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Bulgaria in Global Value Chains: Leveraging Integration with the EU

Giacomo Magistretti and Iglika Vassileva

SIP/2024/023

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Prepared by Giacomo Magistretti and Iglika Vassileva

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June 2024

ABSTRACT: As a small open economy, Bulgaria benefits from economic exchanges with global partners. However, after a boost before the Global Financial Crisis and EU accession, its integration in global value chains has been growing only modestly in recent years and it remains particularly low when it comes to links with EU partners. To capitalize from the integration with the EU Single Market and exploit the opportunities that will come from joining the euro zone and the Schengen area, Bulgaria should focus on enhancing its non-cost competitiveness by improving its governance and investing in infrastructure and human capital.

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SELECTED ISSUES PAPERS

Bulgaria in Global Value Chains: Leveraging Integration with the EU

Bulgaria

Prepared by Giacomo Magistretti and Iglika Vassileva[1]

[1] The authors would like to thank Jean-François Dauphin, Anh Dinh Minh Nguyen, Jean-Jacques Hallaert, Helge Berger, and seminar participants from the Bulgarian National Bank and Bulgarian Ministry of Finance for the constructive discussions and valuable comments. Any error and mistakes are our own.

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BULGARIA

SELECTED ISSUES

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Approved By
European Department

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CONTENTS

BULGARIA IN GLOBAL VALUE CHAINS: LEVERAGING INTEGRATION WITH THE EU[1]

As a small open economy, Bulgaria relies on economic exchanges with global partners. However, after a boost before the global financial crisis (GFC) and European Union (EU) accession, its integration in global value chains (GVCs) has grown only modestly and remains below peers when it comes to links with EU countries. To capitalize on the integration in the EU single market and leverage the opportunities that will come from joining the euro and Schengen areas, Bulgaria should focus on enhancing its non-cost competitiveness, notably by improving governance and investing in infrastructure and human capital.

A. Introduction

1. Economic integration with the rest of the world can be an engine of growth and development but comes with challenges. The benefits of integration can be especially large for small emerging market economies like Bulgaria. They include access to larger markets, job opportunities, goods and knowledge sharing, skills enhancement, productivity improvements, and the possibility to focus on the country's comparative advantages (Taglioni & Winkler, 2016; Kummritz, Taglioni, & Winkler., 2017; Constantinescu, Mattoo, & Ruta, 2019; Ignatenko, Raei, & Mircheva, 2019; Pahl & Timmer, 2020). However, to be an active member in global production networks and, ultimately, reap the benefits of integration, a country needs to be attractive to international investors, remain competitive in global markets, and ensure that the gains from trade transmit to the domestic economy (World Bank, 2020). With rising concerns about geoeconomic fragmentation, it is also important that countries ensure the resilience of their global chains through diversification of their input sources (Aiyar, et al., 2023) and, potentially, some reconfiguration of their production and distribution networks (Baba, et al., 2023).

2. In this paper, we show that Bulgaria's global and regional integration slowed significantly in the last decade. In the leadup to EU accession in 2007 and the 2008-09 GFC, Bulgaria received large foreign direct investment (FDI) inflows and its integration in GVCs, especially European ones, grew substantially. Then, following a trend common to many European (and non-European) countries, the growth of Bulgaria's participation in GVCs lost impetus in the mid-2010's. These developments left the country with levels of integration with EU partners that remain among the lowest across peers. While economic ties with Russia are declining since 2022, those with China are slowly rising, although they remain limited. Despite some increase in complexity in recent years, we find that Bulgaria largely specializes in low-technology, labor-intensive exports, a result consistent with previous studies (Taglioni & Winkler, 2016; Ivanova & Ivanov, 2017).

[1] Prepared by Giacomo Magistretti and Iglika Vassileva (both EUR). The authors thank Jean-François Dauphin, Jean-Jacques Hallaert, and Anh Dinh Minh Nguyen for their useful comments and suggestions, and staff of the Bulgarian National Bank and participants at a seminar at the Ministry of Finance for useful discussions.

3. To boost integration and harness benefits from the eventual euro and Schengen areas accession, Bulgaria should improve its non-price competitiveness. One of Bulgaria's main comparative advantages has historically been the availability of low-cost labor. However, as wages converge toward the EU average, it is crucial that the country focuses on bolstering other aspects of its economy. Our analysis shows that investing in infrastructure, human capital, innovation, and better governance would boost Bulgaria's GVC integration. By improving the economic environment, these policy actions would also make Bulgaria an increasingly attractive destination for investors, including those looking to relocate in Europe amidst geoeconomic fragmentation (Aiyar, Malacrino, & Presbitero, 2024).

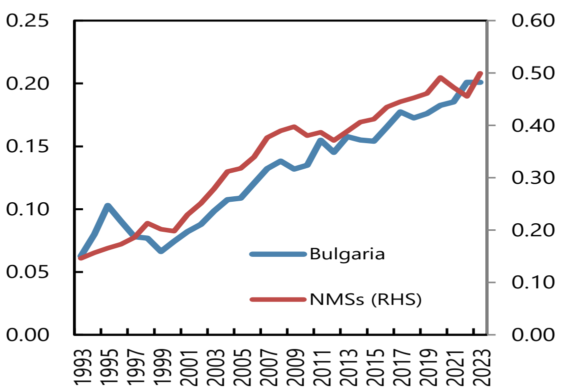
4. The paper is structured as follows. Section B summarizes recent developments in Bulgaria's external sector, including trade and FDI. Section C examines Bulgaria's position in global production chains based on different metrics of integration. Section D investigates the determinants of GVC participation in a panel of EU countries and compares Bulgaria to EU peers with respect to the identified drivers of GVC integration. Section E concludes.

B. Developments in Foreign Trade and FDI in Bulgaria

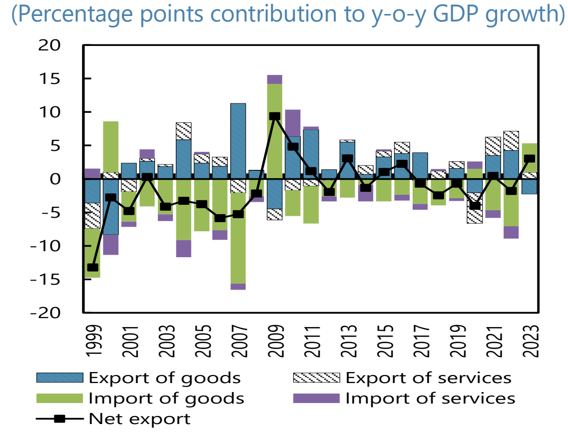
Trade

5. In the past decade, Bulgaria's external sector contributed less negatively to GDP than before the GFC. Similar to other EU newer member states, Bulgaria's share in world exports steadily increased in the last 3 decades.[2] Meanwhile, imports remained strong owing to high consumption, investment, and import content of exports. The contribution to growth of services has been rising over time, especially since the COVID-19 pandemic.

Share in World Export
(Percent)



External Sector Contribution to GDP
(Percentage points contribution to y-o-y GDP growth)

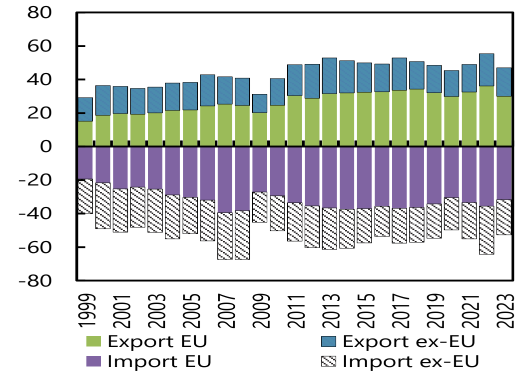


Source: Haver Analytics, Eurostat, and IMF staff calculations.
Notes: NMSs is the simple average of the share in world exports of EU newer member states.

