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The Integration of Global Value Chain in the EU: Stylized Facts and Drivers

With a Special Focus on Belgium and Portugal

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The Integration of Global Value Chain in the EU: Stylized Facts and Drivers With a Special Focus on Belgium and Portugal

Prepared by Younghun Shim, Iglika Vassileva and Mengxue Wang*

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ABSTRACT: This paper examines EU global value-chain (GVC) integration and analyzes its drivers using machine learning models, with case studies of Portugal and Belgium. GVC participation appears to boost productivity and technology upgrading, but also brings concentration risks in the current environment. Results indicate labor cost, labor productivity and human capital as key drivers, supported by infrastructure, manufacturing base, and governance quality. Portugal remains downstream, constrained by low high-tech intensity, while Belgium is highly integrated but exposed to sectoral shocks. Strengthening the EU single market, capital-market integration, and individual countries' investment in skills, innovation, and diversification would bolster resilience while preserving the benefits of openness.

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WORKING PAPERS

The Integration of Global Value Chain in the EU: Stylized Facts and Drivers

With a Special Focus on Belgium and Portugal

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Contents

1. Introduction

Over the past decades, global value chains (GVCs) have reshaped international production, bringing significant opportunities but creating new vulnerabilities. Europe is among the regions most deeply integrated into cross-border networks of trade, investment, and knowledge flows. At the same time, countries participate in these networks in very different ways and at different stages of GVC integration, from being mostly commodity exporters to highly-sophisticated and innovative economies. As a stylized fact, the literature identifies four broad GVC integration profiles: commodity exporters; countries in limited manufacturing; those in advanced manufacturing and services; and innovation-intensive economies built around complex tasks and intangible assets (World Bank's World Development Report (WDR) 2020). These different positions in GVC shape both the magnitude and the composition of gains from trade and specialization, as well as the types of risks countries face.

Participation in GVCs has offered powerful opportunities but also brings risks. For commodity exporters and limited-manufacturing economies, integration into cross-border production networks has historically been an important routes to accelerate productivity growth and income convergence. For economies in advanced manufacturing, services, and in innovative activities, GVC participation supports technological upgrading, greater export sophistication, and the ability to capture rents from R&D and branding. Yet as countries get more integrated into GVCs, their participation becomes more complex and, in many cases, more fragile. Supply-chain disruptions during the pandemic, heightened geopolitical and trade tensions, and policy shifts toward near-shoring and strategic autonomy have highlighted the risks of concentration and propagation inherent in tightly linked production structures. For Europe, where small open economies rely heavily on GVC participation, a key question is how to preserve the gains from openness while managing new vulnerabilities. Understanding the drivers, opportunities, and risks of GVC integration is therefore critical to inform policies that support sustained and resilient growth.

This paper provides stylized facts on current trends in GVC integration in the EU, with a particular focus on Portugal and Belgium, and applies a machine learning approach to identify the drivers of GVC participation. The analysis shows that value-chain integration of EU economies is deep but uneven. There are wide cross-country differences in linkages, complexity, and specialization, combined with rising geopolitical and supply-chain risks. Machine learning (ML) models suggest that labor productivity and costs and human capital are the strongest and most consistent drivers of both global and intra-EU integration in GVCs, while infrastructure, manufacturing depth, governance quality, and digital readiness also play important supportive roles. The two case studies highlight contrasting patterns: Portugal's integration remains concentrated in low-technology, downstream activities, while Belgium is deeply embedded in high-value, upstream segments but faces rising concentration risks.

The remainder of the paper is structured as follows. The next section includes a brief literature review on the benefits and risks of GVC. Section 3 describes the dataset employed in the analysis. Section 4 presents stylized facts on GVC integration in Europe. Section 5 outlines the machine learning framework and discusses the main results. Section 6 examines the case studies of Belgium and Portugal.

2. Literature Review

GVC participation is widely linked to faster productivity growth and income convergence. Several channels are at play: finer specialization in tasks and scale effects that raise efficiency (Baldwin, 2016; Timmer et al., 2014); access to high-quality imported intermediates and embodied technology (Keller, 2004); knowledge diffusion via buyer–supplier linkages, FDI, and management spillovers (Javorcik, 2004; Gorodnichenko et al., 2014; Choi et al., 2025); and upgrading incentives as firms move from assembly to design, branding, and services (Taglioni & Winkler, 2016; World Bank, 2020). Through these channels, deeper GVC participation has generally been associated with higher GDP per capita, faster export growth and diversification, and rising wages, particularly for more skilled workers (Ignatenko et al., 2019; Gal & Witheridge, 2019; Munch and Xiang 2014).

Recent empirical work has also stressed that these gains materialize differently across stages of GVC integration. WDR 2020 has found that moving from the commodity exporters to limited manufacturing is typically associated with the largest acceleration in growth and job creation, as countries plug into global production networks and diversify away from primary products, as also discussed in Kowalski et al., 2015 and Ignatenko et al., 2019. As countries move into advanced manufacturing and services, GVCs tend to reinforce productivity upgrading, more complex and diversified export baskets, and stronger knowledge spillovers (Criscuolo and Timmis, 2017; Gal and Witheridge, 2019). Across all four categories of GVC integration introduced earlier, cross-country and firm-level evidence generally finds that greater GVC integration correlates with higher GDP per capita and TFP growth (WDR 2020, Kowalski et al 2015), but also shows that these gains are contingent on complementary domestic drivers of productivity, such as human capital, infrastructure, macroeconomic stability, and institutional quality, rather than GVC participation alone (Ignatenko et al., 2019; Amador and Cabral 2016).

However, in the current environment, latecomers face challenges integrating into GVCs while already well-integrated economies are confronted with new risks. For latecomers, tighter global financial conditions and the de-globalization trend reduce the payoff to export-led entry, while higher fixed costs of meeting standards, including quality infrastructure, sustainability certification, data and cybersecurity rules, raise the threshold for participation (Constantinescu, Mattoo, and Ruta, 2015; Miroudot, 2020). Geoeconomic fragmentation and policy uncertainty, including tariffs, export controls, subsidy races, and near-shoring, further bias lead firms toward established supplier networks, making it harder for newcomers to overcome capability gaps (Antràs, 2020; IMF, 2023). Supply chain disruptions due to policy disruptions could also lead to sizable economic losses (Panon et al 2024). At the same time, highly integrated economies face concentration and propagation risks: shocks transmit rapidly along input–output links, amplifying exposure to demand shocks, logistics bottlenecks, and geopolitical disruptions (Bonadio et al., 2021; OECD, 2021). These countries also confront stronger resistance to diversifying their industrial outputs, as dense specialization within established cross-border production networks tends to reinforce path dependency. Moreover, heavy reliance on a few anchor industries can crowd out resources and policy attention from emerging activities, raising vulnerability to technological disruption and demand shifts. In this sense, moving up the GVC ladder tends to bring both larger benefits and more complex vulnerabilities. The challenge, particularly for highly-open European economies, is therefore how to preserve and broaden the gains from GVC participation while containing the risks that arise as countries are more integrated into the GVC .

3. Data

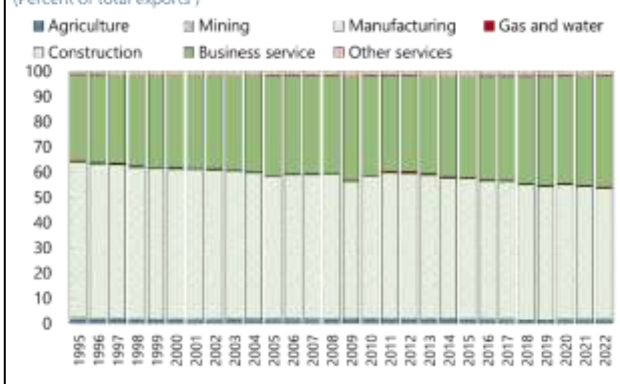
The main dataset used in the paper is the OECD Trade in Value Added (TiVA). The data is constructed from Inter-Country Input–Output (ICIO) tables covering 76 countries and 45 industries over the period 1995–2022. A key strength of TiVA is that it decomposes gross trade flows into their domestic and foreign value-added components, which can be further broken down into contributions from different sectors. Importantly, the dataset covers not only manufacturing sectors but also services, thereby providing a comprehensive and accurate picture of how economies are integrated into global value chains. However, one caveat of the TiVA data is the lag in data collection, as it does not provide information beyond 2022.

To complement this, we also draw on Eurostat and World Bank data to gather data for the GVC drivers, export statistics and economic complexity data from Hausmann et al. (2013). We use economic complexity data to measure the level of sophistication in countries' exported goods. Product-level gross exports data from Eurostat are used to calculate the share of exports by technology intensity. Eurostat also provides variables that capture the drivers of GVC integration. Regarding the GVC drivers, in addition to the Eurostat, we also use data from the World Bank's World Development Indicators and Worldwide Governance Indicators, as well as from the OECD.

4. GVC Integration in Europe

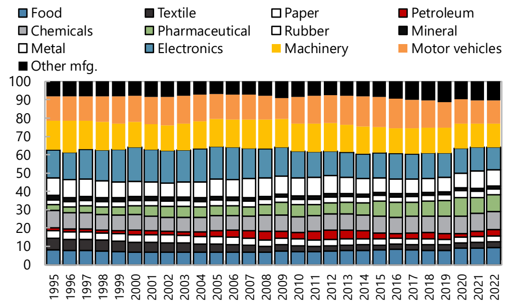
The EU27 export structure remains heavily concentrated in manufacturing, though exports of business services have steadily expanded. Within manufacturing, exports of motor vehicles, machinery, and electronics continue to represent the largest shares. Pharmaceuticals have gained importance in recent years, reflecting the EU's specialization in high-tech and life sciences. On the services side, trade and food-related services dominate, but their share has gradually declined, while information, finance and professional services have increased, pointing to a shift toward more knowledge-intensive activities over the past decades. Overall, the EU's export profile reflects a gradual transition from traditional manufacturing and trade- and tourism-related services toward a more diversified mix that incorporates higher value-added industries and services.

Export of EU27 by Sectors
(Percent of total exports)



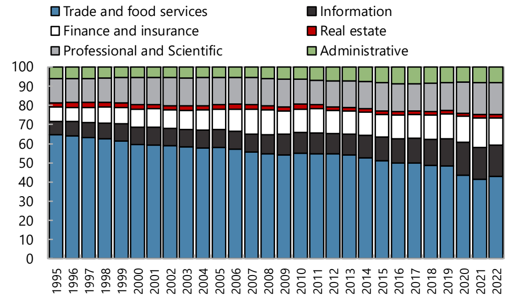
Sources: OECD TiVA and IMF staff calculations.

Export of EU27 in Manufacturing
(Percent of total)



Sources: OECD TiVA and IMF staff calculations.

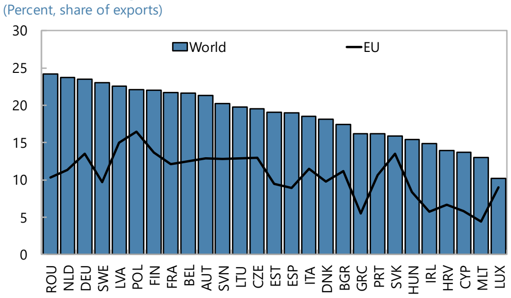
Export of EU27 in Business Services
(Percent of total)



Sources: OECD TiVA and IMF staff calculations.

