

Figure 4: Countries' downstreamness and upstreamness position in global supply chains in raw materials and agriculture (A), manufacturing (M), and services (S). Panels A)-C) show the correlation between upstreamness (GVC-U) and downstreamness (GVC-D) indicators for the three broad sectors. Dark yellow lines denote the linear fit. Panels D)-F) visualize the selected countries' DOWN position in 2018 for the three bread sectors. Panels G)-I) visualize the selected countries' UP positions. Central-Eastern European countries are denoted by blue, and more developed Western European countries by orange. Data source: own calculation based on ICIO database (OECD, 2021).

4.3 GVC positions and economic development

The results so far show that replacing gross exports with the value-added content of exports in the calculation of economic complexity only slightly corrects the role of imported capabilities in exports. Moreover, the ranking of countries remains mostly the same, so this modification does not

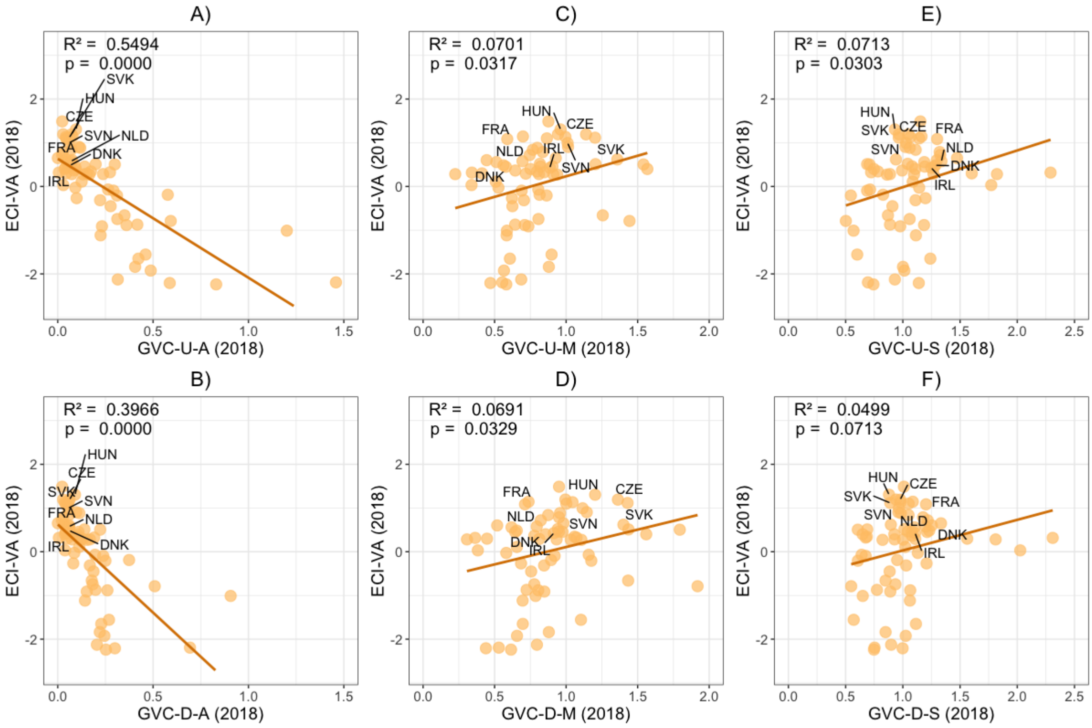

Figure 5: Countries' GVC downstremness (GVC-D) and upstreamness (GVC-U) position in global supply chains versus their value-added based economic complexity (ECI-VA) in 2018. Panels A)-B) show the raw materials and agriculture sectors; panels C)-D) the manufacturing sector; panels E)-F) the services. Dark yellow lines show the linear fit. Data source: own calculation based on ICIO database (OECD, 2021).

completely solve the complexity puzzle. A more precise account of countries' position in GVCs is needed, and in this section, we use upstreamness and downstreamness indicators to estimate the role of this position in economic development.

Figure 5 shows the relationship between the upstreamness position indicators in the three broad sectors and economic complexity. Each point in this figure represents a particular country in a particular year. Panel A) shows that economic complexity is typically low in countries with strong positions in raw materials and agricultural products. Panel B) shows a roughly inverted U-shaped pattern between GVC position in manufacturing and economic complexity. CEE countries (highlighted) have a stronger position in manufacturing GVCs than the more developed WE countries (highlighted). This gap between the two groups of countries in terms of GVC position is larger than the gap in economic complexity. Finally, looking at panel C), we see a typically positive relationship between GVC position in services and economic complexity, with a few outlier countries to the right of the figure creating a downward-sloping tail at high GVC position values. Highlighted WE countries have a stronger position in the service sectors than CEE countries. This picture provides a solid basis for further analysis, where we test the role of GVC positions in shaping economic development.

Figure 6 reproduces Figure 5 with the GDP level of the countries on the vertical axis. In the case of the extractive and agricultural sectors (panel A), we see a typically negative relationship between GVC position and GDP level, with only a few outliers (having strong positions in these types of supply chains) shading this pattern. In the case of manufacturing, the relationship is slightly negative, with higher GDP levels in countries where the GVC position in manufacturing is not as strong. Finally, panel C) shows a strong positive relationship between the GVC position in services and the GDP level of countries. This draws attention to the dominant role of service sectors rather than manufacturing in shaping economic development, so accounting for positions in service value chains is important for solving the complexity puzzle.

To analyze these relationships in more detail, we set up two regression equations building on