[2] Throughout the paper, we compare Bulgaria's performance and indicators to either all EU members or, where more meaningful, to a subset of countries that, like Bulgaria, joined the EU after 2004, namely Croatia, Czech Republic, Estonia, Lithuania, Latvia, Hungary, Poland, Slovakia, and Slovenia, thereafter referred to as newer members states (NMSs).

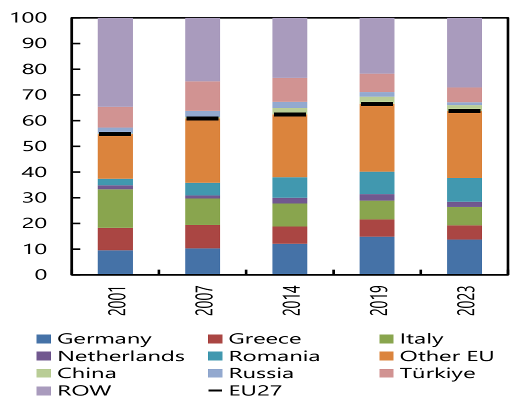
6. Bulgaria's integration in EU trade has slowed significantly after the boost experienced in the leadup to EU accession and the GFC. After rising from 15 percent of GDP in 1999 to 25 percent in 2007, Bulgarian exports to the EU have grown more gradually in the last decade. There is a notable increase in the exports to Germany, Romania and, to a lesser extent, China, while the importance of traditional partners such as Italy, Greece, and Türkiye has been declining. Bulgaria's imports from the EU have decreased lately, except for some neighboring countries. Meanwhile, China, Türkiye and, to some extent, Serbia and US increased their importance as Bulgaria's suppliers.

Trade with EU/non-EU Countries
(Percent of GDP)



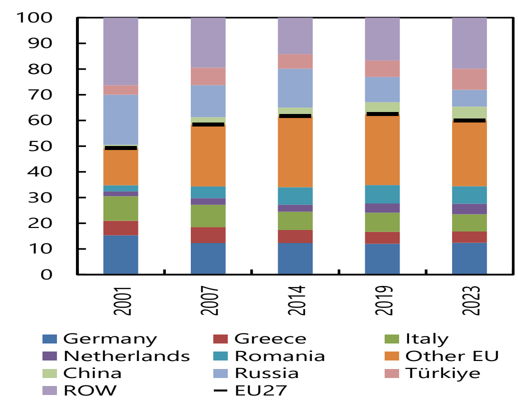
Sources: Eurostat and IMF staff calculations.

Exports by Partners
(Share in total exports)



Sources: Eurostat and IMF staff calculations.

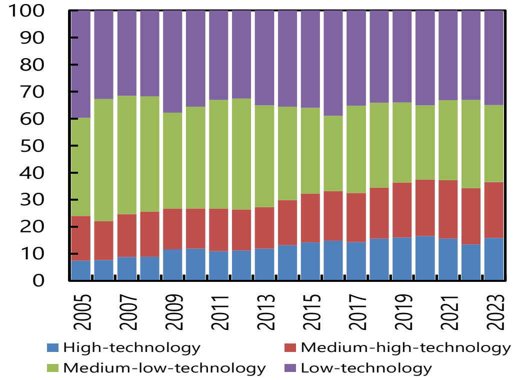
Imports by Partners
(Share in total imports)



Sources: Eurostat and IMF staff calculations.

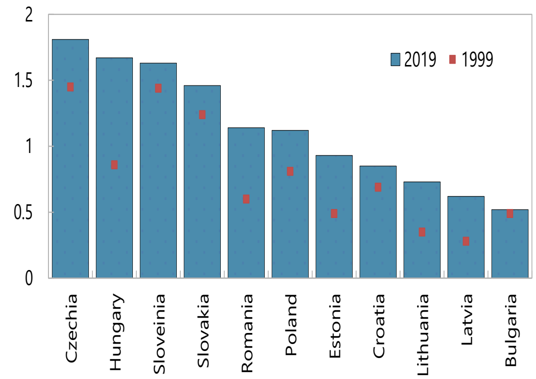
7. Exports are gradually shifting towards more technologically-intensive products, although sophistication remains low. Bulgaria's export is relatively diversified, with higher shares in chemicals, refined fuels, non-ferrous metals, food, and machinery. Over the years, there has been a shift towards higher value-added, more high-tech products (Ivanov & Ivanova, 2021). Exports of electrical and other machinery and chemicals have risen, at the expense of textiles, apparel, and some other low-value-added manufactured goods. However, Bulgaria's export content of productive knowledge, as measured by the Economic Complexity Index (Hausmann, Hidalgo, Bustos, Coscia, & Simoes., 2014), still lags peers and has not increased over the last two decades.

Exports by Technological Intensity
(Share of total export)



Sources: Eurostat and IMF staff calculations.
Note: Export by technological intensity is based on the Eurostat High-tech classification of manufacturing industries.

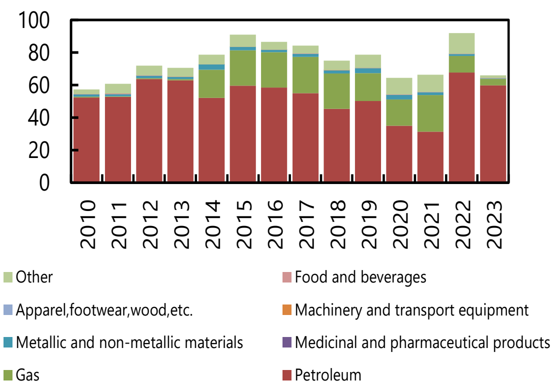
Economic Complexity Index of Exports



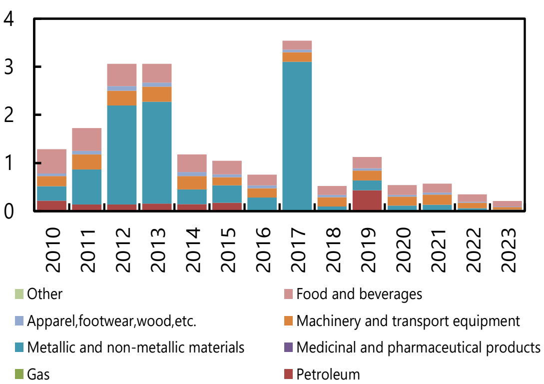
Sources: (Hausmann, Hidalgo, Bustos, Coscia, & Simoes., 2014), (Salinas, 2021), and IMF staff calculations.
Note: The Economic Complexity Index measures the amount of productive knowledge in exports. It is a function of a country's export diversity (number of products exported) and ubiquity (number of countries exporting a product). Red squares are averages 1995-99; blue bars are averages 2015–19.