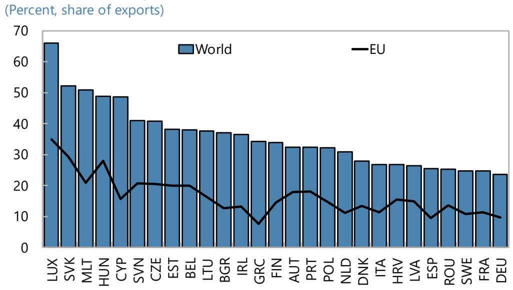
The role EU countries play in GVCs varies significantly across the region. This can be measured through the heterogeneity in forward and backward linkages. Forward linkages measure the share of a country's value added in other countries' exports. Backward linkages capture the share of foreign value added in the country's own exports. High forward linkages indicate a strong role as an upstream supplier, providing critical inputs that are re-exported by trading partners, whereas high backward linkages point to reliance on imported intermediates, signaling deep integration but also greater vulnerability to supply disruptions. Some countries (e.g., Luxembourg and Malta) act more as downstream assemblers dependent on foreign inputs, while others (e.g., Romania and Germany) are positioned predominantly as upstream suppliers as seen in the two charts below. Differences across countries on the two linkages are significant, suggesting that countries in the EU are in different stages of integration into the global value chain. Around half of the forward and backward linkages are related to EU inputs or EU re-exports, giving ample room to further strengthen integration within EU.

Forward Linkages
(Percent, share of exports)



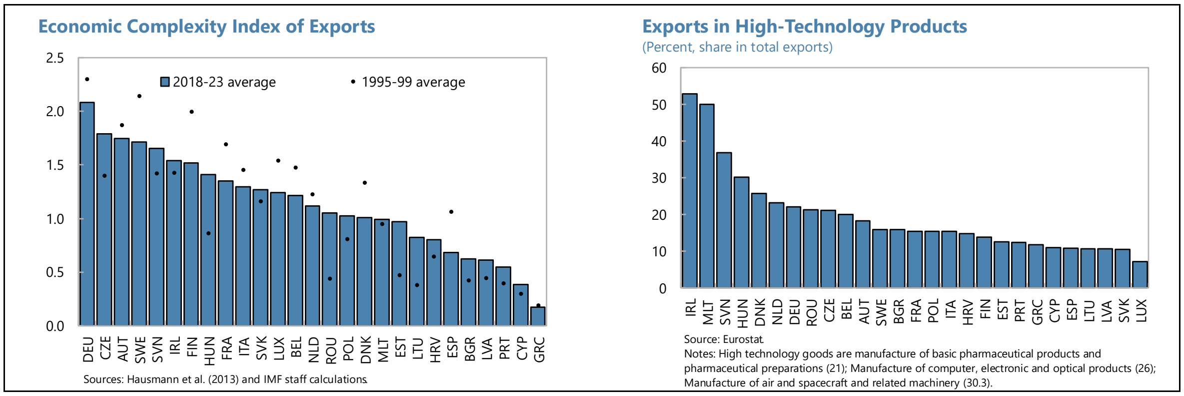
Sources: OECD TiVA 2025 and IMF staff calculations.
Notes: Forward linkages are calculated as domestic value added content of foreign exports.

Backward Linkages
(Percent, share of exports)

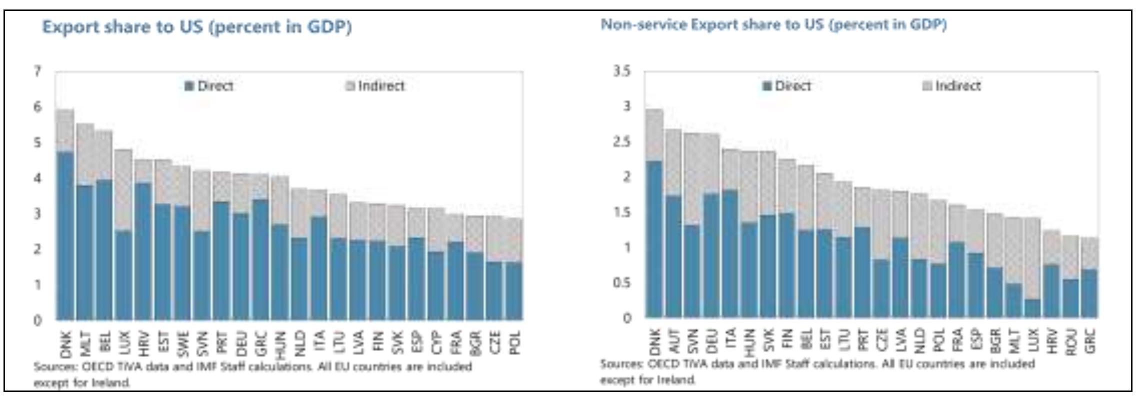


Sources: OECD TiVA 2025 and IMF staff calculations.
Notes: Backward linkages is calculated as foreign value added embodied in domestic exports.

Economic complexity and the share of high-technology exports also differ markedly across EU countries. Economic complexity, as defined by Hausmann et al. (2013), measures both the diversity of a country's exports and the uniqueness of the products it sells. Economies are considered more complex when they export a broad range of goods that few other countries produce. High-technology exports, following Eurostat's definition, include pharmaceuticals, computers, electronic and optical products, and the manufacture of air and spacecraft. Both indicators show significant heterogeneity across Europe. Notably, specialization in high-technology goods does not necessarily translate into greater economic complexity, suggesting that some countries' export structures remain concentrated in a limited range of products, or that those products are also exported by other countries despite their technological sophistication.



With recent global trade disruptions, the high degree of interconnectedness and integration in Europe has also become a source of vulnerability. European economies are deeply intertwined through both intra-regional and extra-regional production networks, leaving them exposed to shocks originating from a range of partners, including geopolitical tensions, supply-chain realignments, and the reconfiguration of critical input sources. While exposure to the United States remains significant, both directly through exports and indirectly through value added embedded in third-country trade, it represents only one channel of potential disruption at this juncture. The re-emergence of tariffs, the growing use of industrial policies, and heightened risks around strategic dependencies, such as energy and critical materials, further underscore the vulnerability of Europe's interconnected value chains. Given the density of these linkages, disruptions affecting even a single sector or partner country can quickly propagate through upstream and downstream networks, magnifying the overall economic impact across the region. These developments highlight the importance of diversifying export products and destinations and increasing the uniqueness and technological sophistication of domestic production to strengthen resilience against external shocks.



5. Drivers of GVC Integrations

In this section, we employ machine learning models to study possible drivers of GVC integrations.

5.1 Methodology, machine learning models, and choice of variables

5.1.a. Machine learning models

ML methods are designed to capture intricate data patterns and relax some of the assumptions of traditional econometrics. In contrast to traditional panel regressions, ML models do not impose strong parametric restrictions on the model functional form and errors. This allows them to capture more complex, nonlinear interactions between the dependent (outcome) variable and its predictors (features). Furthermore, some ML methods are better suited to handle multicollinearity and overfitting in high-dimensional datasets. Since we are not applying causal ML methods, our findings reflect associations and, therefore, do not necessarily identify causal relationships. The apparent disadvantage of the ML models is the lack of interpretability due to the absence of an explicit structure. We overcome this drawback by calculating SHAP values, which are based on the concept of Shapley values from coalition game theory.[1]

SHAP values provide a means to estimate the contribution of each feature to the prediction of the outcome variable. It can be illustrated in the following way:

for each observation in the dataset:

$$Predition\ of\ the\ outcome\ variable = Baseline(average\ prediction) + \sum SHAP\ values\ of\ all\ predictors$$

The baseline shows what the model predicts on average, while the SHAP values explain how each feature adjusts the prediction in a negative or positive direction, compared to the baseline. Because SHAP value ranges differ across models and depend on the scale of the output variable, we normalize them by expressing each as a percentage of the absolute value of the sum of all SHAP values for that model.

We apply six ML algorithms to identify and quantify the determinants of GVC integration.[2]

- *Linear regression*: assumes linear relationships between variables.
- *Elastic Net Regression*: incorporates regularization to address multicollinearity and enhances model sparsity.
- *Support Vector Regression* (SVR): utilizes kernel methods to capture complex, non-linear relationships.
- *Random Forest Regression*: aggregates multiple decision trees to improve predictive accuracy and reduce overfitting.
- *Extreme Gradient Boosting (XGBoost)*: sequentially builds trees to correct errors, optimizing both speed and performance.
- *K-Nearest Neighbors (KNN)*: predicts outcomes based on the proximity of similar observations.

[1] See Annex X for a discussion on SHAP values

[2] See Annex X for a detailed discussion on ML models.

5.1.b. Variables included

GVC integration is affected by numerous factors, varying from purely technical to structural and policy determinants[3]. They can be organized into the following groups:

- The ***technical factors*** measure how easily goods and services can be delivered and include mainly infrastructure and logistics. Physical infrastructure facilitates the movement and trade of goods and might be a key determinant in outsourcing production in certain countries. Digital infrastructure can itself support GVC integration by enhancing coordination and the delivery of some services. Finally, efficient and reliable logistics can also reduce the economic cost of providing goods and services across borders. We include the following technical variables in our specification:
  - *Infrastructure,* estimated by the length of railway and road infrastructure per square meter of country territory;
  - *Digital infrastructure and uptake*, estimated with the OECD Index of Digital Trade Integration and Openness (INDIGO). INDIGO measures the extent to which e-commerce is enabled, open and trusted, cross-border data flows and data localization and wider digital economy issues.

- ***Structural drivers*** include inherent characteristics of the economies, such as geographical location, proximity to large GVC hubs, structure of the economy's gross value added, size of the domestic market, labor market characteristics and others. Typically, larger economies with good industrial bases have deeper forward linkages, while smaller economies that are not resource- or technology-intensive, rely on backward linkages. Meanwhile, regarding the labor market, cost competitiveness is associated with the real wage level (especially in emerging economies), while availability of skilled labor determines the attractiveness of the economy for investment. The following structural drivers are incorporated into our models.
  - *Unit labor cost* (wages-to-labor productivity ratio, or, alternatively, calculated as the compensation of employees divided by real GDP).
  - *Labor productivity.* This is calculated as real GDP divided by total hour worked.
  - *Quality of labor force.* We use the share of employed individuals with educational attainment below upper secondary level, which serves as a proxy for lower human capital quality.
  - *Economic structure,* measured by the share of manufacturing in GDP.

- Finally, ***policy determinants*** include trade and investment openness, institutional quality, etc. Lack of trade tariff and nontariff barriers, free trade agreements, and liberalized investment and capital flows tend to impact positively GVC integration. Meanwhile, geoeconomic fragmentation and geopolitical tensions slow the deepening of GVCs. Finally, ensuring a predictable business environment, the rule-of-law, and proper regulations have a beneficial impact on GVCs. We retain the following policy relevant variables in the ML models.
  - *Economic freedom* index, constructed by the Fraser Institute. It includes four subcomponents: size of government, legal system and property rights, sound money, freedom to trade internationally, and regulation of labor, business and finance.

[3] The empirical literature on the determinants of GVC integration employ a variety of methodological approaches, including country-level panel regressions and gravity models with country fixed effects (Fernandes, Kee and Winkler 2022, Ignatenko, Raei and Mircheva 2019, Buelens and Tirpák 2017) and firm-level data to determine firm-level drivers of GVC participation (Urata and Baek 2020).