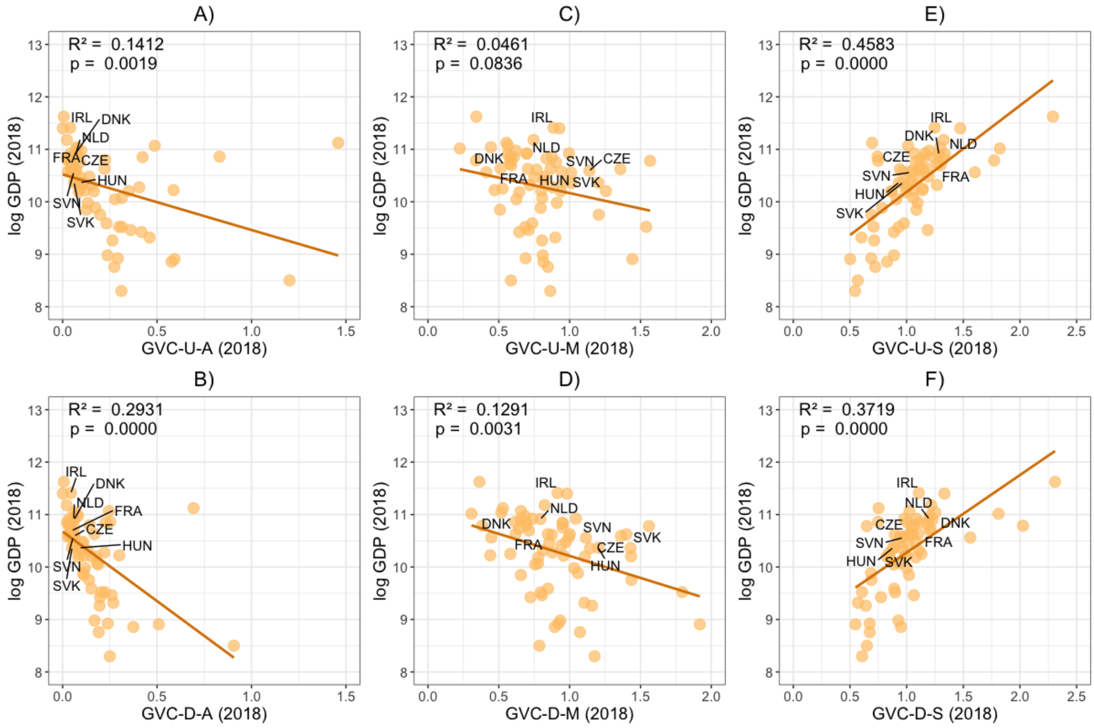

Figure 6: Countries' GVC upstreamness (GVC-U) and downstreamness (GVC-D) position in global supply chains versus their GDP per capita in 2018. Panels A)-B) show raw materials and agriculture; panels C)-D) show manufacturing; panels E)-F) show services. Dark yellow lines denote the linear fit. Data source: own calculation based on ICIO database (OECD, 2021) and GDP data from Penn World Tables (Feenstra et al., 2015).

the works of Hidalgo and Hausmann (2009) and Koch (2021), explaining the GDP level and GDP growth rate of countries with their economic complexity and other variables. In the first equation, the GDP level of country c in time period t is regressed on the economic complexity of the same country in the same period and the country's position in global value chains in the three broad sectors.

$$\begin{aligned}\log GDP_{ct} = \beta_1 ECI_{ct} + \beta_2 GVC^A_{ct} + \beta_3 GVC^M_{ct} + \\ + \beta_4 GVC^S_{ct} + \beta_{\mathbf{X}} \mathbf{X}_{ct} + \mu_t + \omega_c + \varepsilon_{ct}\end{aligned} \tag{11}$$

The second equation regresses the GDP growth rate of country c in time period $t+\delta$ on the same set of right-hand-side variables as in Equation 11 plus the GDP level of country c in period t and the change in economic complexity over the same period ($\Delta ECI_{ct} = ECI_{c,t+\delta} - ECI_{c,t}$):

$$\begin{aligned}\log \frac{GDP_{c,t+\delta}}{GDP_{ct}} &= \beta_0 GDP_{ct} + \beta_1 ECI_{ct} + \beta_3 \Delta ECI_{c,t+\delta} + \\ &+ \beta_4 GVC^A_{ct} + \beta_5 GVC^M_{ct} + \beta_6 GVC^S_{ct} + \\ &+ \beta_{\mathbf{X}} \mathbf{X}_{ct} + \mu_t + \omega_c + \varepsilon_{ct}\end{aligned} \tag{12}$$

We include similar control variables in both setups as Koch (2021), and these are denoted by the vector $\mathbf{X}_{ct}$.[5] Panel specification is used with country and time fixed effects in both setups that

[5]Controls are population (N_{ct}), capital stock (K_{ct}), human capital index (H_{ct}), and the ratio of domestic value-added content in gross export ($DVAC_{ct}$) in the GDP level regressions. In the GDP growth regressions, we use absolute and relative change in the population (ΔN_{ct}, $\log \Delta N_{ct}$), absolute and relative change in capital stock (ΔK_{ct}, $\log \Delta K_{ct}$), absolute and relative change in human capital (ΔH_{ct}, $\log \Delta H_{ct}$) and absolute and relative change in domestic value-added in gross exports ($\Delta DVAC_{ct}$, $\log \Delta DVAC_{ct}$).

control for unobserved heterogeneity across units of observation (countries) and over time. For the GDP level regressions, all sample years are defined as a single time period, whereas for the GDP growth regressions, we employed four adjacent time periods (five years long each, $\delta = 5$: 1998-2003, 2003-2008, 2008-2013, and 2013-2018). In order to account for nonlinearities visible in Figure 6, we include second- and third-order terms for the economic complexity and GVC indicator in the GDP-level regressions (Equation 11).[6] Only linear terms are included for GDP growth regressions, as higher order terms were not significant in these cases. The regression results on GDP levels are shown in Table 3 and 4, while Table 5 and 6 show the results of the regressions on GDP growth rates. For both setups, results are separated for upstreamness and downstreamness indicators as explanatory variables.

We build the regression specifications step by step. First, we reproduce the original specification discussed by Hidalgo and Hausmann (2008), in which GDP levels and GDP growth rates of countries are regressed on economic complexity (calculated on the basis of gross exports), in addition to a set of control variables that typically account for economic development (capital stock, population, and human capital). As in the original paper, economic complexity has a positive and significant effect on the level of development (Model (1) in Table 3), but neither economic complexity nor its change has an effect on GDP growth rates (Model (1) in Table 5).[7]

In the second step, we include economic complexity calculated on the basis of value-added exports (Model (2) in Table 3) and Model (2) in Table 5). The results are in line with that of Koch (2021) in the sense that value-added based economic complexity is significantly linked to the GDP level (Models (2) and (7) in Table 3, Model (5) in Table 4). In the case of the growth regressions, value-added based complexity becomes positive and significant when included together with GVC position indicators (Model (7) in Table 5, Model (5) in Table 6) while gross export based complexity never affects GDP growth (Model (6) in Table 5, Model (4) in Table 6). Some differences between the results here and those presented by Koch (2021) may come from the different datasets used for calculation (ICIO here vs. World Input-Output Database in Koch (2021)).

The next step is to include the GVC position indicators in the regression models. Following the idea of the smile curve, we also include second and third-order terms of GVC positions on the right-hand side to capture non-linearities in the relationship between GVC position and economic development. Model performance improves by including the second-, and third-order terms, and the best fit is achieved with the third-order terms included. We can interpret the direction and shape of the estimated nonlinear relationships by calculating the respective functions over the support of relevant GVC position indicator values (which range between 0 and 2) and with significant coefficients. These shapes indicate that upstreamness in raw materials and agriculture, as well as in services, is positively associated with the GDP level, while the position in manufacturing supply chains seems to have a slight positive effect on GDP, but it vanishes if positions in all three broad sectors are included (Models (4) versus Model (7) in Table 3). In terms of downstreamness, we have a negative effect on GVC position in raw materials and agriculture, a positive for manufacturing, and a U-shaped relationship in services (Models (1)-(5) in Table 4).

The regression results with the GDP level on the right-hand side are not a definitive way to appraise the role of GVC position in economic development. These estimations only included contemporaneous effects and, as such, only reflect whether there is a statistically significant association between the position in GVCs, as measured by the upstreamness and downstreamness indicators, and the GDP level of a country. So far, the results ensure that this association exists and that the strength of positions in the different broad sectors and directions (upstream or downstream) are differently associated with the level of GDP. However, regression results on GDP growth rates can better delineate the relationship between GVC positions and economic development (growth) by considering the time dimension more explicitly.

[6] Third order provided the best fit for the trends in Figure 6.

[7] Note, that economic complexity in this paper is calculated from input-output data at the sectoral level, so results are not directly comparable to previous studies which use product-level trade data to calculate economic complexity.