8. **Recent geopolitical tensions set in motion an energy decoupling from Russia**. Imports from Russia are heavily concentrated in energy products, while exports to Russia are limited. The import of Russian gas has significantly declined in the last two years, following Russia's unilateral decision to stop pipeline gas supply to Bulgaria in April 2022. Meanwhile, import of Russian crude oil increased under the derogation to the EU embargo that the European Commission granted to Bulgaria. A more notable decline in the reliance on Russian oil is expected to be seen only starting from 2024, as the Bulgarian parliament revoked the derogation from March 1, 2024.

Imports from Russia (100 million kg)



Exports to Russia (100 million kg)

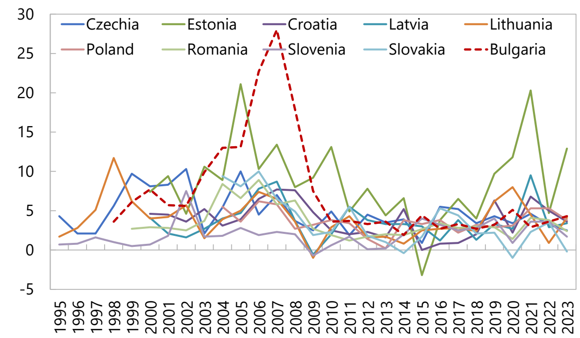


Sources: Eurostat and IMF staff calculations.
Note: Data for the trade flows with Russia display high volatility due to price and accounting changes.

Foreign Direct Investment

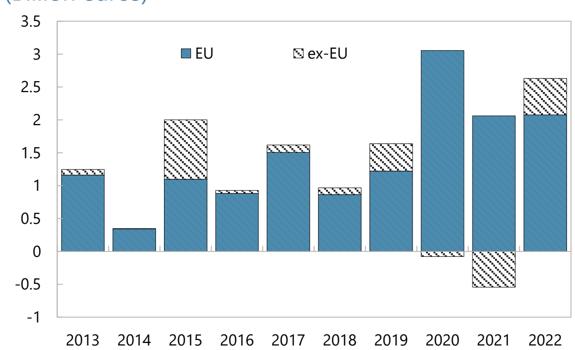
9. FDI remains substantially below its 2007 peak. After a boom in the leadup to EU accession and the GFC, foreign investment flows to Bulgaria have significantly slowed and settled to levels similar to other NMSs. In the last decade, FDI largely came to Bulgaria from EU partners. It was mostly concentrated in the services sector, especially financial activities, including real estate, and wholesale and retail trade. As FDI flows and GVC participation often go together (Antràs, 2020; Buelens & Tirpák, 2017), making Bulgaria's economic environment more attractive to foreign investors would likely also boost integration and allow the country to harness greater benefits from its participation in the EU single market, for instance by attracting multinational firms looking to relocate in Europe.

Inward FDI
(Percent of GDP)



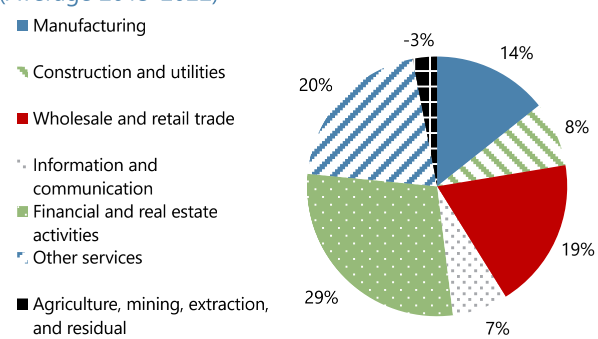
Sources: Eurostat and IMF staff calculations.

Net Inward FDI, by Partner
(Billion euros)



Sources: Eurostat and IMF staff calculations.

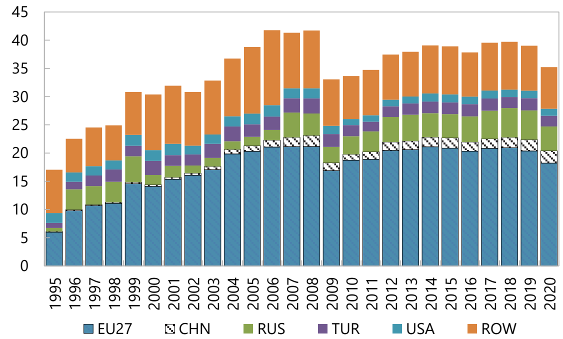
Net Inward FDI, by Sector
(Average 2013-2022)



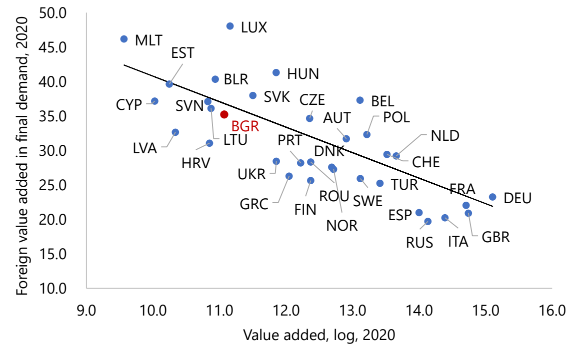
C. Bulgaria's Participation in GVCs

10. Bulgaria relies on foreign production to satisfy a significant portion of its domestic demand. In 2020, 35 percent of its final demand was met by value added coming from abroad, about half of which from other EU countries. This relatively high foreign reliance is in line with the country's economic size and remains below pre-GFC levels, with a decline observed in recent years.

Foreign Value Added in Bulgaria's Final Demand
(Percent of total final demand)



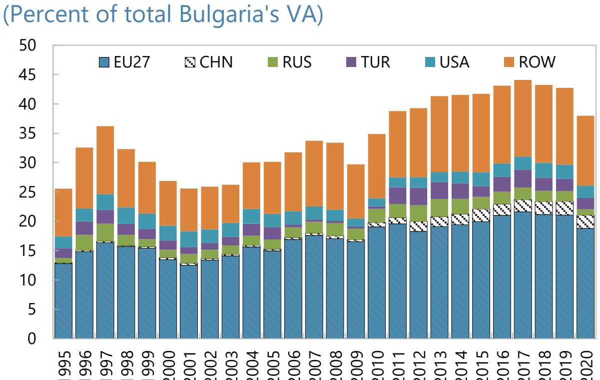
Foreign Value Added in Final Demand and Economic Size



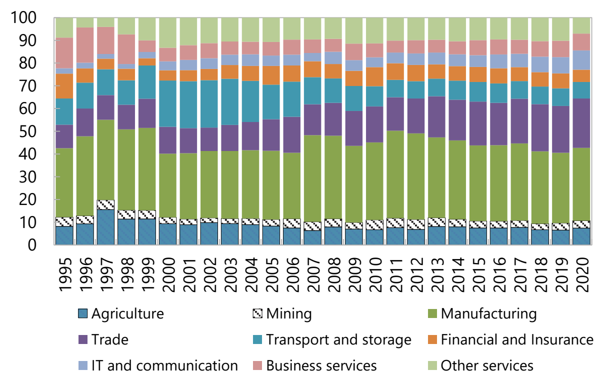
Sources: OECD TiVA 2023 and IMF staff calculations.

11. Bulgaria also sends a sizeable amount of its value added abroad to satisfy foreign demand, especially in services. After peaking at almost 45 percent in 2017, Bulgarian value added going abroad declined to about 38 percent of total domestic value added in 2020, close to the EU average. Almost half of the value added sent abroad went to other EU countries. The share going to China has been steadily growing over time, and the Asian country became the largest destination of Bulgarian value added outside the EU in 2020, overtaking the US. About 25 percent of the domestic value added satisfying foreign final demand in 2020 came from the manufacturing sector (including construction and utilities), 13 percent from agriculture and mining, and the remaining 56 percent from services. Consistently with the sophistication trend already observed for exports, the share of wholesale and retail trade and that of IT and communication has been growing steadily over time.