5.1.c. Panel

We apply ML models to a panel dataset for all EU countries with country fixed effects. We consider four outcome variables – global value chains (GVC), measured as the sum of backward and forward linkages, value-added chains within EU, global GVC for goods, and global GVC for services. We apply the following transformations to the data:

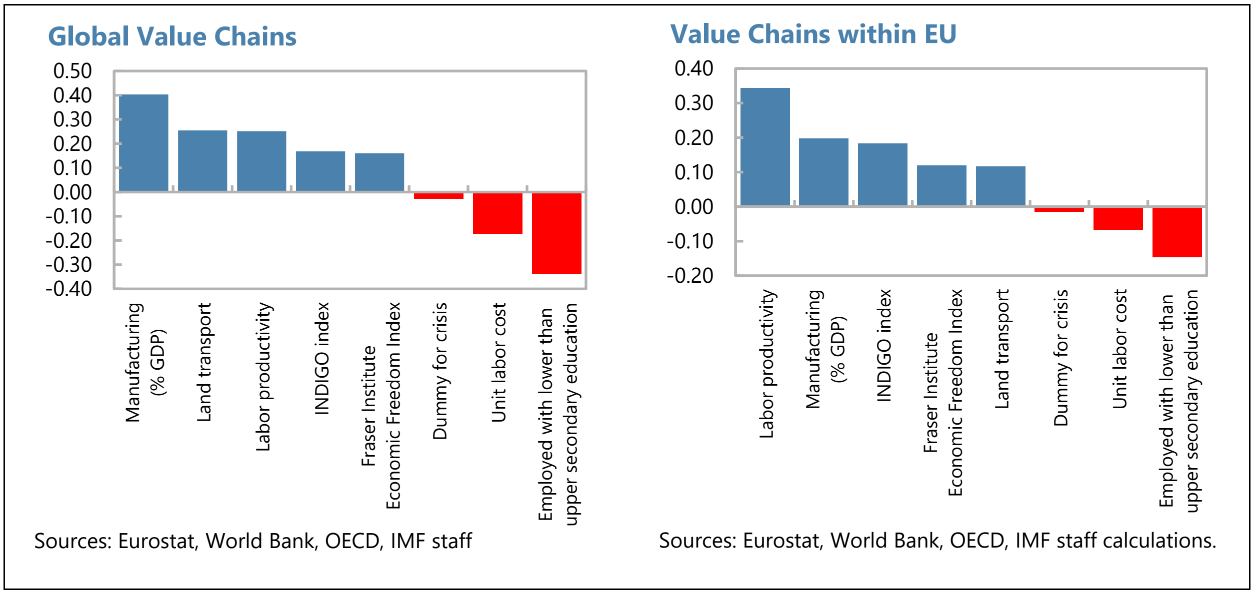
- Each explanatory variable is expressed as a percentage of its EU average to highlight the country-specific dynamics.
- Prior to applying machine learning methods, the data is centered and standardized to mitigate scaling sensitivity and ensure comparability across variables.
- Unit labor costs and labor productivity variables are taken with a lag of one year to remove simultaneity and thus mitigate possible endogeneity.
- We include fixed effects for each EU country and a dummy variable for the global financial and COVID-19 crises.

5.2 Results

5.2.a. Global value-chain vs. EU value-chain integrations

Globally, economic structure, unit labor cost and the quality of human capital emerge as key correlates of value chain participation.[4] They imply importance of industrial capacity, cost competitiveness and skill adequacy in enabling economies to engage in cross-border production networks. Infrastructure quality, proxied by land transport, and labor productivity also exhibit high positive associations. Efficient transport networks reduce transaction costs and facilitate timely delivery. Meanwhile, higher productivity is often linked to technological advancement, superior management practices and process efficiency, all of which enhance competitiveness. Institutional quality and cost competitiveness both contribute moderately, but positively to GVC participation. The positive SHAP values of the INDIGO index and the Fraser Institute's Economic Freedom Index suggest that strong governance and sound regulatory frameworks reduce uncertainty and foster investment, while the use of digital solutions facilitates cross-border coordination. Finally, the global financial crisis and the COVID-19 crisis have contributed marginally negatively to GVC integrations.

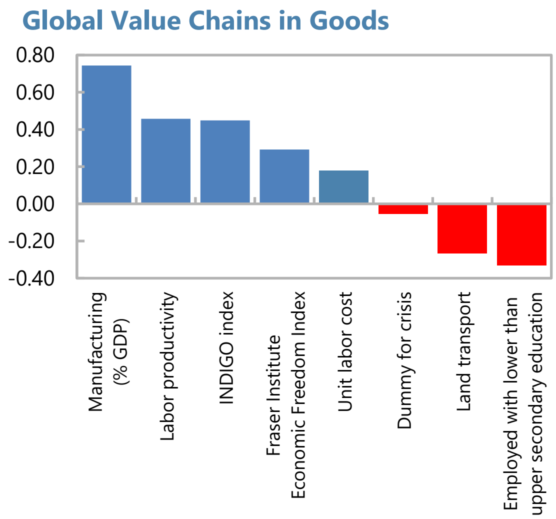
[4] The charts present the SHAP values for each driver, where blue bars indicate positive contributions to GVC integration and red bars denote negative ones.



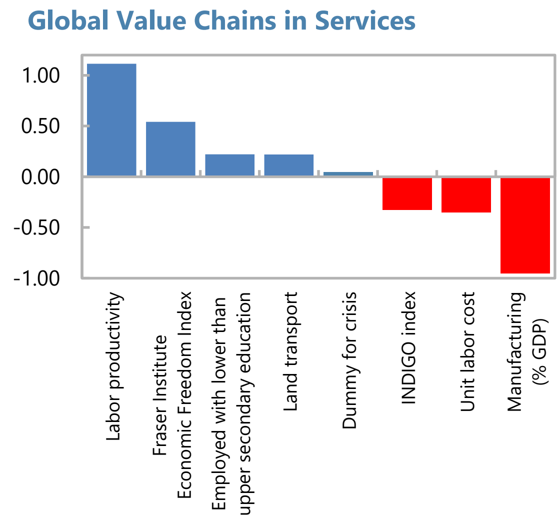
Within the EU, labor productivity emerges as the dominant factor, surpassing manufacturing share as the primary associated variable of GVC participation. This might reflect EU's advanced economic structure, where competitiveness increasingly hinges on efficiency and technological sophistication rather than sheer industrial scale. A developed industrial base remains important, followed by institutional quality, infrastructure, and cost competitiveness. Low educational attainment and high unit labor cost continues to constrain participation at EU scale as well.

5.2.b. Goods value chain v.s. service value chain integrations

While both service and goods value chains depend on high institutional capacity, goods networks benefit strongly from robust industrial base, whereas service GVCs reward productivity. Economic structure plays is highly correlated with both types of trade integration – positively for goods and negatively for services. Productivity is also estimated to have an important association, being the strongest positive correlate for services and the second largest for goods GVC. This reflects the importance of efficiency, technology adoption, and knowledge intensity. However, high labor costs become less relevant for GVC integration in goods while keeping its significant negative impact to GVC integration in services. The estimated positive effect of the ULC on GVC integration in goods could reflect automation or technological upgrading in some sectors or EU economies.



Sources: Eurostat, World Bank, OECD, IMF staff calculations.

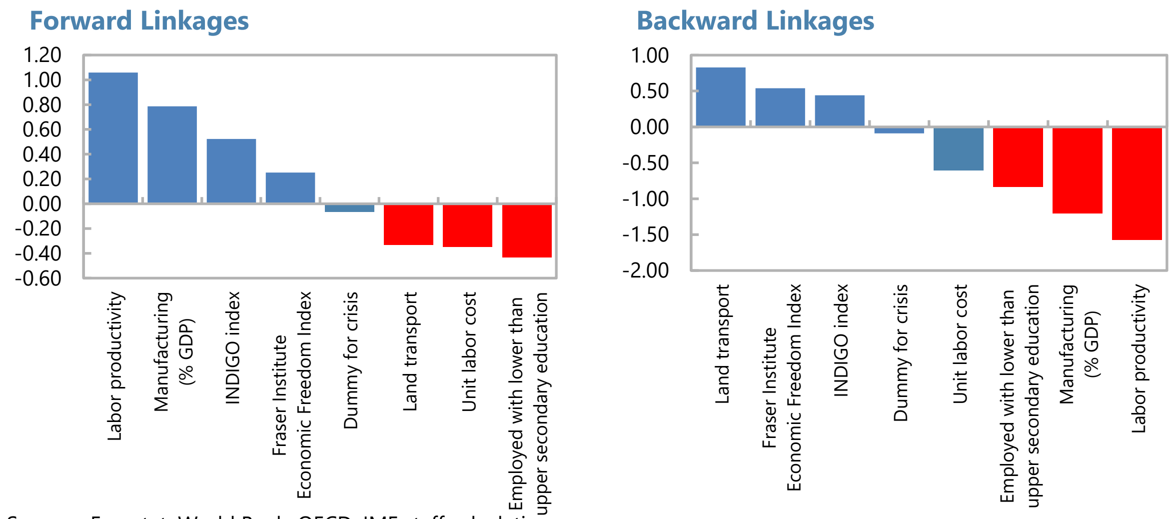


Sources: Eurostat, World Bank, OECD, IMF staff calculations.

5.2.c. Forward vs. backward linkages

Forward linkages favor economies with high productivity, strong manufacturing, and good institutions, while cost and skill constraints remain barriers. More productive economies with well-developed industrial sectors are better positioned to supply intermediate goods and services to global production networks. Furthermore, INDIGO and Fraser Institute Freedom indices exert moderate positive influence, suggesting that governance and openness facilitate integration into upstream segments of GVCs. In contrast, high labor costs and skill shortages undermine competitiveness in supplying intermediate goods. Finally, land transport has a less relevant but negative effect, possibly because forward linkages rely more on air and maritime transport than on roads and railways.

Backward linkages exhibit high correlation with land transport and institutional quality, while economies with strong domestic production and high productivity tend to have lower dependence on foreign inputs. The prominent positive contribution of the land transport suggests that EU economies source intermediate goods largely though road or railway networks and, making physical connectivity a critical enabler of backward integration. In contrast, the negative signs of labor productivity and manufacturing share might indicate that highly productive, industrialized economies tend to rely less on foreign inputs, possibly due to domestic supply capacity. Institutional and digital capacity exert a more moderate but positive effect, while low skill level and high labor costs constrain backward linkages.

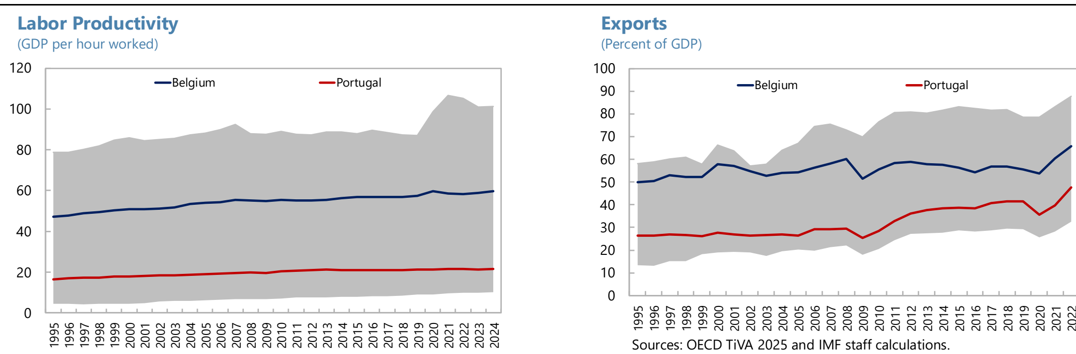


Sources: Eurostat, World Bank, OECD, IMF staff calculations.