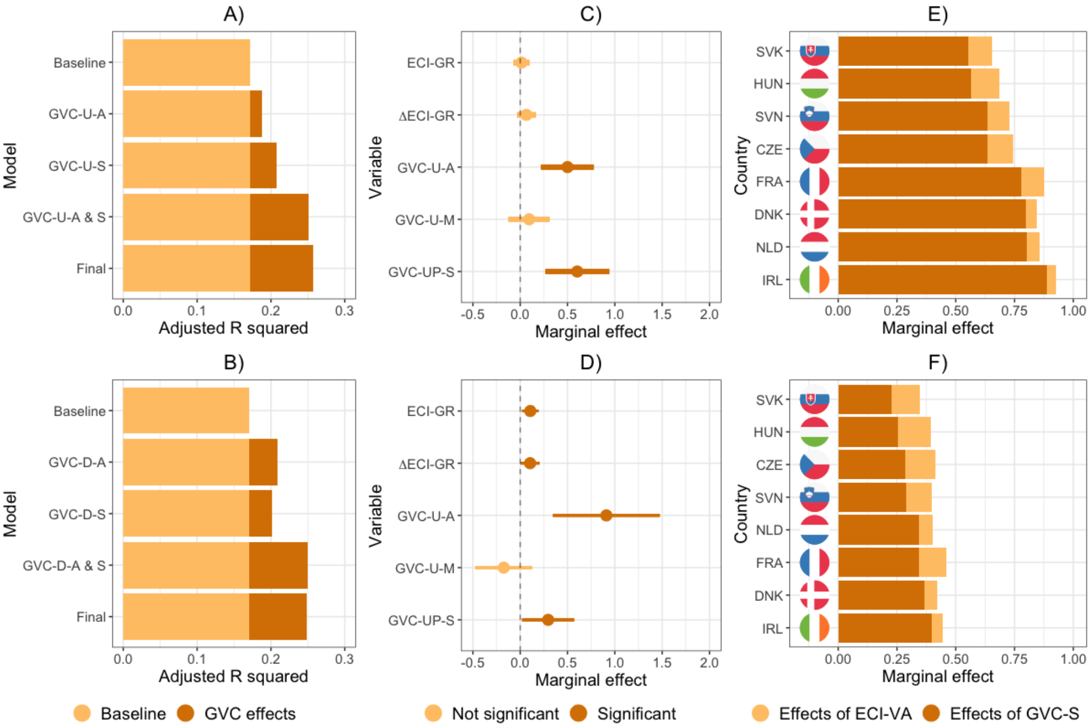

Figure 7: Estimated effects of GVC position on GDP growth. The baseline model on panels A) and B) is the Model (1) in Table 5. For the other models, as in Tables 5 and 6, we added GVC indicators to the explanatory variables step by step. The final model on panel A) is Model (7) in Table 5, while on panel B) the Model (5) in Table 6. Panels C) and D) show the coefficients and their significance of the relevant variable by confidence intervals in both final models. Panels E) and F) show the estimated effect of value-added-based economic complexity (ECI-VA) and the position of service sectors (GVC-U-S and GVC-D-S). Data source: own calculation based on ICIO database (OECD, 2021).

Figure 7 summarizes visually the regression results for GDP growth. The first row in the figure (panels A), C) and E) reflects results for the upstreamness indicators while the second row (panels B), D) and E) show those for downstreamness (Tables 5 and 6 respectively). The baseline is Model (2) in Table 5), which contains the controls, fixed effects, and the value-added based economic complexity (both its level and its change). Following Hidalgo and Hausmann (2009), we test how additional explanatory variables affect the fit of the models with the adjusted R^2. This is shown by panels A) and B) for upstreamness and downstreamness, respectively, as we add the GVC position indicators. First, the indicators for raw materials and agriculture and those for services are added separately, then the two indicators are added together, and the final model refers to Models (7) and (5) in Tables 5 and 6, where the manufacturing position is included, although the latter is not significant in these specifications. The green areas reflect the improvement in the explanatory power of the models. It is clear that including the positional variables in the growth regressions significantly improves the fit of the models for both upstreamness and downstreamness, with a slightly higher marginal improvement in the case of the former.

Panels C) and D) of Figure 7 then build on these final models and visualize the size of the estimated coefficients with respect to the main explanatory variables. While economic complexity, measured in value-added terms, has a positive significant effect on growth, GVC position in raw materials, agriculture, and service has a much larger effect. Interestingly, though, position in manufacturing value chains is not a significant contributor to growth (either upstream or downstream). While the raw materials, agriculture, and services positions have practically the same effect in terms of upstreamness, the position in raw materials and agricultural value chains is shown to be the strongest determinant, even over services in case of downstreamness. Those countries achieved higher growth rates in terms of their GDP which had stronger positions along service value chains and also along raw materials and agriculture value chains. Position along raw material

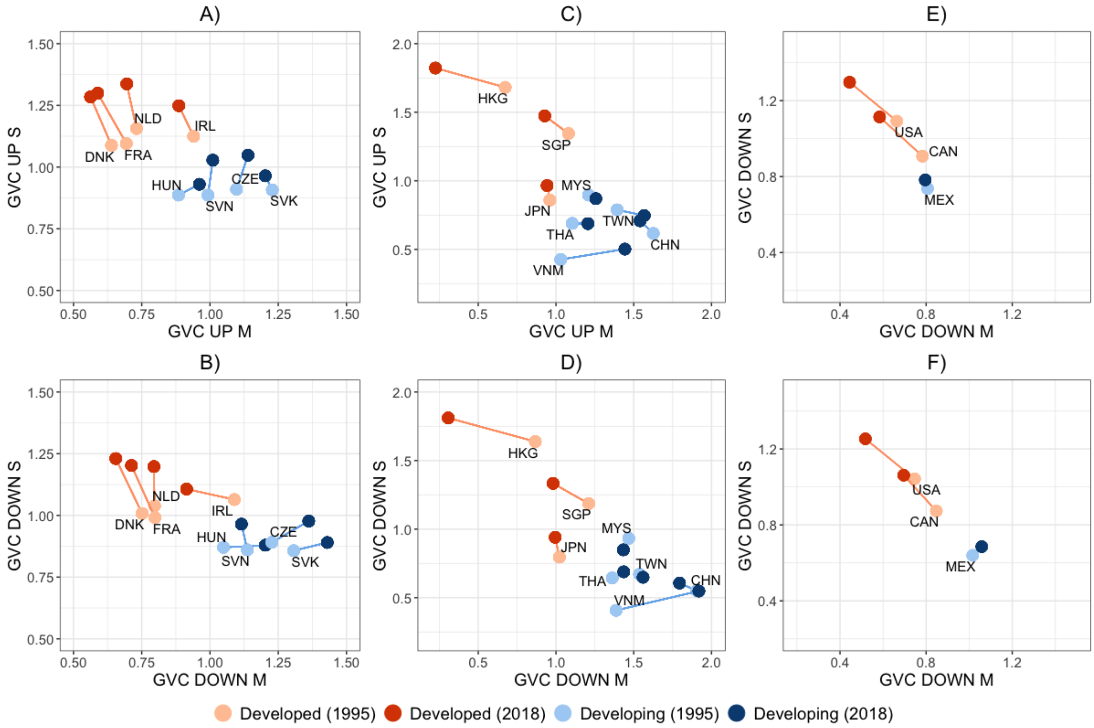

Figure 8: Development paths along sectoral value chains. Panels A)-B) show the movement of select European countries in GVC's position in manufacturing (GVC UP M and GVC DOWN M) and service sectors (GVC UP S and GVC DOWN S) between 1998 and 2018. Panels C)-D) show it for Asian countries, while E)-F) for America. Data source: own calculation based on ICIO database (OECD, 2021).

and agricultural value chains have an even larger effect in terms of downstreamness positions, i.e. for those countries that use sophisticated, complex inputs along these sectors and themselves are also relatively close to the final users.