Bulgaria's Value Added in Foreign Final Demand
(Percent of total Bulgaria's VA)



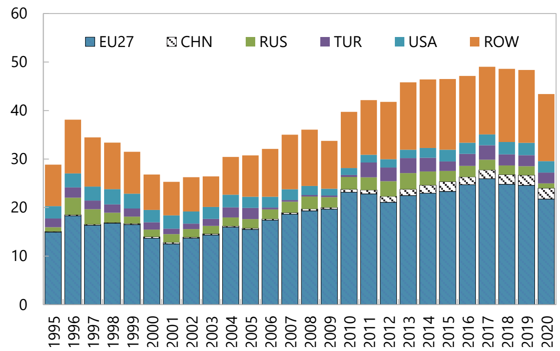
Bulgaria's VA in Foreign Final Demand, by Industry
(Percent of VA in foreign final demand)



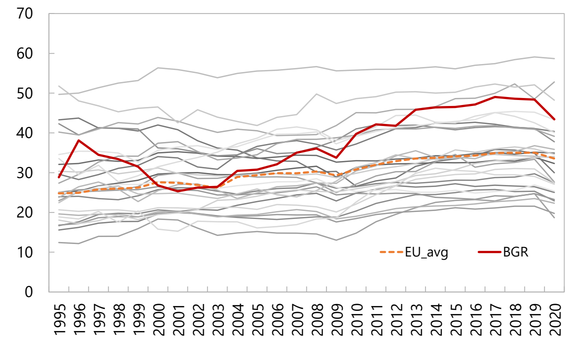
Sources: OECD TiVA 2023 and IMF staff calculations.

12. The interconnectedness of Bulgaria with the rest of the world is most pronounced when considering the labor market. The fraction of Bulgarian employment sustained by foreign demand rose from 35 percent during the GFC to about 50 percent by the end of the 2010's, before slightly declining to 46 percent in 2020. Bulgaria's share is the fourth highest in the EU behind Ireland, Luxembourg, and Malta. Relatively higher foreign dependance for employment vis-à-vis value added is consistent with earlier findings in the literature noting that Bulgaria specializes in low value-added/labor intensive GVCs (Taglioni & Winkler, 2016; Ivanova & Ivanov, 2017).

Bulgaria's Employment Sustained by Foreign Demand (Percent of total employment)



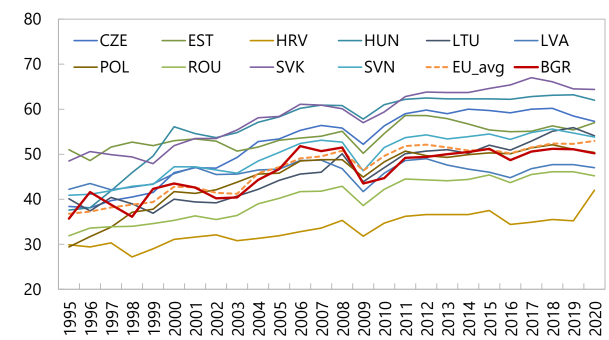
Employment Sustained by Foreign Demand (Percent of total employment)



Sources: OECD TiM 2023 and IMF staff calculations.
Note: In the right-hand-side chart, EU_avg is the simple average across EU-27 countries. Grey lines correspond to EU countries other than Bulgaria.

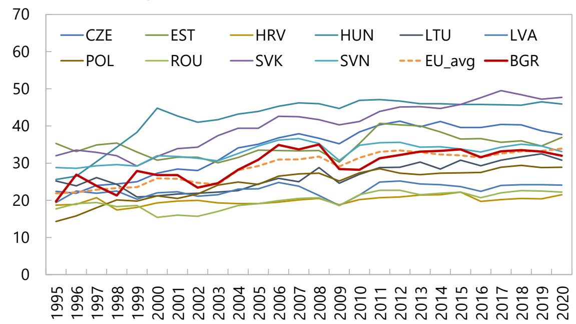
13. Aggregate metrics of GVC's integration show Bulgaria's involvement slowing in the last decade and lagging peers. After twenty years of rising integration leading up to EU accession and the GFC, Bulgaria's participation in GVCs declined in 2009, and it only partially recovered in the following two years. After that, Bulgaria's GVC integration increased only marginally. This trend, common to many European countries, leaves Bulgaria's participation in GVC trailing most of NMSs and the EU average, preventing its economy to benefit from deeper global integration. Looking beyond aggregate numbers, backward linkages (i.e., foreign value added embodied in domestic exports) are in line with peers and the EU average. Forward linkages (i.e., domestic value-added content of foreign exports) are, instead, more limited. Although slightly increasing in recent years, they remain below the EU average and more contained than in peer countries.

Bulgaria's Integration in GVCs
(Percent of exports)

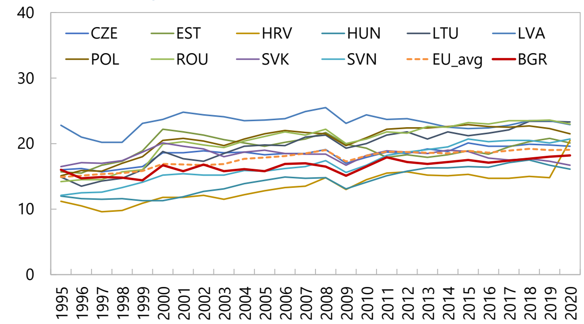


Sources: OECD TiVA 2023 and IMF staff calculations.
Note: Integration in GVCs is the sum of backward linkages and forward linkages. EU_avg is the simple average across EU-27 countries.

Backward Linkages
(Percent of exports)



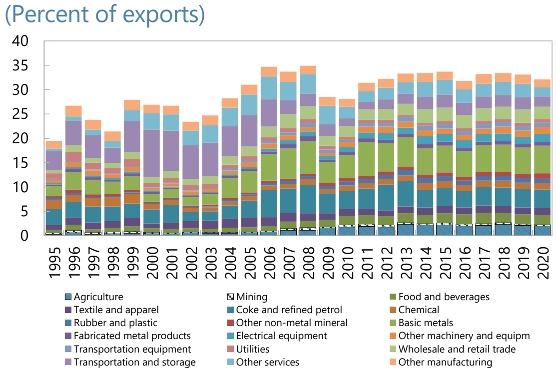
Forward Linkages
(Percent of exports)



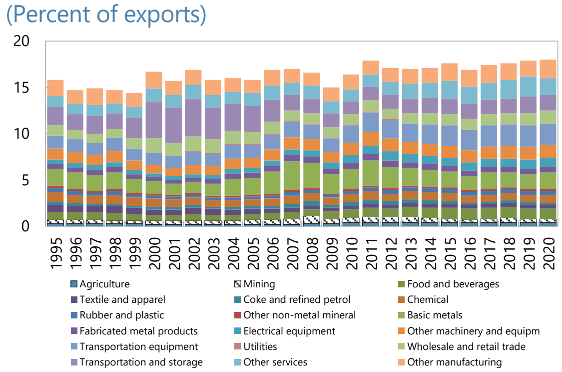
Sources: OECD TiVA 2023 and IMF staff calculations.
Note: EU_avg is the simple average across EU-27 countries.