Sources: Eurostat, World Bank, OECD, IMF staff calculations.

6. Country Case Studies

Although Portugal and Belgium are similar in size, the two countries exhibit distinct structural characteristics. Belgium's labor productivity is among the highest in Europe, while Portugal's remains comparatively low. Moreover, Belgium has high export shares, whereas Portugal's exports as a share of GDP, are lower. Both backward and forward linkages for Belgium exceed the EU average, while those for Portugal remain below it.



Sources: Eurostat and IMF staff calculations.
Notes: Shaded area shows the range (max–min) across EU-27 countries.

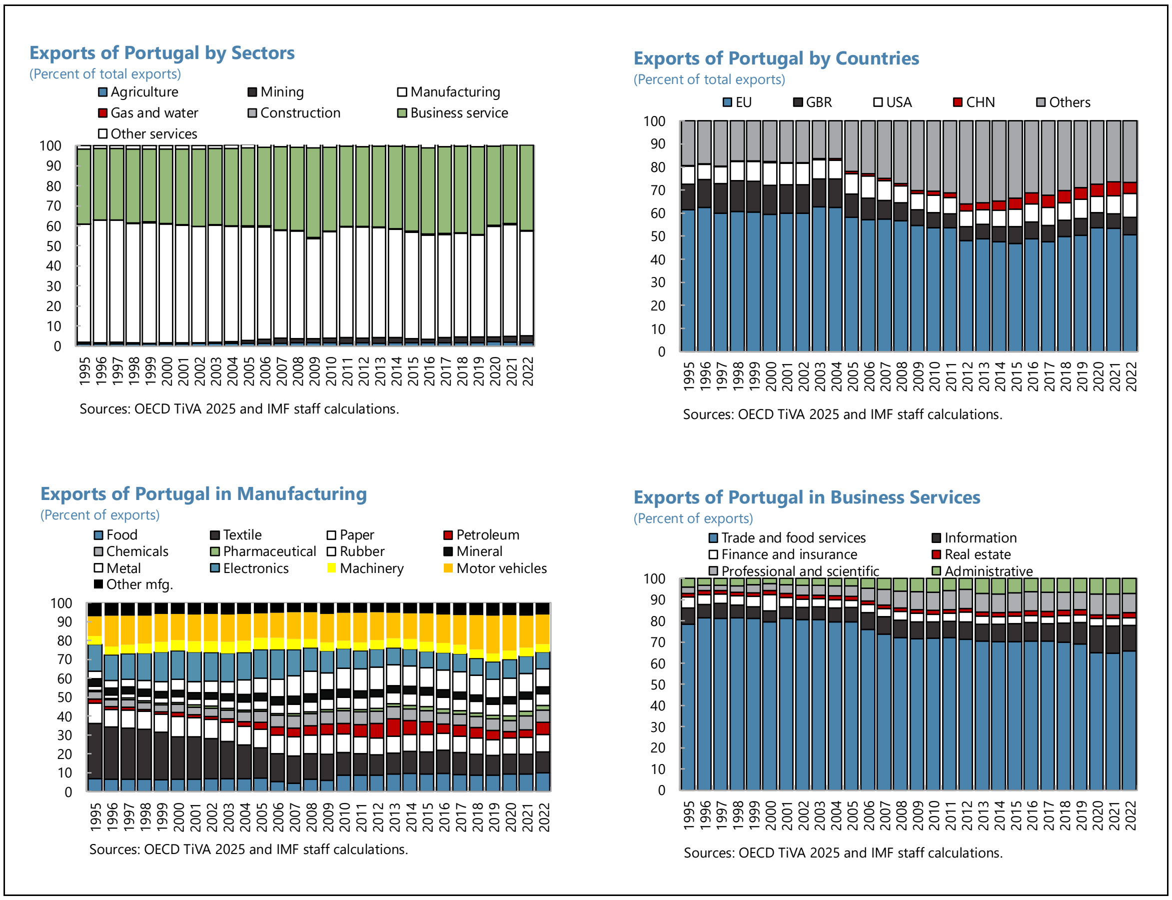
Sources: OECD TiVA 2025 and IMF staff calculations.
Notes: Shaded area shows the range (max–min) across EU-27 countries, excluding Ireland, Luxembourg, and Malta.

6.1 Portugal

6.1.a Exports

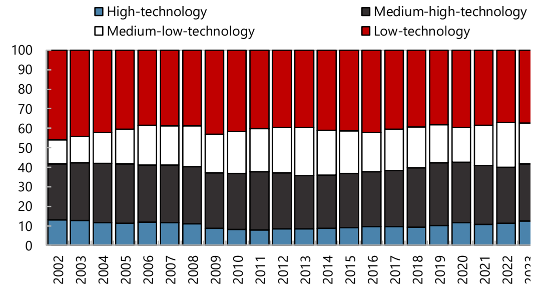
Portugal's export structure has undergone a gradual transformation, similar to the overall EU trend, with business services growing in importance to the detriment of manufacturing. Portugal's exports are concentrated in manufacturing and business services, which together account for the majority of exports. Other sectors, such as mining and agriculture, make up less than 10 percent. Within the manufacturing sector, the composition has been relatively stable. The share of pharmaceutical goods has grown over time, while that of textiles has declined sharply. In business services, trade and food services remain the largest components, reflecting the importance of tourism, although their shares have fallen. By contrast, information, and professional and scientific services have gained prominence, albeit from a small base.

The EU remains Portugal's main export destination. Although its share has declined over time, the EU still accounted for about half of Portugal's gross exports in 2022. The United Kingdom and the United States account for about 7% and 10%, respectively. Exports to China remain small but have grown in recent years.



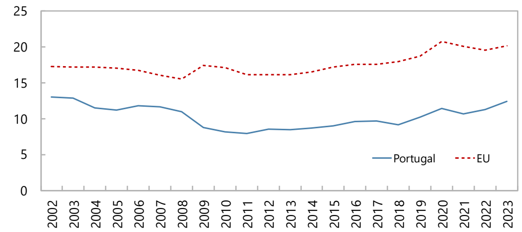
Technology intensity of Portugal's exports has been lower than that of other European countries. A large share of Portugal's exports continues to come from low- and medium-low-technology products, with only a modest contribution from high-technology sectors. The share of high-technology exports, such as pharmaceuticals, computers, and aerospace/spacecraft, has persistently lagged the EU average and shown limited convergence over time. This is also reflected in the low economic complexity for Portugal which, as shown in the previous section, remains among the lowest in Europe alongside Greece and Cyprus.

Exports by Technological Intensity
(Share of total export)



Source: Eurostat.

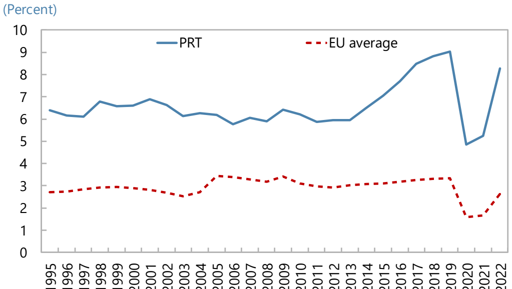
Exports in High-Technology Products
(Share of total exports)



Source: Eurostat.
Notes: High technology goods are manufacture of basic pharmaceutical products and pharmaceutical preparations (21); Manufacture of computer, electronic and optical products (26); Manufacture of air and spacecraft and related machinery (30.3) Manufacture of computer, eletronic and optical products (26); Manufacture of air and spacecraft and related machinery (30.3) EU is the exports share of entire EU countries.

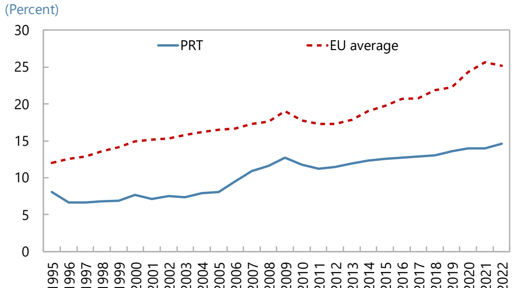
Portugal's exports show a similar pattern in services as in goods. The share of tourism in Portugal's exports has been higher than the EU average, while the share of knowledge-intensive services has been lower. Notably, the share of knowledge-intensive services has declined since 2009 and has since stagnated.

Tourism-Related Service Share in Gross Exports
(Percent)



Sources: OECD TiVA 2025 and IMF Staff calculations.
Notes: Tourism-related sector is accommodation and food service activities.

Knowledge-Intensive Service Share in Gross Exports
(Percent)

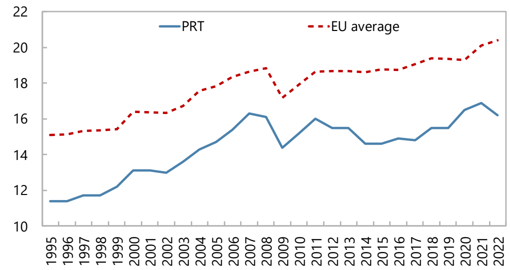


Sources: OECD TiVA 2025 and IMF Staff calculations.
Notes: Knowledge-intensive service sector is information and communication, financial intermediation, real estate, and professional business service.

6.1.b Integration in GVC, opportunities and risks

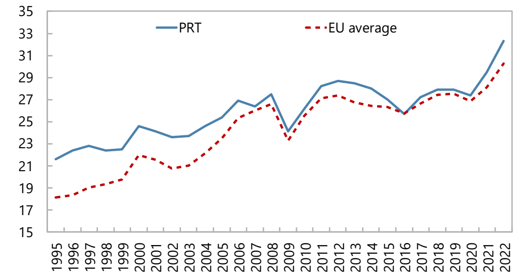
Portugal's integration in global value chain has been lagging, especially in forward linkages. Portugal's forward linkages have shown some convergence with the EU average (weighted by countries' gross exports) until 2007 but have stagnated since, indicating that Portuguese exports are not increasingly used as intermediates in foreign exports. In contrast, Portugal's backward linkages have been broadly in line with, or slightly above the EU average. This pattern suggests that Portugal remains more integrated as a downstream importer of intermediates than as an upstream supplier within cross-border production networks. Measure to enhancing upstream integration and strengthening domestic value creation, would help Portugal reap more of GVC benefits.

Forward Linkages
(Share of exports)



Sources: OECD TiVA 2025 and IMF staff calculations.
Notes: Forward linkages are calculated as domestic value added content of foreign exports.

Backward Linkages
(Share of exports)



Sources: OECD TiVA 2025 and IMF staff calculations.
Note: Backward linkages are calculated as foreign value added embodied in domestic exports.