Panels C) and D) have already shown that GVC position indicators have larger marginal effects in terms of GDP growth than economic complexity, even if the latter is calculated on the basis of value-added. These marginal effects are visualized on panels E) and F), where we took the country-specific value of the economic complexity indicator (based on value-added) and the positional indicators in the service sectors for 2013 and calculated the estimated contribution of these variables on the GDP growth rate between 2013 and 2018. Both the initial level and the change is significant for economic complexity, and these effects are added and marked with lighter-colored bars. The darker colored bars reflect the sole marginal contribution of the position in service value chains. These marginal effects are calculated for the eight highlighted countries that are used throughout the paper. The results indicate that the marginal effect of GVC position in services is much larger than that of value-added complexity for these countries. The lighter-colored bars are larger for CEE countries than for WE countries (except France), and the darker-colored bars are undoubtedly larger for WE countries. This reflects that while economic complexity explains economic growth, countries' positions in GVCs add a significant portion to the explanation. Particularly, the position in service sectors contributes to solving the complexity puzzle: although economic complexity calculated on the basis of value-added helps in controlling for imported capabilities to some extent, taking into account the position that countries have in GVCs adds more to explaining growth. Hence, economic development depends to a large extent on *where* countries are located along value chains and how knowledge and capabilities that determine the complexity of exported products are distributed along these value chains. In the specific case of the European countries that we use as highlights, it is the service sector value chains that matter considerably, while positions in manufacturing supply chains do not seem to be significant in this respect.

These findings clearly point to the solution of the complexity puzzle. While CEE countries are well embedded in manufacturing supply chains, their position in service chains is less favorable. However, our results show that a favorable position within these service supply chains is the most effective contributor to economic growth and the level of development. This means that while CEE countries have been able to improve their position in manufacturing supply chains over the past decades, their progress in service chains has not been as strong. On the contrary, WE countries have significantly improved their position in the service supply chains over the same period.

This conclusion is supported by Figure 8, which shows the development of the highlighted European countries along the manufacturing and services supply chains on panel A). While CEE countries gained positions along the manufacturing chains, they only slightly increased their position along the service chains. However, WE countries improved their position more in the service chains while their position in the manufacturing chains declined. Panel B) extends this picture with select American and Asian countries, where similar patterns can be observed. Mexico, Thailand, Vietnam, and Malaysia are considered "factory economies", similar to CEE countries in Europe, where low value-added assembly type of manufacturing is located. While the developed "counterparts" of these economies (US, Japan, Hong Kong) follow a similar pattern as WE countries (weakening positions in manufacturing and strengthening positions in services), Malaysia, Thailand, and Vietnam show significant improvements in their manufacturing positions while their position in service value chains improved only moderately. Mexico did not change its position significantly. We highlighted China in the figure as well: it has an extremely strong position in manufacturing, which decreased over the sample period, while its position in services increased significantly. Hence, patterns of these factory economies seem to be similar in terms of their development along global value chains.

4.4 Activity complexity and GVC positions

The analysis so far has focused on countries, the complexity of their economic activities, and their positions in supply chains. However, the granularity of our data is at the country-sector level, which allows for a different perspective on these issues. In this section, we focus on activity complexity, which is the conceptual counterpart of economic complexity. While economic complexity reflects a country's capabilities based on its export portfolio, activity complexity reveals the capabilities required to produce products or to provide services. Given our dataset, activity complexity can be interpreted at the sectoral level, so every sector has an activity complexity index (ACI). By revealing the relationship between activity complexity and positions in global value chains, we can better understand the role of value chains in shaping economic development and the background to the complexity puzzle.

Figure 9 shows the correlation between activity complexity by sector and the GVC position of the sectors. We use average sector-level position indicators across countries, weighted by the countries' share in the global output of the respective sector. The association is shown separately for the upstreamness and downstreamness indicators. Recall that the upstreamness of a given sector will be higher if the output of that sector is used as an intermediate input by many other sectors and steps in further production processes. Similarly, the downstreamness indicator of a given sector will be higher if the inputs of that sector are produced through more steps or stages of production.

We find that upstreamness is only slightly correlated with ACI (correlation coefficient is 0.0120, panel A), while downstreamness strongly correlates with ACI (correlation coefficient is 0.4648, panel B). In particular, manufacturing sectors with a high ACI also have strong positions according to their downstreamness indicator. On the contrary, service activities have low activity complexity and weak downstream positions. Low activity complexity of services may be rooted first in the country bias of our sample, and as such, it contradicts the findings of Stojkoski et al. (2016). While most developed countries show a large share of services within their economic output, this is not followed by the industry structure (level of detail) of the dataset. In contrast to a 60-80% share of services, only less than 50% of the sectors belong to the service industries. This results in a disproportionately lower detail in the complexity of service industries as the latter is determined by the number of distinctive categories (industries in our case) to which items (exports with revealed

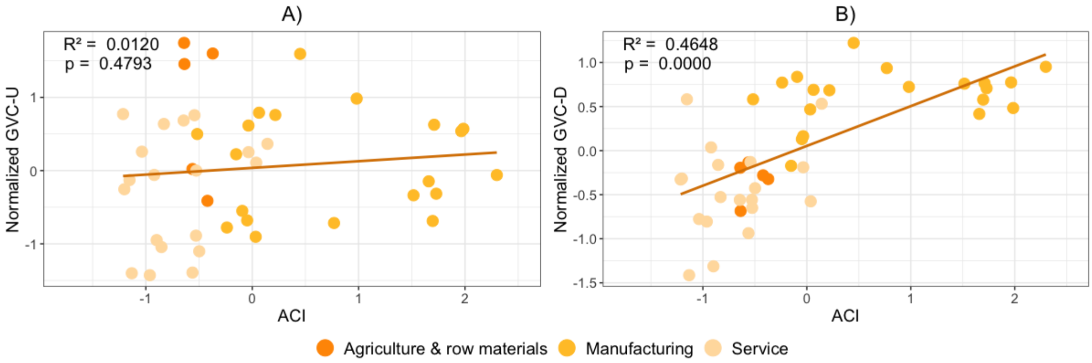

Figure 9: Activity complexity and the average normalized GVC position indicators (upstreamness (GVC-U) and downstreamness (GVC-D). GVC positions are transformed into a value between zero and one. Data source: own calculation based on ICIO database (OECD, 2021).

comparative advantage in our case) can belong.