14. Bulgaria's GVCs are well diversified. In terms of backward linkages, the most significant involvement is in GVCs for basic metals and coke and refined petrol products, which accounted for almost a third of total foreign value added in Bulgaria's exports in 2020. Forward linkages are well-balanced across manufacturing and services industries.

Bulgaria's Backward Linkages, by Industry
(Percent of exports)



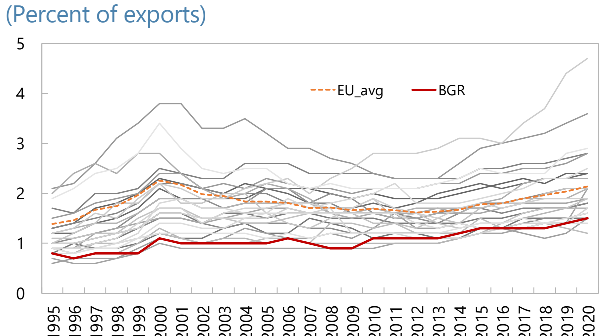
Bulgaria's Forward Linkages, by Industry
(Percent of exports)



Sources: OECD TiVA 2023 and IMF staff calculations.

15. Sophistication of Bulgaria's GVCs, however, remains low. Involvement in information GVCs—a proxy for the level of sophistication that encompasses the production of computers and electronics and the provision of communication, IT, and information services—is among the lowest in the EU. Yet, as already observed for exports, Bulgaria is climbing the quality ladder and the sophistication of its GVCs has been slowly increasing. Recent FDI commitments are set to continue this trend, with the potential to

Forward Linkages in Information Industries
(Percent of exports)

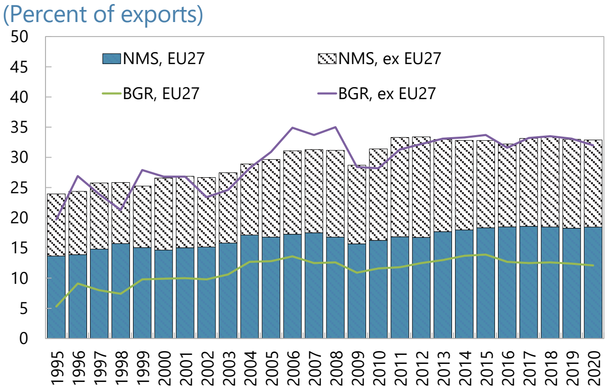


Sources: OECD TiVA 2023 and IMF staff calculations.
Note: EU_avg is the simple average across EU-27 countries. Grey lines correspond to EU countries other than Bulgaria.

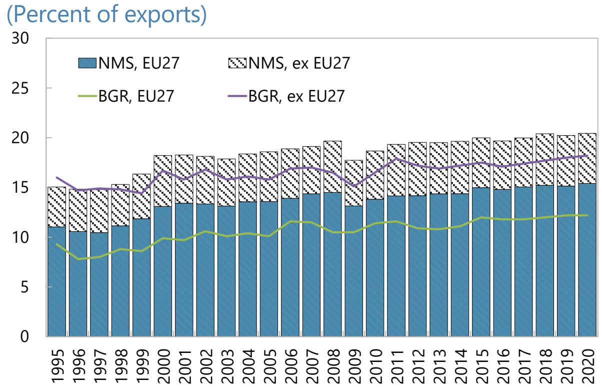
increase Bulgaria's foothold in rapidly expanding GVCs, such as those for electric vehicles' batteries.[3]

16. There is room for further increase in GVC integration with the EU, on both the selling and, especially, the buying side. Bulgaria consistently lags peers in integration with other EU countries. On the buying side, relatively low backward linkages with the EU have been historically compensated by a significantly larger dependence on Russia and, to a lesser extent, Türkiye. The relatively-large role of Russia as a supplier in Bulgarian value chains was still visible in 2020, the latest available data, when Russian inputs amounted to 8 percent of Bulgaria's backward linkages compared to 12 percent for EU partners. However, the geoeconomic fallout from Russia's invasion of Ukraine is expected to weaken the economic relationship between the two countries. On the selling side, Bulgaria's forward linkages with the EU are the lowest among peers, amounting to 12.2 percent of exports in 2020.

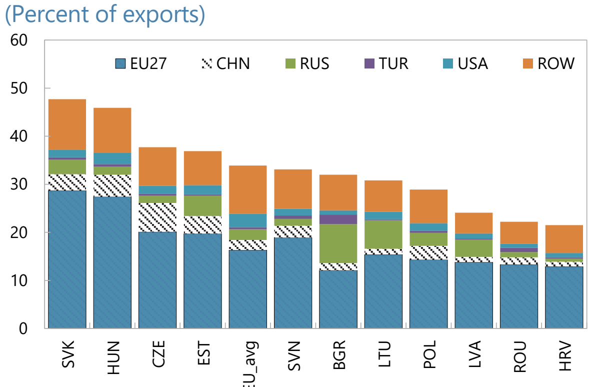
Backward Linkages by EU vs non-EU Partners
(Percent of exports)



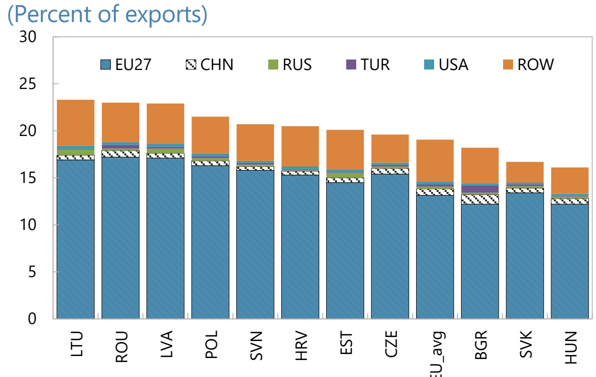
Forward Linkages by EU vs non-EU Partners
(Percent of exports)



Backward Linkages in 2020, by Partner
(Percent of exports)



Forward Linkages in 2020, by Partner
(Percent of exports)



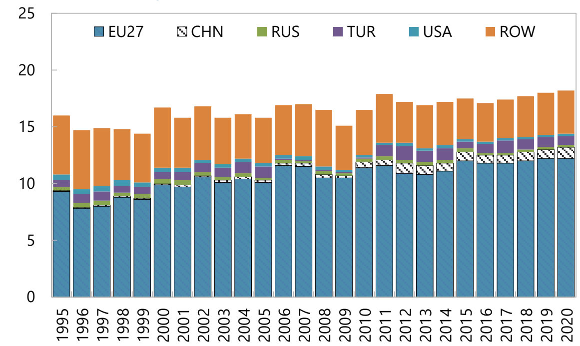
Sources: OECD TiVA 2023 and IMF staff calculations.