Portugal's gap in forward linkages from EU countries are mostly driven by sectoral composition. We decompose the differences in forward linkages as below:

$$fwd^{EU} - fwd^{PT} = \sum_s \{\alpha_s^{EU}(fwd_s^{EU} - fwd_s^{PT}) + (\alpha_s^{EU} - \alpha_s^{PT})fwd_s^{PT}\}.$$

Here, α_s denotes gross export share of sector *s*, and fwd_s represents value added exports in sector *s* that is reexported by other countries, divided by gross exports in sector *s*. In the equation, the first term represents the within-sector contribution, while the second term denotes contribution from sectoral composition. For Portugal, the sectoral composition effect accounts for 90 percent of forward linkages gap relative to other EU countries. This implies that much of Portugal's weaker forward GVC integration reflects its export mix: Portugal has smaller export shares in high-forward-linkage sectors (e.g., IT services) and larger shares in low-forward-linkage sectors (e.g., tourism-related services) compared to other EU countries.

Portugal's integration in global value chains brings both benefits and vulnerabilities, reflecting its reliance on imported inputs and limited upstream participation. With foreign value-added accounting for roughly 30 percent of Portugal's gross exports, disruptions in imported intermediate inputs could weigh on export performance. By contrast, Portugal's limited forward linkages temper its exposure to external demand shocks: as its value-added contribution to other countries' exports is smaller than in most European economies. For example, Portugal's direct and indirect reliance on U.S. demand is limited, implying that trade frictions between the U.S. and the EU would likely have a more muted impact on Portugal than on its peers.

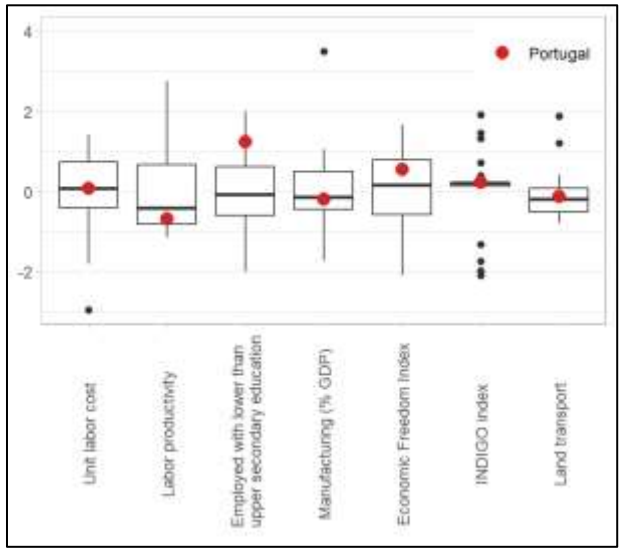
6.1.c Drivers of GVC integrations for Portugal5

Building on the analysis of GVC drivers in Section 5, we examine how Portugal is positioned relative to these key determinants (visualized using boxplots).[6]

[5] Results and boxplots for other EU countries are available upon requests.

[6] Boxplots show the distribution of the centered and normalized indicators for all EU countries. The lower and upper edges of the boxes correspond to the 25th and 75th percentile of the distribution, the middle line in the box corresponds to the median, and the whiskers denote the range of the distribution. Any dots outside the whiskers represent outliers.

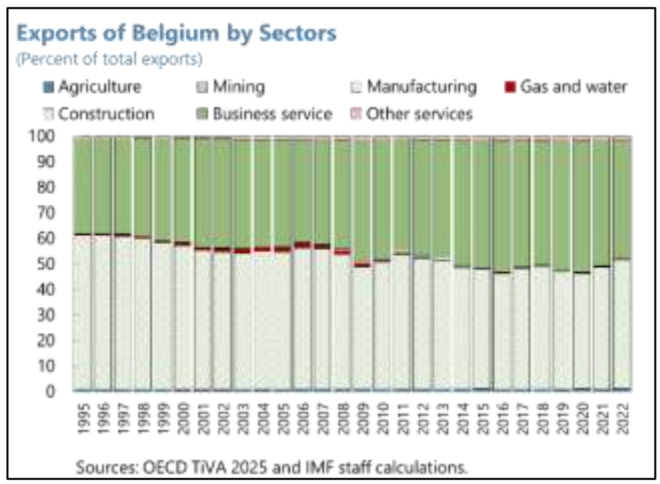
Portugal benefits from a relatively good institutional framework but lags in labor productivity and human capital education level. Portugal has higher-than-average economic freedom index but has much lower labor productivity and higher share of employment with lower education. The lower labor productivity and the quality of the labor force could potentially constrain the country's ability to move into knowledge-intensive segments and create risks for remaining locked into lower-value stages of production, where competitive pressures are high and margins are thin.

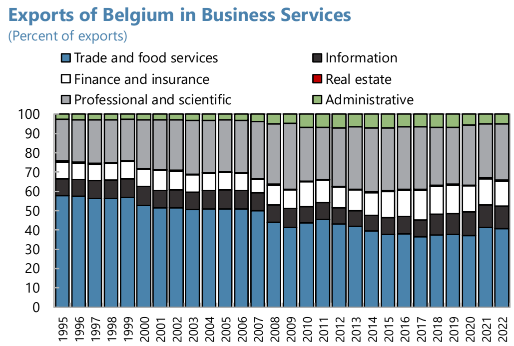


6.2 Belgium

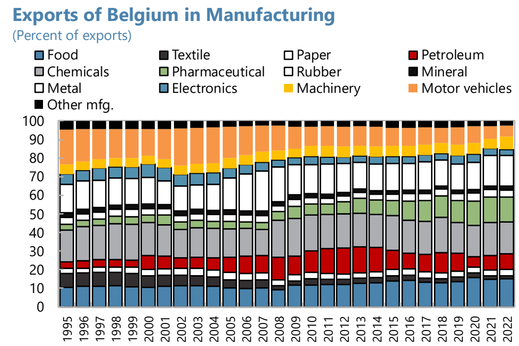
6.2.a Exports

Belgium's export structure has undergone a notable transformation, with a growing prominence of high value-added manufacturing and knowledge-intensive services, similar to EU exports. Belgium's exports are dominated by manufacturing and business services, together accounting for more than 90 percent of total exports, while agriculture, mining, construction, and utilities remain marginal. Within manufacturing, there has been a noticeable shift over time: the share of pharmaceuticals has increased markedly, making it one of Belgium's largest export items, while motor vehicles have declined as a share of total exports. Chemicals also remain a strong and stable contributor, alongside petroleum products and metals. In the area of business services, professional and scientific services stand out as the largest and rising component, together with finance and insurance and information services, while trade and food services has seen gradual declines in its relative importance. Taken together, these patterns highlight Belgium's transition toward higher value added manufacturing, particularly in pharmaceuticals and chemicals, and toward knowledge-intensive services in its export profile.





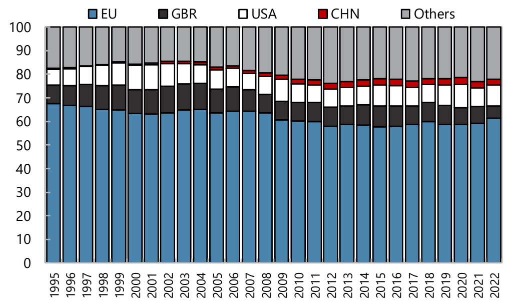
Sources: OECD TiVA 2025 and IMF staff calculations.



Sources: OECD TiVA 2025 and IMF staff calculations.

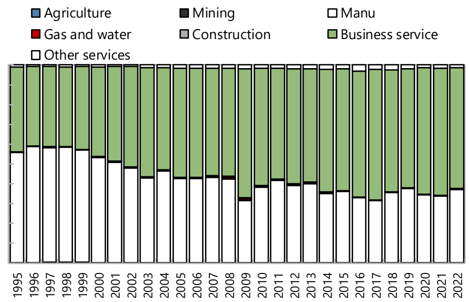
Belgium's export patterns reveal a strong dependence on the European Union, and a gradually-expanding role of the U.S. as a destination for high-value manufacturing and business services. The share of EU27 destinations has gradually declined, with a modest increase in exports directed to the U.S. and other non-European partners, suggesting a slow diversification away from intra-EU trade. However, sectoral composition for different destinations varies. For example, within exports to the U.S., manufacturing dominates alongside business services. In manufacturing, pharmaceutical products have gained a rapidly rising share over time. On the services side, professional and scientific services expanded rapidly and stand out as the main export category to the U.S compared to Belgium's overall export to the world, reflecting Belgium's even more important role for the US in knowledge-intensive business services. Overall, the U.S. market represents a growing but still secondary destination for Belgium, but with a sectoral export profile tilted more towards pharmaceutical products and professional services.

Exports of Belgium by Countries
(Percent of total exports)



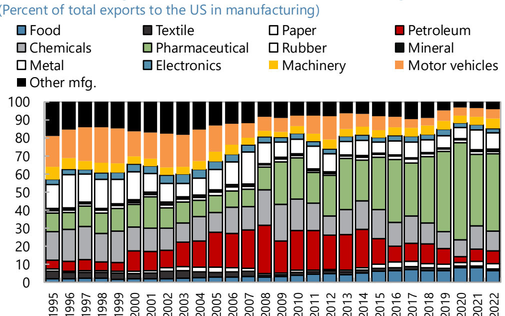
Sources: OECD TiVA 2025 and IMF staff calculations.

Exports of Belgium to the US by Sectors
(Percent of total exports to the US)



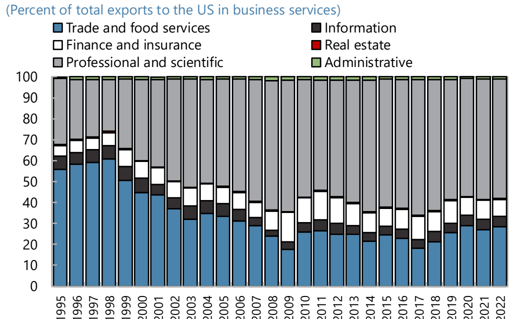
Sources: OECD TiVA 2025 and IMF staff calculations.

Exports of Belgium to the US in Manufacturing
(Percent of total exports to the US in manufacturing)



Sources: OECD TiVA 2025 and IMF staff calculations.

Exports of Belgium to the US in Business Services
(Percent of total exports to the US in business services)

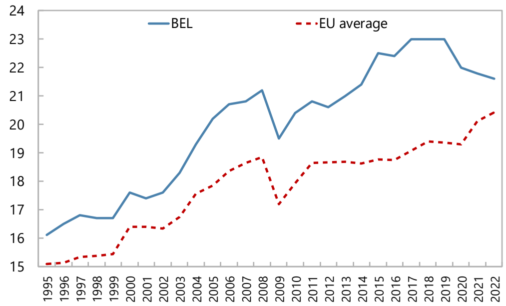


Sources: OECD TiVA 2025 and IMF staff calculations.

6.2.b Forward and backward linkages

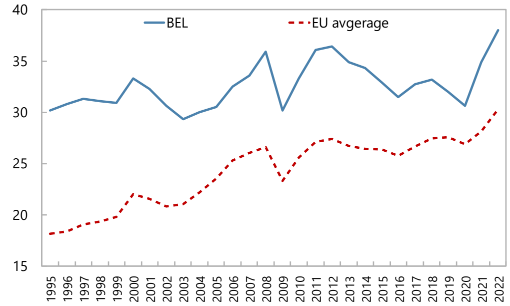
Belgium exhibits consistently stronger global value chain integration than the EU average, both through forward and backward linkages. The forward linkages for Belgium haven risen steadily overtime and underscore Belgium's role as a supplier of intermediates in international production networks. However, a recent decline emerged during the COVID period. The backward linkages also reflect Belgium's reliance on imported inputs for its export industries with a significant pickup in 2021 and 2022.