The main conclusion to be drawn from this picture is that the complex activities are those that are rare and have relatively long supply chains, involving complex production, assembly, and delivery processes. This finding has clear methodological implications. Measuring complexity in the standard way over-emphasizes the presence of long supply chains behind the production of certain products or activities. In contrast, many services are produced along shorter supply chains, and as a result, the standard method may underestimate the complexity of services, which contributes to the emergence of the complexity puzzle. CEE countries are found to be strong in an interpretation of complexity that overweights activities that are more exposed to disaggregation through GVCs. At the same time, this method underestimates strength in services, which may also be complex but in a different way, being less integrated into long global supply chains. In other words, these countries appear to be complex in a structure (vertically and globally diversified manufacturing activities) that is being left behind by more advanced and innovative economies.

5 Conclusions

5.1 Summary

In this paper, we contributed to resolving the complexity puzzle whereby CEE countries that stand out in economic complexity rankings have typically a strong dependency on borrowed/imported capabilities together with a recent slowdown in upgrading in terms of GVC of functions and struggling to further catching up with more developed economies in terms of income per capita. We argued that CEE countries represent a broader class of economic development strategies deployed in "factory economies" that focus on upgrading their economic structure and income level by specializing in manufacturing functions along GVCs.

To do so requires, as suggested recently by Frenken et al. (2023), to relax the assumption that all necessary capabilities to carry out an economic activity need to be locally available. This sift makes it necessary to disentangle how places leverage their existing capability base in conjunction with non-local capabilities that are embodied in intermediate stages of production.

Using input-output data on 45 sectors of 67 territories over more than 20 years, we first measured the economic complexity of sectors and countries based on the domestic value-added content of their exports instead of their gross exports to better capture local capability endowments. As the domestic value-added content of exports steadily decreased over our analysis period, this makes it all the more pressing to separate the the role of local and non-local capability bases in producing economic complexity. Similarly to Koch (2021) and Koch and Schwarzbauer (2021), who first proposed such an approach using a different dataset, we found that the value-added-based calculation changed the economic complexity ranking of countries. This approach also reduced the apparent gap between the complexity of CEE countries and developed WE economies.

Second, while domestic value-added content accounts for local capabilities, it must be complemented by considering the functional division of labor that allows countries to build their productive specializations on intermediate production stages brought about by complementary capabilities elsewhere. To account for this dimension, we relied on upstreamness and downstreamness as established indicators of GVC positions that are widely used in input-output analysis and in the GVC literature. Upstreamness accounts for the direct and indirect influence of an input to downstream production, while downstreamness captures the extent to which intermediate stages of production contribute to carrying out an economic activity. As such, both measures reflect the complexity of coordinating capability bases across sectors and places. In this respect, we found that complex economic activities tend to also be more downstream, showing that sophisticated specializations in terms of value-added are sustained by a complex division of labor across the value chain. More upstream activities, on the other hand, show little association with their value-added-based complexity, reflecting that both high- and low-complex activities can act as influential intermediate production stages. The weak positive correlations of economic complexity and GVC position of countries in manufacturing and service activities, in particular, indicate that sophisticated value-added specialization portfolios do not automatically mean a specific level of influence on GVCs. This further supports the approach of considering the two aspects of local and non-local capability bases together.

Therefore, we brought together the components of value-added-based economic complexity and GVC positions to test their joint predictive power on income level and economic growth by re-estimating the benchmark regressions used by Hidalgo and Hausmann (2009) and Koch (2021). Overall, the results of these regressions show an improvement in explanatory power when considering complexity and GVC position in the same setup. By grouping GVC positions into broad categories of raw materials and agriculture, manufacturing, and services, we find that it is not embeddedness in manufacturing but rather a position in raw materials and agriculture, and even more so in service supply chains, that contributes to economic growth. The in-depth analysis of countries' development paths and diversification patterns lent further support to this finding as countries considered "factory economies" with a strong dependence on imported skills and specialized export markets have shown significant improvement along manufacturing value chains but little or no improvement along service value chains. Most developed countries, on the other hand, experienced strong improvements along the service value chains. Additionally, countries tended to reinforce their existing GVC positions in manufacturing or services, which points to a related diversification pattern at play. Considering these observations, together with the estimated relationship between growth and GVC positions, helps explain why countries such as Hungary or Mexico have struggled to modernize their production systems and catch up with more developed countries regarding per capita income.

5.2 Policy implications

In the capability framework of economic development, countries and regions reach portfolios of increasingly sophisticated specializations and ultimately higher prosperity by the gradual accumulation of complementary capabilities (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011; Neffke et al., 2018; O'Clery et al., 2021; Frenken et al., 2023). The policy-related bottom line of the arguments and findings put forward in this paper is that leveraging local capability accumulation *together* with building on non-local capabilities that are embodied in intermediate stages of production along the value chains co-creates economic development. To appraise our findings in light of economic development strategy more specifically, we rely on the *4W* framework (what, where, when, and who) recently put forward by Hidalgo (2023).

First, the *what* question concerns the specific activities that places diversify into. CEE countries went through substantial upgrading in economic complexity during the analysis period of this paper (Figure 1), as well as more broadly (Pinheiro et al., 2022). Taken together with the gradual catching up of these countries to, for instance, the EU average level of GPD per capita, this lends support to the success of the FDI-driven economic development strategy deployed in these countries. That being said, our results also show that this upgrading was primarily achieved by increasing specialization in manufacturing activities much more so than in services which tend to be more complex activities (Stojkoski et al., 2016), characteristic of many developed economies. Additionally, we found that measuring economic complexity on the basis of domestic value-added decreased the apparent complexity gap between CEE and WE countries. What follows is that the recent capability accumulation behind the upgrading in economic complexity in CEE countries may have been overestimated and overall tends to focus on the middle of the GVC smile curve with comparatively lower value-added functions like manufacturing and assembly. Hence, a potential follow-up strategy to FDI- and manufacturing-driven economic development may require shifting the focus from *what* in terms of sectors or products to *what* in terms of specific functions along the value chain. As for many less developed countries, manufacturing activities remain a dominant area to employ and gradually develop their workforce (Shin et al., 2012), a possible solution here can be servitization in manufacturing. This would allow for building on the capability base that countries have developed within manufacturing sectors and value chains while at the same time shifting the activity portfolio towards service sectors (Miroudot and Cadestin, 2017). The recent developments characterized by the slowdown of international trade and the strengthening of protectionism point towards the restructuring of value chains in a way where domestic or local capabilities appreciate in value (Coe and Yeung, 2019; Braun et al., 2021).

Second, the *where* question relates to the geographical distribution and access to productive knowledge. In this paper, we argue that what specializations countries develop need to be considered together where the intermediate stages of production can be accessed, in order to account for both local and non-local capabilities. Cases like the northern parts of Mexico upgrading in economic complexity due to the geographical proximity to and participation into US value-chains underscore the importance of non-local complementary capabilities Hidalgo (2023). The *where* question, however, generalizes into a relational space where complementary capabilities distributed across space are brought together through complex global value chains. Based on our findings, value-added-based economic complexity and positions in GVCs together predict better the economic prospects of the sample countries (Figure 7). This highlights that the FDI-driven and GVC-integration-based economic development strategy in CEE countries and factory economies more broadly requires considering a desired economic structure *together* with the existing role in GVCs. Upgrading in economic complexity and, ultimately, economic development also requires upgrading in value chains towards downstream activities with higher complexity and more complex co-ordination of intermediate production stages or upstream activities that are unique and influential on downstream sectors.