17. Although it remains relatively limited, China's importance as a buyer in Bulgaria's GVCs has been steadily growing. In 2020, China became the largest GVC partner destination for Bulgaria's value added outside of the EU. These deepening ties are even more apparent when

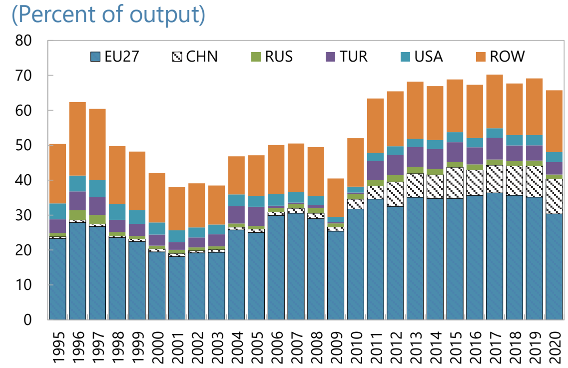
[3] For instance, the Belgian battery manufacturer ABEE is reportedly planning to invest €1.1 billion in Bulgaria in three sites, a battery factory, a research and development center, and a recycling facility.

measured in terms of foreign market reliance (FMR), i.e., the ratio of domestic output used in foreign production to total domestic production, a measure of "total" exposure of domestic activity to downstream disruptions in GVCs (Baldwin & Freeman, 2022; Schwellnus, Antton, Samek, Pechansky, & Cadestin, 2023).[4] The dependence is particularly elevated in sectors such as basic metals and mining and quarrying of non-energy products.

Bulgaria's Forward Linkages, by Partner
(Percent of exports)



Bulgaria's Foreign Market Reliance
(Percent of output)



Sources: OECD TiVA 2023 and IMF staff calculations.

D. Explaining Bulgaria's Position in GVCs

Identification of GVC Correlates

18. Commonly identified drivers of GVC participation include transport connectivity, cost competitiveness, and institutional quality. These are part of a broader set of determinants of GVC integration typically identified in the literature (Fernandes, Kee, & Winkler, 2022; Antràs, 2020), which include: (i) land and other natural resources endowments, labor and capital, (ii) geographic position with respect to large GVC hubs, (iii) domestic industrial capacity, (iv) openness to trade (tariffs and free trade agreements) and FDI, (v) institutional quality, (vi) transport connectivity, and (vii) macroeconomic factors, such as cost competitiveness and degree of financial development.[5] Based on these possible contributing factors, our work considers a parsimonious set of key GVC integration drivers for EU countries over the period 2002 to 2020.

[4] Differently from GVC forward linkages, FMR also considers Bulgaria's exports consumed in the destination countries, not only those that enter the production of foreign exports. Moreover, FMR is based on gross trade flows, whereas forward linkages only consider the value-added component of trade. As such, FMR "double counts" the value added of inputs that cross borders multiple times. However, precisely because of this feature, FMR considers not only the size of the exposure to a partner, but also the distance from that partner in global chains. Implicitly, FMR assumes that the entire shipment (not only its value-added component) can be held up at any point in the global supply chain, thus providing a more comprehensive picture of global chain risks.

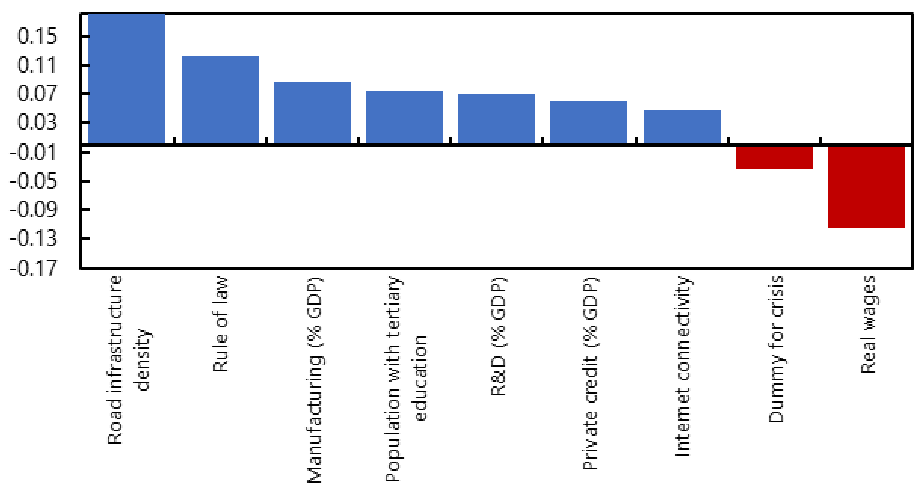
[5] The relative importance of different factors in this list varies in the literature. Some studies find evidence of a significant impact of factor endowments, country's geographic position, institutional quality, trade policies and FDIs and domestic industrial capacity (Fernandes, Kee, & Winkler, 2022). Other studies establish that openness, FDIs, labor force quality, infrastructure and governance are the most important determinants of GVC participation (Urata & Baek, 2020).

19. We estimate a panel regression, using machine learning (ML) techniques.[6] ML models allow to uncover complex (often non-linear) relationships across variables, while being less susceptible to multicollinearity and endogeneity problems than standard econometric techniques. Considering results from various ML estimation methods, we identify the main correlates of GVC integration. The contribution of each driver in the explanation of the prediction of the outcome variable is measured by SHAP values. The ML models' performance is assessed based on: (i) the coefficients of determination and mean square errors of each model in the test subsample, and (ii) a Diebold-Mariano test, which is used for comparing the forecasting performance between models (see Appendix 1 for methodological details).

20. Our research shows that infrastructure, cost competitiveness, and governance are major drivers of GVC integration for EU countries. ML models generally confirm the main correlates of GVC integration identified in the literature. High transport connectivity, strong rule of law, and low wages represent the three main drivers to GVC integration in our models. The structure of the economy—measured by the share of manufacturing in GDP—is also an important determinant. Other identified factors from the literature, namely, the education of the labor force, the level of investment in innovation, the depth of financial markets, and internet connectivity (measured as the share of households using internet) also matter. Finally, our analysis confirms the deceleration in GVC integration during the two most recent crises for which data is available—the GFC and the COVID pandemic (see Appendix 2 for more details on the results from the different ML models).[7]

Drivers of GVC integration in EU countries

(Weighted average of SHAP values from six machine learning models)



Sources: Eurostat, World Bank, OECD, and IMF staff calculations.
Notes: Models are linear regression, elastic net, support vector machine, random forest, extreme gradient boosting and k-nearest neighbors, estimated with data for EU countries over 2002–20. Variables are considered in percent of the EU average. All models include country dummies to control for fixed effects (not reported in the figure).

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

[7] The available vintage of the OECD TiVA database includes data only up to 2020 at the time of this publication. Therefore, our work does not cover the impact of Russia's war in Ukraine on European GVCs.

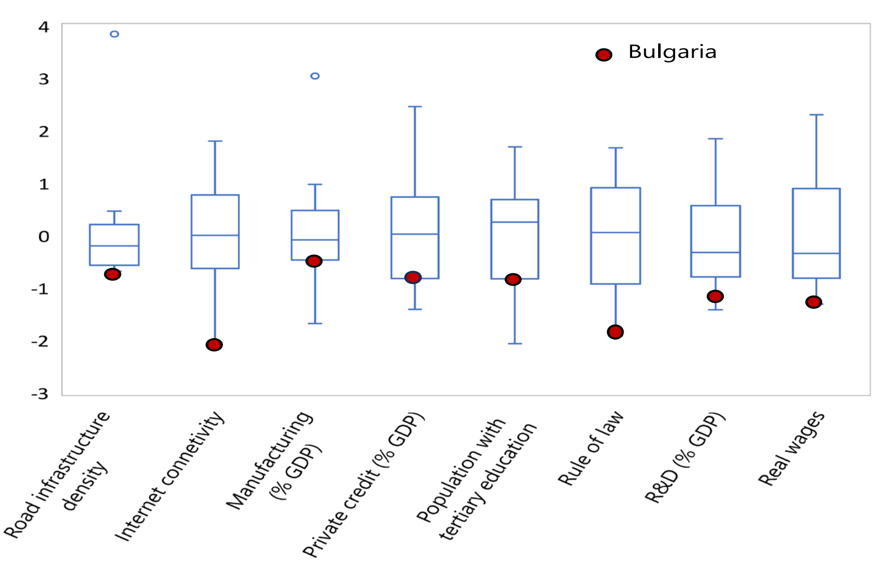
Bulgaria's Position with Respect to GVC Drivers in the EU Landscape

21. Bulgaria belongs to the group EU countries benefiting from low labor costs, but with deficiencies in infrastructure, financial intermediation, and rule of law. A cluster analysis based on the dataset used for the ML models shows that, with respect to the drivers of GVC participation, Bulgaria belongs to a group of (mostly) small open EU economies. This group is characterized by relatively low wages, less developed infrastructure and financial intermediation, and predominantly low rule-of-law scores (see Appendix 3 for details on the cluster analysis and its results).