Forward Linkages
(Share of exports)



Sources: OECD TiVA 2025 and IMF staff calculations.

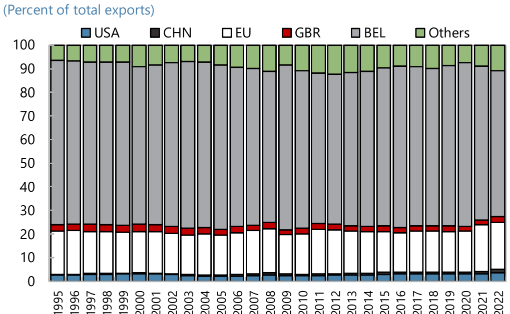
Backward Linkages
(Share of exports)



Sources: OECD TiVA and IMF staff calculations.

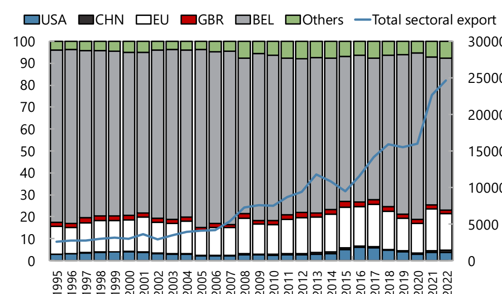
Belgium's exports rely mostly on domestic value added as well as inputs from the rest of the EU. The shares of the U.S., UK, China and other parts of the world have remained steady. The sectoral decomposition shows some differences: in pharmaceuticals, foreign value added, particularly from the EU and the US, has grown alongside the sector's rising total exports, although there was some recent reversal. Petroleum products draw on a more diversified set of foreign inputs, consistent with the global nature of energy supply chains. The motor vehicles sector receives a small but increasing contribution from China and the rest of the world, even though the sector's overall export has not expanded over the past decades. Together, these trends confirm Belgium's deep reliance on both domestic and European value added, with increasing exposure to global suppliers in some main manufacturing sectors.

Origin of Value Added in Total Exports
(Percent of total exports)



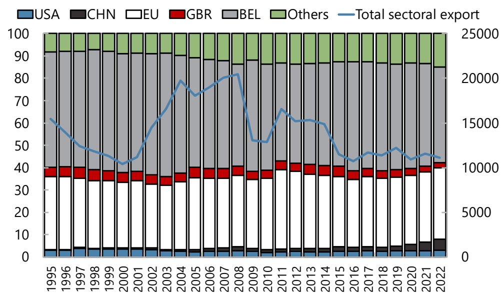
Sources: OECD TiVA and IMF staff calculations.

Origin of Value Added in Exports: Pharmaceutical Products
(Percent of total exports)



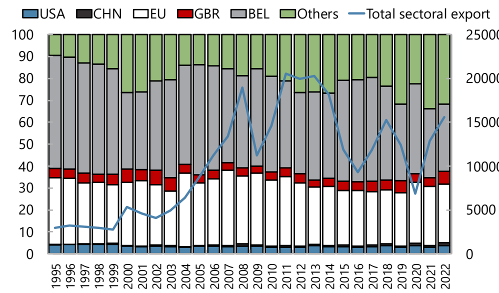
Sources: OECD TiVA and IMF staff calculations.

Origin of Value Added in Exports: Motor Vehicles
(Percent of total exports)



Sources: OECD TiVA and IMF staff calculations.

Origin of Value Added in Exports: Petroleum Products
(Percent of total exports)

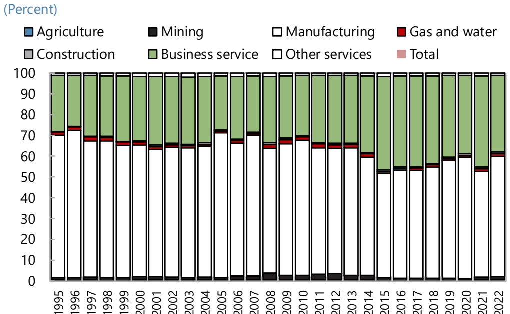


Sources: OECD TiVA and IMF staff calculations.

6.2.c The Pharmaceutical Industry

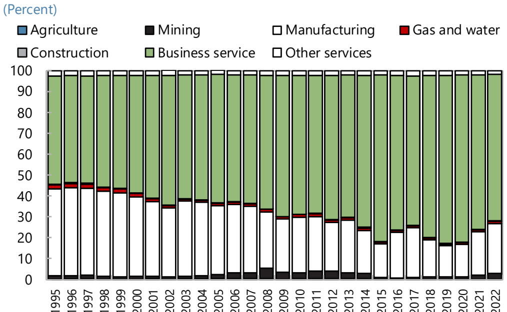
Belgium's pharmaceutical industry has experienced rapid growth over the past decades, both in its export profile and in its integration into global value chains. Looking at the source activities of value added in pharmaceuticals, manufacturing has long been the dominant contributor. However, the role of business services has grown steadily, highlighting the rising importance of R&D, marketing, and other knowledge-intensive activities sourced from abroad. There is also a noticeable share of the mining industry, suggesting that some input ingredients for the pharmaceutical industry could be sourced abroad. A similar pattern appears regarding value added originating from the U.S.: while manufacturing continues to provide the backbone, business services have gained significance, reflecting the deepening integration of Belgian pharmaceuticals with U.S. service-based inputs such as research, licensing, and intellectual property.

Source Activities of VA in Pharma for BEL
(Percent)



Sources: OECD TiVA and IMF staff calculations.

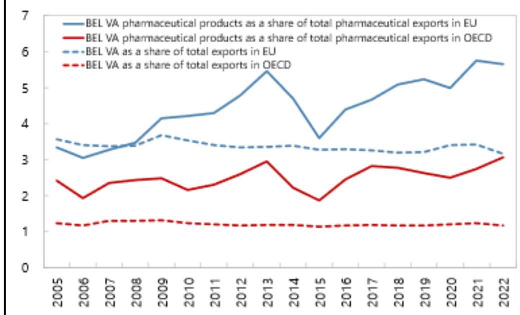
Source Activities of VA in Pharma for BEL from the US
(Percent)



Sources: OECD TiVA and IMF staff calculations.

Belgium's global position in pharmaceuticals is further highlighted by its rising share of value added in other countries' exports, which has outpaced its share in total exports. This indicates a growing specialization and competitiveness of the Belgian pharma sector relative to other industries.

Belgium's Value Added in Total EU or OECD Exports
(Percent)

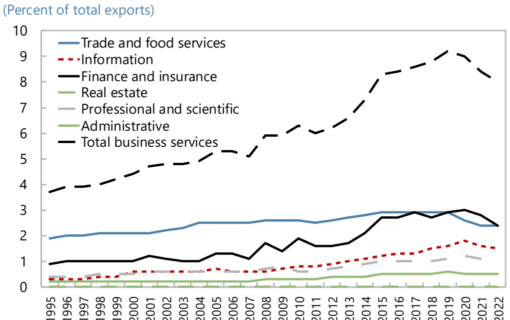


Sources: TiVA and IMF staff calculations

6.2.d Risks for Belgium

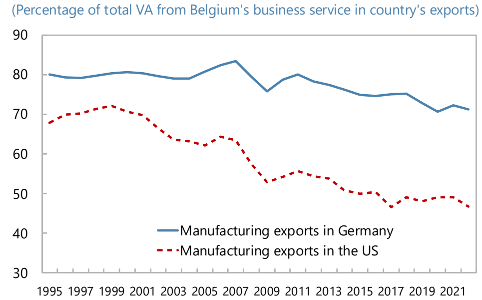
The evolution of forward and backward linkages during COVID highlights some potential risks due to GVC integration. The recent reversal in forward linkages has been driven mainly by business services. Professional and scientific activities, and information sector had previously boosted Belgium's upstream role but softened during the COVID period. Among other possible explanations, e.g., the tax system and how it affects special purpose entities in the economy, this could also potentially due to lower downstream demand from foreign industries, as these sectors are deeply intergated into different sectors, mainly manufacturing, of exports in foreign countries.[7] By contrast, the pickup in backward linkages stems largely from manufacturing, especially pharmaceuticals, chemicals, and petroleum, reflecting greater reliance on foreign intermediates in these sectors. These developments illustrate how Belgium's deep and complicated GVC integration can amplify the impact of global shocks. As an example, see Goswami et al (2024) for an illustratoin of the interwined pharmaceutical supply chain. Disruptions such as the pandemic can quickly reduce demand for Belgian value added abroad, while demand for vaccines could boost imports of related intermediate inputs, leading to sudden and sharp swings in economic activities.

Forward Linkages in Business Services
(Percent of total exports)



Sources: OECD TiVA and IMF staff calculations.

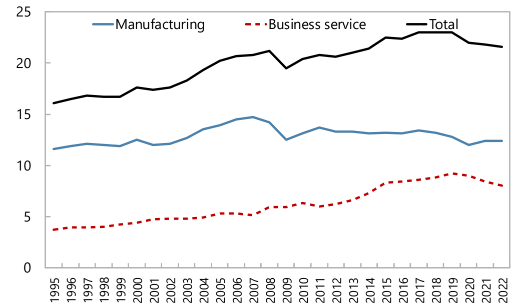
VA from Belgium's Business Services in Countries' Manufacturing Export
(Percentage of total VA from Belgium's business service in country's exports)



Sources: OECD TiVA 2025 and IMF staff calculations.

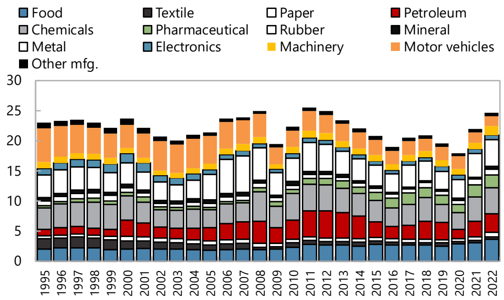
[7] See for example Duprez, C.and Dresse, L. (2013)

Forward Linkages by Sectors
(Percent of total export)



Sources: OECD TiVA and IMF staff calculations.

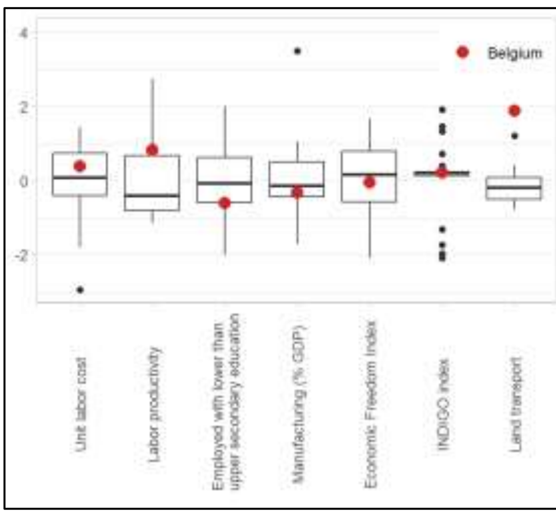
Backward Linkages in Manufacturing
(Percent of total exports)



Sources: OECD TiVA 2025 and IMF staff calculations.