Third, the *when* question concerns to the timing of unrelated diversification, or diversification into specific activities more broadly. The window of opportunity for unrelated diversification opens at a relatively high level of economic complexity (Pinheiro et al., 2022). Notwithstanding that the value-added-based approach employed in this paper adjusts the complexity rankings, CEE countries still show a relatively high level of economic complexity. Taken together with recent apparent challenges in further growth and convergence (Bohle, 2018; Cieślik and Wciślik, 2020; Gál and Gábor, 2022), the next stage of the economic development strategy for these countries likely needs to involve some attempts at unrelated diversification. As we find a pattern of related diversification whereby CEE countries tend to reinforce their positions in manufacturing value-chains further (Figure 8), which may bottleneck efforts to open for instance towards services. Strongly related to the *what* question, diversification into new, preferably higher value-added functions like R&D or related services along the value chain may be a suitable follow-up strategy for these countries as capabilities needed for unrelated diversification into high-complex activities may be accumulated by extending on their existing specializations in global value chains. From the perspective of the *when* question, the window of opportunity for the next stage in upgrading economic complexity is likely to open for these countries.

Finally, the *who* question refers to the micro-agents of structural change, like firms, universities, or local governments. In the corresponding literature, the subject of analysis is often how regions or countries diversify into new economic activities. This, including our present work, is for the sake of simplicity rather than ascribing agency to these spatial units. Overall diversification is the collective outcome of the actions of micro-agents. What follows is that policy strategy often needs to target specific groups of agents to foster and bring about structural change. The dominant development strategy in CEE countries historically relied on foreign-owned firms as such agents of structural change. This may be well-warranted as these firms tend to bring more unrelated activities to regions and foster the upgrading of domestic firms (Javorcik et al., 2018; Elekes et al., 2019; Lo Turco and Maggioni, 2019). What our paper highlights in this respect is that the same economic development strategy that created structural upgrading through foreign-owned firms also resulted in a deep embedding of CEE countries and factory economies in specific parts of (manufacturing) global value chains. Moving forward, the next stage of such development strategies has to involve considering the existing strategic couplings of their foreign and domestic firm base, as well as the division of labor between the two. As the boundaries of our present analysis cannot offer more granular insights at this level of analysis, we must relegate the *who* question to future research.

5.3 Limitations and further research

Our study is limited first by the resolution of the data at hand. While necessary to chart global value chains and domestic value-added content, the OECD ICIO data offers information on 45 highly aggregated sectors in contrast to hundreds of export products or technology codes that are commonly used to map economic complexity (e.g., Hidalgo et al. (2007); Hidalgo and Hausmann (2009); Balland and Rigby (2017)). This high level of aggregation unavoidably obscures nuances in the economic specializations of the sample countries, inducing some similarity among their specialization portfolios and potentially translating into lower values of revealed comparative advantage in some cases. This way, our measures of economic complexity and GVC positions may overemphasize countries with strong embeddedness in GVCs and that have a diverse economic structure. Hence, our results are most straightforwardly comparable with studies using data with similar constraints, such as those of Koch (2021) and Koch and Schwarzbauer (2021).

Second, while the ICIO global input-output tables cover the entirety of world trade, many countries and their interactions are combined into a single "rest of the world" block, significantly reducing the level of detail at which economic linkages can be traced and measured across places. While the data explicitly covers a comparatively good number of developed and many developing countries over an extensive period of time (compared, for instance, with the World Input-Output Dataset), most less developed countries are lumped into the "rest of the world" block. This leads to a bias towards more developed countries. This is likely an additional reason why service sectors are found in this paper to have a comparatively lower activity complexity. Hence, our findings regarding the complexity puzzle apply to countries that have already experienced some pronounced integration into global value chains.

Lastly, while the measures used in this paper to capture GVC positions along value chains are extensively used in the literature, they are, at best, indirect proxies for actual functional specializations of places. That is to say, we could not give a detailed breakdown of various functions along value chains *within* sectors. Recently Hernandez-Rodriguez et al. (2023) used EU-level regional input-output tables to capture domestic value-added content and a combination of industry and occupation specializations to infer functions. Our work complements their results in the context of the global economy while also highlighting the kind of development puzzles that this approach sheds light on. And indeed, moving forward, we see it as a major challenge for the literature on economic complexity and evolutionary economic geography to be able to provide a systematic account of structural change in terms of functions, thereby empirically exploring the interplay of local and non-local capabilities.

Despite these limitations and open questions, the findings put forward here offer hitherto scarce insights into local capability accumulation, together with coordinating complementary non-local capabilities through value chains, which jointly create opportunities and constraints for economic development.

Data availability

All data can be downloaded free of charge. OECD ICIO Database (release November 2021): http://oe. cd/icio; Penn World Tables (version 10.0): https://www.rug.nl/ggdc/productivity/pwt/.

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Appendix

Appendix A: Input-output data

OECD countries		Non-OECD countries	
Code	Country	Code	Country
AUS	Australia	ARG	Argentina
AUT	Austria	BRA	Brazil
BEL	Belgium	BRN	Brunei Darussalam
CAN	Canada	BGR	Bulgaria
CHL	Chile	KHM	Cambodia
COL	Colombia	CHN	China
CRI	Costa Rica	HRV	Croatia
CZE	Czech Republic	CYP	Cypurs
DNK	Denmark	IND	India
EST	Estonia	IDN	Indonesia
FIN	Finland	HKG	Hong Kong, China
FRA	France	KAZ	Kazahstan
DEU	Germany	LAO	Lao People's DR
GRC	Greece	MYS	Malaysia
HUN	Hungary	MLT	Malta
ISL	Iceland	MAR	Morocco
IRL	Ireland	MMR	Myanmar
ITA	Italy	PER	Peru
JPN	Japan	PHL	Philippines
KOR	Korea	ROU	Romania
LVA	Latvia	RUS	Russian Federation
LTU	Lithuania	SAU	Saudi Arabia
LUX	Luxembourg	SGP	Singapore
MEX	Mexico	ZAF	South Afirca
NLD	Netherlands	TWN	Chienese Taipei
NZL	New Zealand	THA	Thailand
NOR	Norway	TUN	Tunesia
POL	Poland	VNM	Viet Nam
PRT	Portugal	ROW	Rest of the World
SVK	Slovak Republic		
SVN	Slovenia		
ESP	Spain		
SWE	Sweden		
CHE	Switzerland		
TUR	Turkey		
GBR	United Kingdom		
USA	United States		

Table 1: Countries in ICIO Database (OECD, 2021).