22. Bulgaria will need to move from cost to non-cost competitive advantages to increase its participation in GVCs. With respect to the identified key determinants of GVC integration, Bulgaria has had a relative advantage, by EU standards, in cost competitiveness, given that it has the lowest real wage in the EU. However, as wages in Bulgaria are catching up with the EU average, this cost advantage is eroding. Therefore, Bulgaria will need to boost its non-cost competitiveness to maintain and, ideally, deepen its GVC integration.

23. Bulgaria can significantly improve its integration in GVCs by stepping up investment in transport infrastructure and strengthening governance. The most important non-cost competitiveness correlates of GVC integration are the density of road infrastructure and the rule of law—both areas in which Bulgaria substantially lags its peers. Additionally, there is scope to invest more in R&D and internet connectivity, where there is a notable gap between Bulgaria and other EU countries. Relatively to other correlates, Bulgaria is faring better in terms of industrial intensity of the economy, share of labor force with a tertiary degree, and financial intermediation development, although there is room for significant improvements also in these areas, especially in the quality of education.

Bulgaria's Position with Respect to GVC Integration Determinants in 2021



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

E. Conclusion

24. Bulgaria has room to increase its integration with the EU. Bulgaria's GVCs display substantially lower levels of integration with EU partners than many peers. The prospects of joining the euro and Schengen areas provide opportunities for forging stronger ties with countries in the region. A deeper integration, however, would require Bulgaria to fill gaps with EU peers to make its economy more competitive and attractive for foreign investors.

25. Links with Russia are weakening, while ties to China are on the rise. Russia has historically played an outsized role as a supplier for Bulgaria's GVC inputs, especially energy products. However, since Russia's invasion of Ukraine in 2022, a decoupling is unfolding. On the selling side, China's foothold in Bulgaria's global production chains has been rising since the GFC, with several measures showing China as the largest non-EU buying partner in recent years.

26. As the cost advantage erodes, Bulgaria needs to improve its non-price competitiveness. Our analysis shows that investing in infrastructure and R&D, improving governance and the business environment, and enhancing the skills of the workforce will take Bulgaria closer to its EU peers, thereby providing a more conducive environment to boost the country's integration in GVCs. Improvements in these areas will also help Bulgaria increase the sophistication of its exports and climb the value ladder, consistently with the country's convergence toward more economically advanced EU countries.

Appendix 1: Application of Machine Learning Models to the Analysis of the Drivers of GVC Integration

Data Sources and Transformations

1. The GVC data used in our analysis come from the OECD TiVA dataset, 2023 vintage. As for the drivers of GVC integration, most of the data are sourced from Eurostat as of April 17, 2024. The World Bank World Development Indicators database was used for the share of private credit in GDP and the World Governance Indicators for institutional quality. Road infrastructure density indicator comes from the OECD transport infrastructure database.

2. Since some of the machine learning methods are sensitive to scaling, before the application of the ML methods, the data has been centered and standardized to put all variables on the same scale. All explanatory variables have been calculated as a percentage of their EU average values to isolate the country-specific component of the dynamics.

Machine Learning Models

3. ML methods include various computational algorithms, which aim at identifying patterns in a dataset. Their main advantage is that they can capture relationships in the dataset that might be complex and difficult to model explicitly. While the ML methods have been developed mainly for forecasting purposes, recent advances in the field allow to use them for estimation purposes as well.

4. As per the usual practice in ML, we split the dataset into training (used for model fitting) and testing (for checking the performance of the model). In all models, we use 75 percent of the data for training and the remaining 25 percent for testing.

5. We set the main models' hyperparameters (i.e., the parameters of the ML methods) using a cross-validated grid-search over a predefined parameter grid. 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.

6. The ML methods applied in this work are:

- ***Linear Regression.*** While this method is relatively simple, it inherently assumes a linear relationship in the data. Moreover, linear regression is more subject to overfitting and sensitive to outliers.

- ***Elastic Net.*** This method is an extension of the linear regression, where penalties are incorporated in the loss function. As a result, it achieves sparseness in the model definition.

- ***Support Vector Regression.*** The support vector machine maps the dataset in a higher dimension space, using a kernel, to separate the observations into distinct categories. The support vector regression usually has a good generalization capacity and is robust to outliers. However, it is less effective for large datasets, and in cases when the dataset has more noise.

- ***Random Forest Regression.*** This method constructs an ensemble of multiple decision trees, thus improving their individual performance.

- ***Extreme Gradient Boosting.*** The XGBoost builds on the random forest by adding new trees one by one to correct for the prediction errors made by the existing ones. Furthermore, the XGBoost has optimized algorithms, which ensure faster execution.

- ***K-Nearest Neighbors.*** K-Nearest Neighbors uses proximity as a criterion. For a continuous variable the most popular distance measures include Euclidean, Manhattan, or Makowski distances. The training of the model is performed on the entire dataset and the prediction is made based on the mean or median of the k-most similar observations.

Methods for Enhancing the Interpretability of Machine Learning Models

7. Since very few ML models are straightforward to use for analytical purposes, current research focuses on the development of tools for ML model interpretation. They fall into two categories: summary-based (providing insights about the average contribution of the included features for the explanation of the outcome variable) and instance-based (focusing on a breakdown of a specific observation). The most popular model-agnostic techniques for interpretation include permutation feature importance, Partial Dependence Plots (PDP), Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP).

8. In our work, we use the SHAP values (Lundberg & Lee, 2017). These are based on the concept of Shapley values from coalition game theory. The Shapley values provide a means to calculate the contribution of each feature value to the outcome prediction minus the average prediction for all instances. More specifically, for each feature $\boldsymbol{i}$ the Shapley value:

- estimates $\boldsymbol{i}$'s expected marginal contribution to the deviation of the outcome projection from its mean;

- is calculated as a weighted average $\boldsymbol{i}$'s contribution to all possible combinations of features with its participation.

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

9. As shown above, the Shapley values are calculated as the average marginal contribution of each feature given all possible permutations of the other 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 creates perturbed samples by dropping some features and replacing them with expected values. This derived dataset is then used to train a linear regression, whose coefficients are considered to be proxies for the Shapley values.

10. SHAP values are widely preferred as they have solid theoretical foundations and satisfy the following useful 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.