Belgium's high degree of GVC integration has brought important vulnerabilities alongside its benefits. Strong backward linkages create dependence on foreign intermediates, leaving production exposed to supply-chain disruptions, logistics bottlenecks, or trade restrictions on key inputs such as active pharmaceutical ingredients. At the same time, strong forward linkages tie Belgium's performance closely to external demand, making its exports sensitive to slowdowns in partner countries' production and trade. The concentration of exports in a few sectors, particularly pharmaceuticals and chemicals, could heighten the macroeconomic impact of sector-specific shocks or industry-specific policy changes. Belgium's growing reliance on the U.S. market, especially for pharmaceuticals, introduces additional risks linked to shifting U.S. regulatory and pricing policies, patent cycles, and shifts in industrial strategy. In the pharmaceutical sector more broadly, integration into global R&D and licensing networks brings exposure to intellectual property and data-governance risks, while strict compliance requirements can trigger sudden production disruptions. Finally, rising geopolitical tensions and geoeconomic fragmentation, including the U.S.–EU trade frictions, competition for strategic technologies, and security concerns in medical supply chains, further heighten the risks associated with Belgium's heavy reliance on this globally connected industry.

6.2.e Drivers of GVC integrations for Belgium



Belgium's primary strength as a GVC driver lies in its high labor productivity, educated labor, and exceptional connectivity. This explains Belgium's specialization in high-value-added activities such as pharmaceuticals and financial services, positioning Belgium with a comparative advantage in knowledge-intensive stages of GVCs, rather than in cost-sensitive production. With the densest land transport infrastructure in the EU and a strategic geographical location, Belgium serves as a critical logistics and distribution hub, facilitating smooth integration within European and global supply chains. However, the high unit labor cost limits its competitiveness in traditional manufacturing segments**.** A low share of manufacturing in GDP could also prevent it from fully capitalizing the benefits from GVC integrations.

7. Conclusions

Both global and intra-EU value-chain integration appear to be primarily driven by labor productivity, labor cost, economic structure and human capital quality. ML models also underscore that infrastructure, governance, and digital readiness are also key factors supporting value-chain integration. EU countries with competitive wage structures, skilled labor, efficient transport networks, and sound institutions are better positioned to attract investment, specialize in higher-value segments, and sustain participation in the global production networks. At the same time, GVC participation itself can contribute to higher productivity, diversification, and knowledge diffusion, which in turn supports further integration, creating a potential virtuous circle where stronger fundamentals and deeper GVC participation reinforce each other. While underlying fundamentals shape both the level and the type of integration that is viable in each economy, reforms that enhance education, innovation, and regulatory efficiency remain central and can help deepen integration and foster productivity growth.

At the EU level, GVC participation is strong but heterogeneous. Manufacturing, particularly in motor vehicles, machinery, electronics, and pharmaceuticals, continues to anchor Europe's export base, while services are becoming more knowledge intensive. However, member states occupy distinct positions along the supply chain and exhibit varying degrees of integration, reflecting differences in economic structure, specialization, and domestic capabilities. As examples, Belgium is highly integrated both upstream and downstream, leveraging its logistics strength and specialization in high-value industries such as pharmaceuticals and professional services, but faces risks from sectoral concentration and external demand shocks. Portugal, by contrast, remains more downstream, with modest forward linkages and limited high-tech exports, reflecting structural constraints in human capital and innovation capacity. These differences highlight the need for tailored strategies that combine EU-wide market integration with country-specific upgrading efforts.

Going forward, the challenge is to preserve the gains from openness while managing new vulnerabilities. GVC participation offers opportunities for productivity growth, diversification, and technological upgrading, but also exposes economies to supply-chain disruptions, policy fragmentation, and shifting industrial strategies. Fostering greater diversification of products and destinations, strengthened innovation and human capitals, and deeper EU single market and saving and investment union would promote resilience and efficient resource allocation, and help countries navigate challenges.

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Annex I. Application of Machine Learning Models to the Analysis of the Drivers of GVC Integration

Machine Learning Models and Validations

To achieve generalization and avoid overfitting, we split our dataset into training (used for model fitting) and testing (for checking the performance of the model) subsamples. Since all data is assumed to be drawn from the same distribution, splitting ensures that the models are validated on a sample that has the same distribution but was not used in the training. In all models, we use 75 percent of the data for training and the remaining 25 percent for testing.

Subsequently, we perform a cross-validated grid search to optimize all model hyperparameters. The cross validation is a resampling procedure, where the dataset is split into 'k' subsamples. One subsample is treated as test data and the rest as train data. This procedure is repeated several times and the average outcome is reported.

Finally, model performance is assessed using the coefficient of determination (R^2) and mean squared error (MSE) on the test set. The Diebold-Mariano test is applied to compare the forecasting accuracy of different models.

The machine learning methods applied in this study include:

- **Linear model**. A simple approach that assumes a linear relationship among variables. However, it is prone to overfitting and highly sensitive to outliers.
- **Elastic Net**. An extension of linear regression that incorporates both L1 and L2 penalties in the loss function, promoting sparsity and improving model regularization.
- **Support Vector Regression**. It uses kernel functions to map data into a higher-dimensional space, enabling robust regression. It generally offers good generalization and resilience to outliers but performs less effectively on large or noisy datasets.
- **Random Forest Regression**. An ensemble method that combines multiple decision trees to enhance predictive accuracy and reduce overfitting.
- **Extreme Gradient Boosting**. Builds sequential decision trees, where each new tree corrects errors from previous ones. XGBoost incorporates optimized algorithms for faster execution and improved performance.
- **K-Nearest Neighbors**. A non-parametric method that predicts values based on the proximity of observations, using distance metrics such as Euclidean or Manhattan. Predictions are typically based on the mean or median of the k nearest neighbors, with training performed on the entire dataset.

Methods for Enhancing the Interpretability of Machine Learning Models

Since very few ML models are inherently interpretable, recent research focuses on the development of tools for ML model explanation. These techniques fall into two categories:

(i) summary-based methods, which provide insights about the average contribution of the included features for the explanation of the outcome variable, and

(ii) instance-based methods, which focus on a breakdown of a specific observation.

Among the most widely used model-agnostic techniques for interpretation are permutation feature importance, Partial Dependence Plots (PDP), Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP).

In our work, we use the SHAP values (Lundberg and Lee 2017), which are grounded in the concept of Shapley values from cooperative game theory. Shapley values quantify the marginal contribution of each feature to a prediction relative to the average prediction across all instances. More specifically, for each feature i the Shapley value represents its weighted contribution to the model output, considering all possible feature combinations. Formally, this consists in

- estimating feature i's expected marginal contribution to the deviation of the outcome projection from its mean;
- calculating as a weighted average feature i's contribution to all possible combinations of features with its participation.

$$\phi_i(f,x) = \underbrace{\sum_{s'\subseteq x'}}_{\substack{\text{Sum over all}\\\text{possible}\\\text{combinations}\\\text{of features}\\\text{that } \boldsymbol{i} \text{ can join}}} \underbrace{\frac{|s'|!\,(M-|s'|-1)!}{M!}}_{\substack{\text{Weights, based}\\\text{on the probability}\\\text{of observing a}\\\text{configuration of}\\\text{features}}} \underbrace{\left[f_x(s') - f_x(s' \setminus i)\right]}_{\substack{\text{Change in the}\\\text{marginalized}\\\text{prediction of the}\\\text{outcome variable due}\\\text{to the inclusion of}\\\text{feature } \boldsymbol{i}}}$$

As shown above, the Shapley values are calculates as the average marginal contribution of each feature across all possible permutations of the remaining features, which makes this approach computationally intensive. Therefore, the preferred approach is to approximate the Shapley values, instead of calculating them. In particular, we use the Kernel SHapley Additive exPlanations. This approach generates perturbed samples by omitting certain features and replacing them with expected values. This synthetic dataset is then used to train a linear regression, whose coefficients serve as proxies for the Shapley values.

SHAP values are widely preferred as they have solid theoretical foundations and satisfy the following desirable properties:

- *Efficiency* – the sum of the feature contributions adds up to the difference of the prediction for the feature value at this instance and the average.
- *Symmetry* – if two features contribute equally to all possible coalitions, their Shapley values would be the same.
- *Dummy* – if a feature does not change the predicted value in all possible coalitions, it has a Shapley value of 0.
- *Additivity* - the Shapley value for an aggregated object is the sum of the Shapley values of its components.

Annex II. Machine Learning Models Forecasting Performance

The appropriateness of the machine learning models has been assessed based on their forecasting accuracy. It is measured by the coefficient of determination and the mean squared error of the models (ran only on the testing subsample) and the Diebold-Mariano test for forecasting performance. The forecast statistics are given in Table 1. Based on it, one can infer that all models perform similarly in terms of forecasting accuracy, with k-Nearest Neighbors, Support Vector Machine, and Random Forest doing slightly better than the rest of the models.

Table 1. Machine learning models' forecasting statistics.

Model	MSE	R2	Model	MSE	R2
Global value chains			**European value chains**		
Linear regression	0.07	0.92	Linear regression	0.04	0.96
Elastic net	0.07	0.92	Elastic net	0.04	0.96
k-Nearest Neighbors	0.05	0.95	k-Nearest Neighbors	0.02	0.98
Support vector machine	0.05	0.95	Support vector machine	0.02	0.98
Random forest	0.03	0.96	Random forest	0.02	0.97
Extreme gradient boosting	0.05	0.95	Extreme gradient boosting	0.04	0.95
Global value chains in goods			**Global value chains in services**		
Linear regression	0.07	0.94	Linear regression	0.07	0.92
Elastic net	0.07	0.94	Elastic net	0.07	0.92
k-Nearest Neighbors	0.03	0.97	k-Nearest Neighbors	0.05	0.95
Support vector machine	0.03	0.97	Support vector machine	0.05	0.94
Random forest	0.03	0.97	Random forest	0.05	0.95
Extreme gradient boosting	0.04	0.97	Extreme gradient boosting	0.07	0.93
Forward linkages			**Backward linkages**		
Linear regression	0.07	0.94	Linear regression	0.07	0.93
Elastic net	0.07	0.94	Elastic net	0.07	0.93
k-Nearest Neighbors	0.04	0.96	k-Nearest Neighbors	0.04	0.96
Support vector machine	0.04	0.96	Support vector machine	0.04	0.96
Random forest	0.04	0.96	Random forest	0.03	0.97
Extreme gradient boosting	0.05	0.95	Extreme gradient boosting	0.06	0.94

The modified Diebold-Mariano test for forecast comparison[8] also confirms these conclusions (Table 2). It shows that the kNN and SVM models have a statistically significant better forecasting performance than the other models and that the random forest performs better than the extreme gradient boosting model. Generally, the first two linear models exhibit slightly worse statistics than the remaining models, but recalculation of the SHAP values, excluding them, did not yield conceptually different results, so we kept them for completeness.

[8] We are implementing the (Harvey, Leybourne and Newbold. 1997) modification of the test proposed by (Diebold and Mariano 1995), which improves the finite sample properties of the test by correcting the almost entirely the bias of the Diebold-Mariano test – an approximately unbiased estimate of variance of loss differential is obtained.

Table 2. Modified Diebold-Mariano test for forecast comparison.