Code	Industry	SITC Rev.4	Group
D01T02	Agriculture, hunting, forestry	01, 02	A
D03	Fishing and aquaculture	03	A
D05T06	Mining and quarrying, energy producing products	05, 06	A
D07T08	Mining and quarrying, non-energy producing products	07, 08	A
D09	Mining support service activities	09	A
D10T12	Food products, beverages, tobacco	10, 11, 12	M
D13T15	Textiles, textile products, leather and footwear	13, 14, 15	M
D16	Wood and products of wood and cork	16	M
D17T18	Paper products and printing	17, 18	M
D19	Coke and refined petroleum products	19	M
D20	Chemical and chemical products	20	M
D21	Pharmaceuticals, medicinal chemical, and botanical products	21	M
D22	Rubber and plastics products	22	M
D23	Other non-metallic mineral products	23	M
D24	Basic metals	24	M
D25	Fabricated metal products	25	M
D26	Computer, electronic and optical equipment	26	M
D27	Electrical equipment	27	M
D28	Machinery and equipment, nec	28	M
D29	Motor vehicles, (semi-)trailers	29	M
D30	Other transport equipment	30	M
D31T33	Manufacturing nec	31, 32, 33	M
D35	Electricity, gas, steam, and air conditioning supply	35	M
D36T39	Water supply; sewerage, waste management, and remediation act.	36, 37, 38, 39	M
D41T43	Construction	41, 42, 43	M
D45T47	Wholesale and retail trade; repair of motor vehicles	45, 46, 47	S
D49	Land transport and transport via pipelines	49	S
D50	Water transport	50	S
D51	Air transport	51	S
D52	Warehousing and support activities for transportation	52	S
D53	Postal and courier activities	53	S
D55T56	Accommodation and food service activities	55, 56	S
D58T60	Publishing, audiovisual and broadcasting activities	58, 59, 60	S
D61	Telecommunications	61	S
D62T63	IT and other information services	62, 63	S
D64T66	Financial and insurance activities	64, 65, 66	S
D68	Real estate activities	68	S
D69T75	Professional, scientific and technical activities	69 to 75	S
D77T82	Administrative and support services	77 to 82	S
D84	Public administration and defence; compulsory social security	84	S
D85	Education	85	S
D86T88	Human health and social work act.	86, 87, 88	S
D90T93	Arts, entertainment and recreation	90, 91, 92, 93	S
D94T96	Other service activities	94,95, 96	S
D97T98	Activities of households as employers	97, 98	S

Table 2: Sectorss in ICIO Database (OECD, 2021).

Appendix B: Detailed regression results

	Dependent variable: $\log GDP_{c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ECI^{GROSS}_{c,t}$	0.8999					-1.2503	
	(2.4263)					(2.3605)	
$ECI^{GROSS^2}_{c,t}$	4.2577***					3.6345***	
	(1.4133)					(1.3012)	
$ECI^{GROSS^3}_{c,t}$	-1.2511					-1.0983	
	(0.8224)					(0.7726)	
$ECI^{VA}_{c,t}$		1.1372					1.4835
		(2.5039)					(2.4186)
$ECI^{VA^2}_{c,t}$		3.9737***					2.9146**
		(1.3215)					(1.1422)
$ECI^{VA^3}_{c,t}$		-0.6439					-0.5041
		(0.8166)					(0.68909
$GVC^{UP,A}_{c,t}$			-2.7785			-2.9456	-3.1458
			(2.3618)			(2.8760)	(2.9120)
$GVC^{UP,A^2}_{c,t}$			5.0905***			5.1797***	5.4708***
			(1.0187)			(1.0628)	(1.0780)
$GVC^{UP,A^3}_{c,t}$			-1.8624*			-1.4822*	-1.6918*
			(0.8003)			(0.7589)	(0.7366)
$GVC^{UP,M}_{c,t}$				2.2877*		1.9194	2.0630
				(1.3732)		(1.4276)	(1.4406)
$GVC^{UP,M^2}_{c,t}$				0.0493		0.5068	0.4637
				(0.7661)		(0.8891)	(0.9022)
$GVC^{UP,M^3}_{c,t}$				-0.5173		-0.3249	-0.3993
				(0.4723)		(0.4128)	(0.4389)
$GVC^{UP,S}_{c,t}$					-0.8516	-1.1485	-1.6343
					(2.3593)	(2.3854)	(2.4353)
$GVC^{UP,S^2}_{c,t}$					-1.2784	-0.5131	-0.6801
					(1.1442)	(1.3586)	(1.3299)
$GVC^{UP,S^3}_{c,t}$					1.4133**	1.3379*	1.4348**
					(0.6013)	(0.6993)	(0.7018)
N_{c_t}	0.0002	0.0002	0.0007*	0.0005	0.0002	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
$\log K_{c_t}$	0.4212***	0.4155***	0.3816***	0.3904***	0.3926***	0.3846***	0.3732***
	(0.0487)	(0.0501)	(0.0482)	(0.0515)	(0.0524)	(0.0428)	(0.0448)
H_{c_t}	0.0654	0.0663	0.0694	0.0725	0.0399	0.0513	0.0581
	(0.0918)	(0.3662)	(0.03874)	(0.0888)	(0.0928)	(0.0911)	(0.0881)
$DVAC_{c_t}$	0.7686**	0.6810*	0.8675**	0.8360**	0.6832*	0.9944**	0.9574**
	(0.3634)	(0.3662)	(0.3874)	(0.3962)	(0.3699)	(0.4015)	(0.4003)
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Observations	1584	1584	1584	1584	1584	1584	1584
R^2	0.4304	0.4116	0.4280	0.3870	0.3908	0.4843	0.4711
Adjusted R^2	0.3940	0.3741	0.3914	0.3478	0.3519	0.4480	0.4339

Table 3: The connection between GDP and GVC position by upstreamness. Robust standard errors are applied for heteroskedasticity. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Dependent variable: $\log GDP_{c,t}$				
	(1)	(2)	(3)	(4)	(5)
$ECI_{c,t}^{GROSS}$				0.4568	
				(2.2878)	
$ECI_{c,t}^{GROSS^2}$				3.3198**	
				(1.4402)	
$ECI_{c,t}^{GROSS^3}$				-1.9226**	
				(0.8543)	
$ECI_{c,t}^{VA}$					0.2557
					(2.2507)
$ECI_{c,t}^{VA^2}$					3.0358**
					(1.4130)
$ECI_{c,t}^{VA^3}$					-1.3943*
					(0.8321)
$GVC_{c,t}^{DOWN,A}$	-7.2231**			-8.0242***	-8.3166***
	(3.5281)			(2.7868)	(2.8718)
$GVC_{c,t}^{DOWN,A^2}$	2.2135			2.3634	2.3690
	(2.7090)			(1.9200)	(1.9824)
$GVC_{c,t}^{DOWN,A^3}$	0.1900			0.9535	0.8421
	(1.5659)			(1.2953)	(1.3409)
$GVC_{c,t}^{DOWN,M}$		3.9959**		1.3915	1.2813
		(1.5663)		(1.9289)	(1.9541)
$GVC_{c,t}^{DOWN,M^2}$		1.7087*		2.4821**	2.4699**
		(0.9843)		(1.1451)	(1.1489)
$GVC_{c,t}^{DOWN,M^3}$		-0.4801		0.7772	0.7828
		(0.6337)		(0.7218)	(0.7217)
$GVC_{c,t}^{DOWN,S}$			-4.7557**	-5.7766**	-6.4234**
			(2.3578)	(2.5737)	(2.6978)
$GVC_{c,t}^{DOWN,S^2}$			0.6560	2.4147**	2.1577*
			(1.0856)	(1.1132)	(1.1219)
$GVC_{c,t}^{DOWN,S^3}$			1.2719	0.4890	0.6907
			(0.8038)	(0.7651)	(0.8018)
N_{c_t}	0.0007*	0.0004	0.0004	0.0006**	0.0006**
	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0004)
$\log K_{c_t}$	0.3909****	0.3835***	0.3888***	0.3799***	0.3747***
	(0.0518)	(0.0539)	(0.0519)	(0.0489)	(0.0505)
H_{c_t}	0.1157	0.0661	0.0307	0.0893	0.0876
	(0.0924)	(0.0866)	(0.0939)	(0.0803)	(0.0779)
$DVAC_{c_t}$	0.7253***	1.0783**	0.6593**	0.8943***	0.7875***
	(0.2687)	(0.4313)	(0.3290)	(0.2703)	(0.2519)
Country FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	1584	1584	1584	1584	1584
R^2	0.4408	0.4026	0.4073	0.5424	0.5284
Adjusted R^2	0.4051	0.3645	0.3695	0.5102	0.4952

Table 4: The connection between GDP and GVC position by downstreamness. Robust standard errors are applied for heteroskedasticity. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

	Dependent variable: $\log\left(GDP_{c,t+\delta}/GDP_{c,t}\right)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ECI_{c,t}^{GROSS}$	-0.0271					0.0136	
	(0.0511)					(0.0437)	
$\Delta ECI_{c,t}^{GROSS}$	0.0454					0.0650	
	(0.0587)					(0.0505)	
$ECI_{c,t}^{VA}$		0.0476					0.090**
		(0.0495)					(0.0425)
$\Delta ECI_{c,t}^{VA}$		0.0821					0.1017**
		(0.0567)					(0.0485)
$GVC_{c,t}^{UP,A}$			0.2796***			0.4998***	0.5145***
			(0.0936)			(0.1408)	(0.1421)
$GVC_{c,t}^{UP,M}$				-0.1014		0.0946	0.0664
				(0.1231)		(0.1106)	(0.1178)
$GVC_{c,t}^{UP,S}$					0.3858***	0.6029***	0.6177***
					(0.1436)	(0.1718)	(0.1702)
$GDP_{c,t}$	-1.42e-5***	-1.36e-5***	-1.39e-5***	-1.38e-5***	-1.47e-5***	-1.53e-5***	-1.47e-5***
	(1.45e-6)	(1.46e-6)	(1.93e-6)	(1.48e-6)	(1.32e-6)	(1.77e-6)	(1.80e-6)
$\log \Delta N_{c,t}$	-0.5352	-0.4788	-0.6448	-0.5688	-0.2900	-0.3144	-0.2492
	(0.6379)	(0.6574)	(0.6539)	(0.6432)	(0.5623)	(0.5444)	(0.5436)
$\log \Delta K_{c,t}$	0.2452***	0.2547***	0.2497***	0.2549***	0.2557***	0.2414***	0.2529***
	(0.0502)	(0.0486)	(0.0503)	(0.0512)	(0.0519)	(0.0507)	(0.0491)
$H_{c,t}$	0.0470	0.0465	0.0093	0.0352	0.0489	-0.0049	-0.0121
	(0.1123)	(0.1107)	(0.1099)	(0.1098)	(0.1054)	(0.1040)	(0.1011)
$\Delta H_{c,t}$	0.2414	0.2279	0.2086	0.1990	0.2530	0.3068	0.2862
	(0.1612)	(0.1698)	(0.1764)	(0.1646)	(0.1815)	(0.2044)	(0.2102)
$DVAC_{c,t}$	-0.1627	-0.1084	-0.2751	-0.1567	-0.0237	-0.2108	-0.1980
	(0.3410)	(0.3303)	(0.3358)	(0.3337)	(0.3062)	(0.3008)	(0.2822)
$\Delta DVAC_{c,t}$	0.6684**	0.6992**	0.6278*	0.6930**	0.7721**	0.7334**	0.7483**
	(0.3243)	(0.3244)	(0.3435)	(0.3302)	(0.3285)	(0.3438)	(0.3426)
Country FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Observations	1584	1584	1584	1584	1584	1584	1584
R^2	0.4144	0.4130	0.4229	0.4100	0.4359	0.4829	0.4878
Adjusted R^2	0.1719	0.1700	0.1884	0.1702	0.2066	0.2569	0.2639

Table 5: The connection between GDP growth and GVC position by upstreamness. Robust standard errors are applied for heteroskedasticity. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Dependent variable: $\log\left(GDP_{c,t+\delta}/GDP_{c,t}\right)$				
	(1)	(2)	(3)	(4)	(5)
$ECI_{c,t}^{GROSS}$				0.0409	
				(0.0451)	
$\Delta ECI_{c,t}^{GROSS}$				0.0777	
				(0.0541)	
$ECI_{c,t}^{VA}$					0.1067**
					(0.0434)
$\Delta ECI_{c,t}^{VA}$					0.1046**
					(0.0512)
$GVC_{c,t}^{DOWN,A}$	0.8424***			0.9026***	0.9106***
	(0.2672)			(0.2899)	(0.2859)
$GVC_{c,t}^{DOWN,M}$		-0.2550**		-0.0914	-0.1174
		(0.1190)		(0.1418)	(0.1514)
$GVC_{c,t}^{DOWN,S}$			0.3108***	0.2921**	0.2956*
			(0.1118)	(0.1424)	(0.1393)
$GDP_{c,t}$	-1.33e-5***	-1.44e-5***	-1.41e-5***	-1.34e-5***	-1.30e-5***
	(1.72e-6)	(1.50e-6)	(1.30e-6)	(1.72e-6)	(1.71e-6)
$\log \Delta N_{c,t}$	-0.6311	-0.5199	-0.4666	-0.5618	-0.4871
	(0.6336)	(0.6082)	(0.5897)	(0.5763)	(0.5718)
$\log \Delta K_{c,t}$	0.2549***	0.2545***	0.2498***	0.2461***	0.2580***
	(0.0486)	(0.0520)	(0.0518)	(0.0504)	(0.0495)
$H_{c,t}$	0.0027	0.0227	0.0155	-0.0368	-0.0430
	(0.1041)	(0.1123)	(0.1082)	(0.1008)	(0.0981)
$\Delta H_{c,t}$	0.1626	0.1987	0.2103	0.1766	0.1538
	(0.1829)	(0.1536)	(0.1783)	(0.1918)	(0.1940)
$DVAC_{c,t}$	-0.1861	-0.2725	-0.0670	-0.0409	-0.0499
	(0.3002)	(0.3389)	(0.3041)	(0.3362)	(0.3237)
$\Delta DVAC_{c,t}$	0.6632*	0.6925**	0.7756**	0.7921**	0.7887**
	(0.3367)	(0.3234)	(0.3237)	(0.3215)	(0.3224)
Country FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	1584	1584	1584	1584	1584
R^2	0.4370	0.4264	0.4298	0.4710	0.4774
Adjusted R^2	0.2081	0.1933	0.1981	0.2398	0.2489

Table 6: The connection between GDP growth and GVC position by downstreamness. Note: Robust standard errors are applied for heteroskedasticity. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.