	Elastic net	Support vector machine	Random forest	Extreme gradient boosting	k-Nearest Neighbors
Global value chains					
Linear regression	0.66	1.99**	2.08**	1.5	2.12**
Elastic net		1.98**	2.08**	1.49	2.12**
Support vector machine			1.71*	-0.25	0.13
Random forest				-2.89***	-1.2
Extreme gradient boosting					0.31
European value chains					
Linear regression	-0.44	4.03***	2.72***	-0.47	3.62***
Elastic net		4.04***	2.72***	-0.47	3.61***
Support vector machine			-0.69	-1.41	-0.33
Random forest				-1.64	0.47
Extreme gradient boosting					1.34
Global value chains in goods					
Linear regression	-0.31	4.67***	5.7***	4.44***	5.24***
Elastic net		4.75***	5.85***	4.55***	5.33***
Support vector machine			1.43	-0.61	1.56
Random forest				-2.26**	-0.03
Extreme gradient boosting					1.76*
Global value chains in services					
Linear regression	0.5	2.01**	2.9***	0.56	2.29**
Elastic net		2**	2.87***	0.55	2.27**
Support vector machine			0.23	-1.65	0.44
Random forest				-1.81*	0.28
Extreme gradient boosting					1.37
Forward linkages					
Linear regression	-0.31	3.03***	3.66***	1.64	3.55***
Elastic net		3.08***	3.76***	1.68*	3.62***
Support vector machine			0.48	-1.2	0.58
Random forest				-2.37**	0.06
Extreme gradient boosting					1.38
Backward linkages					
Linear regression	0.61	2.11**	2.2**	0.71	2.01**
Elastic net		2.1**	2.19**	0.71	2.01**
Support vector machine			1.55	-1.41	1.04
Random forest				-3.1***	-1.05
Extreme gradient boosting					2.24**

Note: *p<0.1; **p<0.05; ***p<0.01

Note: A positive sign of the statistics indicates that the model in the column performs better than the model in the row.

Annex III. Comparison of EU member states on GVC drivers

To uncover patterns among EU member states we conducted cluster analysis, based on the previously identified GVC determinants. To this end the data was centralized and standardized, and the average values for the 2010-2022 period were computed. We then applied Ward's method for hierarchical clustering, which minimizes the total within-cluster variance, using Euclidean distance as a measure of distance (Ward 1963). This approach yielded three distinct clusters:

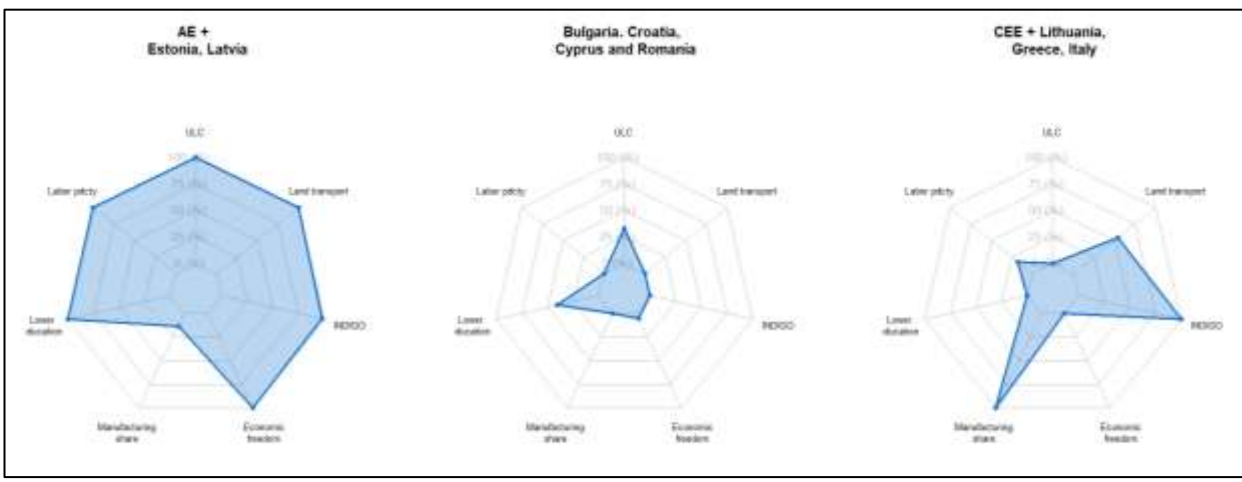
- Advanced economies, Estonia and Latvia,
- Southeastern European Economies, including Bulgaria, Romania, Croatia and Cyprus,
- Central European Economies, Lithuania, Italy and Greece.

Figure 1. Cluster analysis of EU member states, based on the identified GVC determinants.

The first cluster comprises of advanced economies that integrate into GVCs primarily through efficiency and institutional quality rather than manufacturing intensity. These countries are characterized by high labor productivity, good infrastructure and strong governance frameworks. However, they face constraints in cost competitiveness and educational attainment, and their economic structure is less manufacturing-oriented, reflecting a shift towards knowledge-based integration.

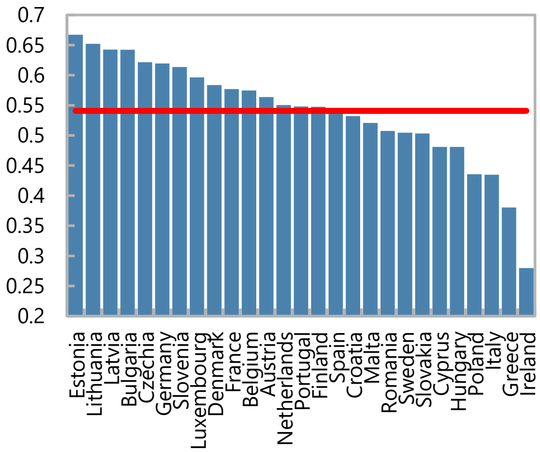
In contrast, the second cluster consists of transitional economies with balanced but modest drivers and limited specialization. While lower wages provide some cost advantage, this benefit is eroded by low productivity, reducing overall competitiveness. Consequently, these Southeastern European economies depend on incremental improvements in productivity and governance to deepen GVC participation.

Finally, the third cluster includes economies that leverage manufacturing intensity, educational and infrastructural strength as key strengths, complemented by favorable labor costs. However, these advantages are offset by weaknesses in governance and labor productivity, which constrain their ability to move into higher-value segments of GVCs.

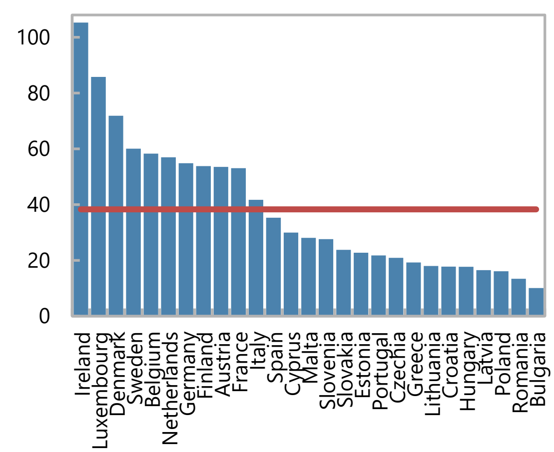


Below, a comprehensive ranking of all EU member states with respect to the GVC drivers is given.

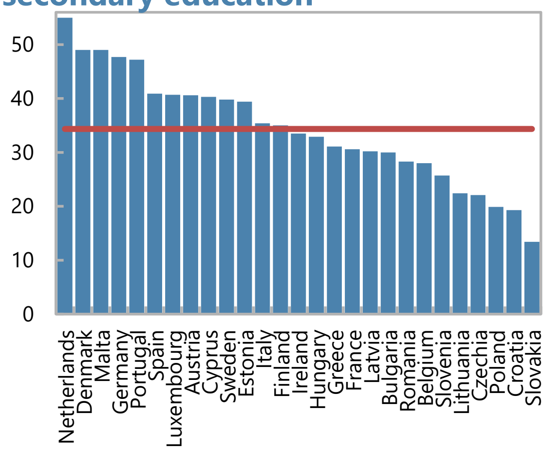
Unit labor cost



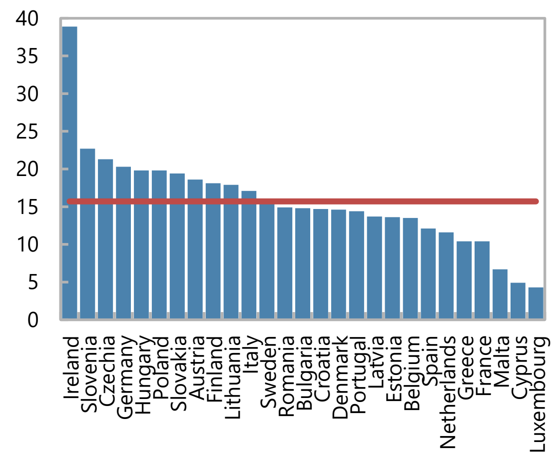
Labor productivity



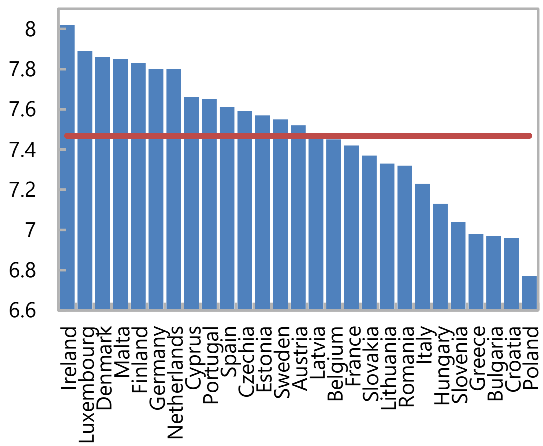
Employed with lower than upper secondary education



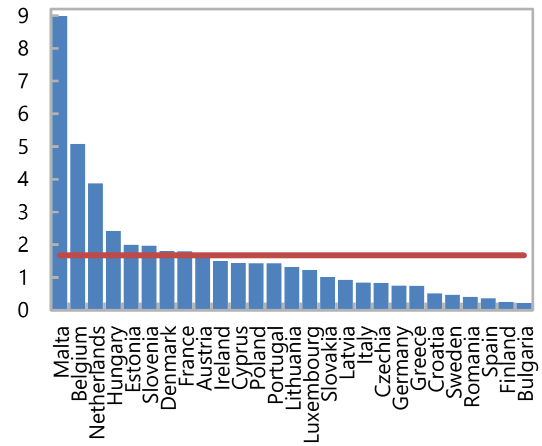
Manufacturing (% GDP)



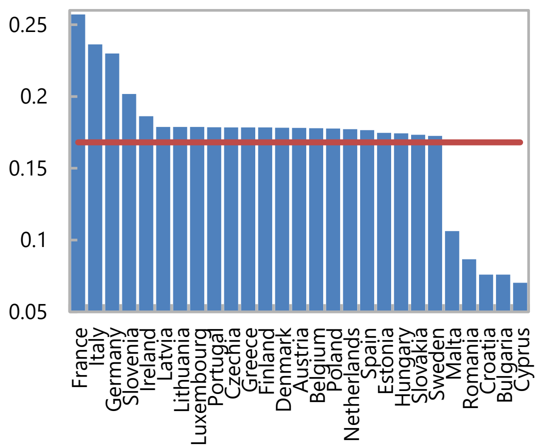
Economic Freedom Index



Land transport



INDIGO index



PUBLICATIONS

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