Appendix 2: Detailed Results from the ML Models for the Analysis of the Drivers of GVC Integration

Machine Learning Models Forecasting Performance

1. **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 Model's Forecasting Statistics

Model	MSE	R2
Linear regression	0.07	0.93
Elastic net	0.07	0.93
k-Nearest Neighbors	0.05	0.95
Support vector machine	0.05	0.95
Random forest	0.06	0.94
Extreme gradient boosting	0.09	0.91

2. **The modified Diebold-Mariano test for forecast comparison**[1] **also confirms these conclusions** (Table 2). It shows that the SVM and kNN 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.

Table 2. Modified Diebold-Mariano Test for Forecast Comparison

	Elastic net	Support vector machine	Random forest	Extreme gradient boosting	k-Nearest Neighbors
Linear regression	0.21	2.44**	0.73	-1.35	2.79***
Elastic net		2.43**	0.71	-1.35	2.72***
Support vector machine			-1.02	-2.68***	-0.5
Random forest				-2.34**	0.71
Extreme gradient boosting					2.53**

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.

[1] We are implementing the (Harvey, Leybourne, & Newbold., 1997) modification of the test proposed by (Diebold & 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.

3. Despite some differences in the forecasting performance of the ML models, overall they perform similarly. Therefore, we consider all of them and cast our results in terms of the average SHAP values.

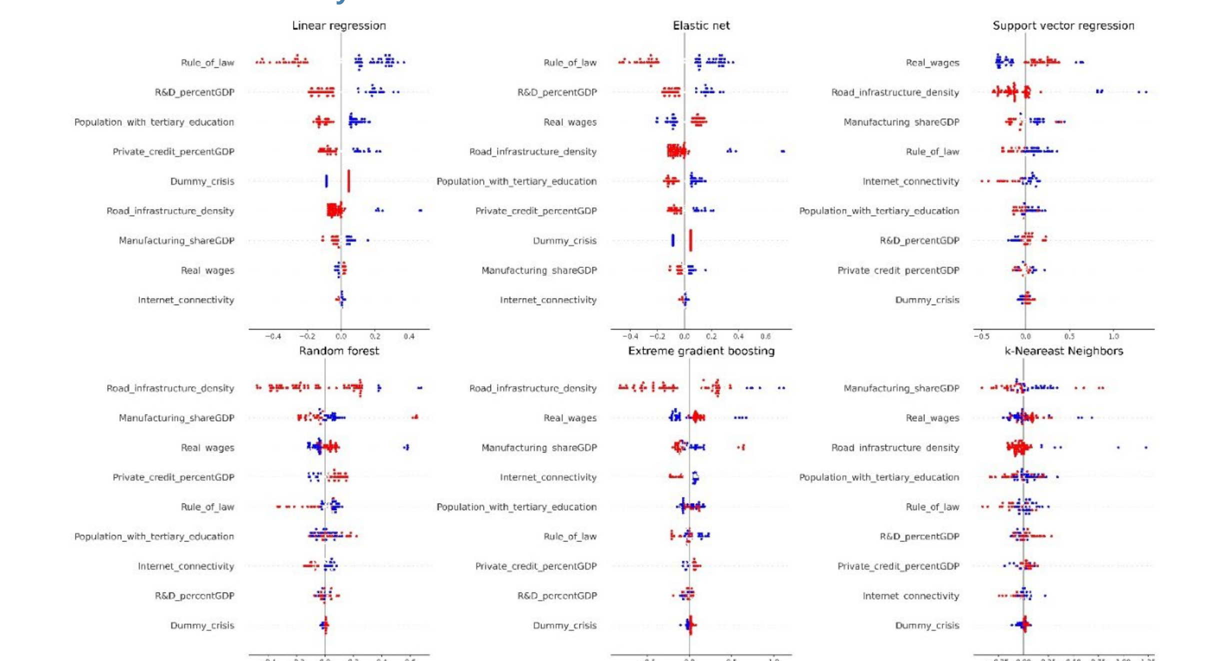
Detailed Results from the Application of the ML Models

4. The figure below shows the distribution of the SHAP values by feature for each observation in the sample. A wider spread of the values implies higher variability in the SHAP values, or, equivalently, greater impact of the feature on the forecast of the GVC integration.

5. Furthermore, the SHAP values are color-coded, based on the original values of the features—high values are blue, low values are red. Thus, if a feature's positive SHAP values (i.e., to the right of the vertical line) are blue, it means that higher values of the feature are associated with positive deviations of the output variable forecast from its expected value (e.g., the rule of law). And vice versa, if a feature's positive values are red (e.g., real wages), this is an indication that there is a negative relationship between the feature and the output variable.

6. Although there is some variability across models, they generally all indicate high contribution of road infrastructure, real wages, and rule of law to the explanation of GVC participation. Meanwhile, internet connectivity and the share of population with higher education are typically lower ranking features. Additionally, their impact on the output variable is less homogeneous across models.

Summary of the Estimated SHAP Values from Each ML Model



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

Note 1: The features are ordered according to their contribution to the explanation of the deviation of the GVC integration forecast from its mean.

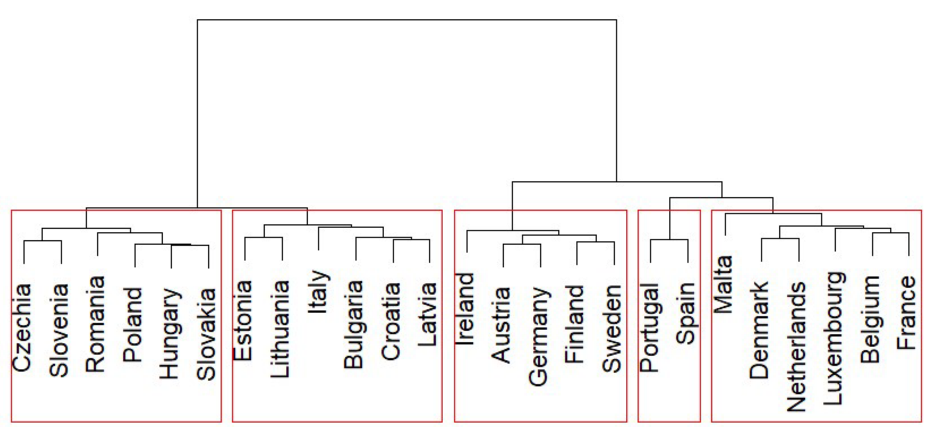
Note 2: Variables are considered in percent of EU average.

Appendix 3: Results from the Cluster Analysis of the Drivers of GVC Participation

A closer look at the GVC drivers in the EU suggests that there are two categories of economies among the member states. The first group of countries is characterized by large non-price competitiveness advantages, mainly in infrastructure, governance, human capital, innovation, and financial depth. The second group, instead, shows high cost-competitiveness and a higher share of manufacturing in GDP. We confirm this observation within a cluster analysis[2] on our dataset, based on the following (clusters of) GVC correlates:[3]

- Infrastructure, calculated as a simple average of road infrastructure and internet connectivity scores of the countries;
- Cost competitiveness, measured by the real wages;
- Human capital and innovation, calculated as a simple average from the scores on share of population with higher education and the share of R&D in GDP;
- Governance, measured by the rule-of-law indicator of the World Bank;
- Financial depth, measured as the share of private credit in GDP; and,
- Economic structure, measured as the share of manufacturing in GDP.
- Based on the within group sum of squares, we identify five clusters. Below is a dendrogram, showing the identified five clusters and the hierarchical relationship between different clusters.

Dendrogram from the Cluster Analysis



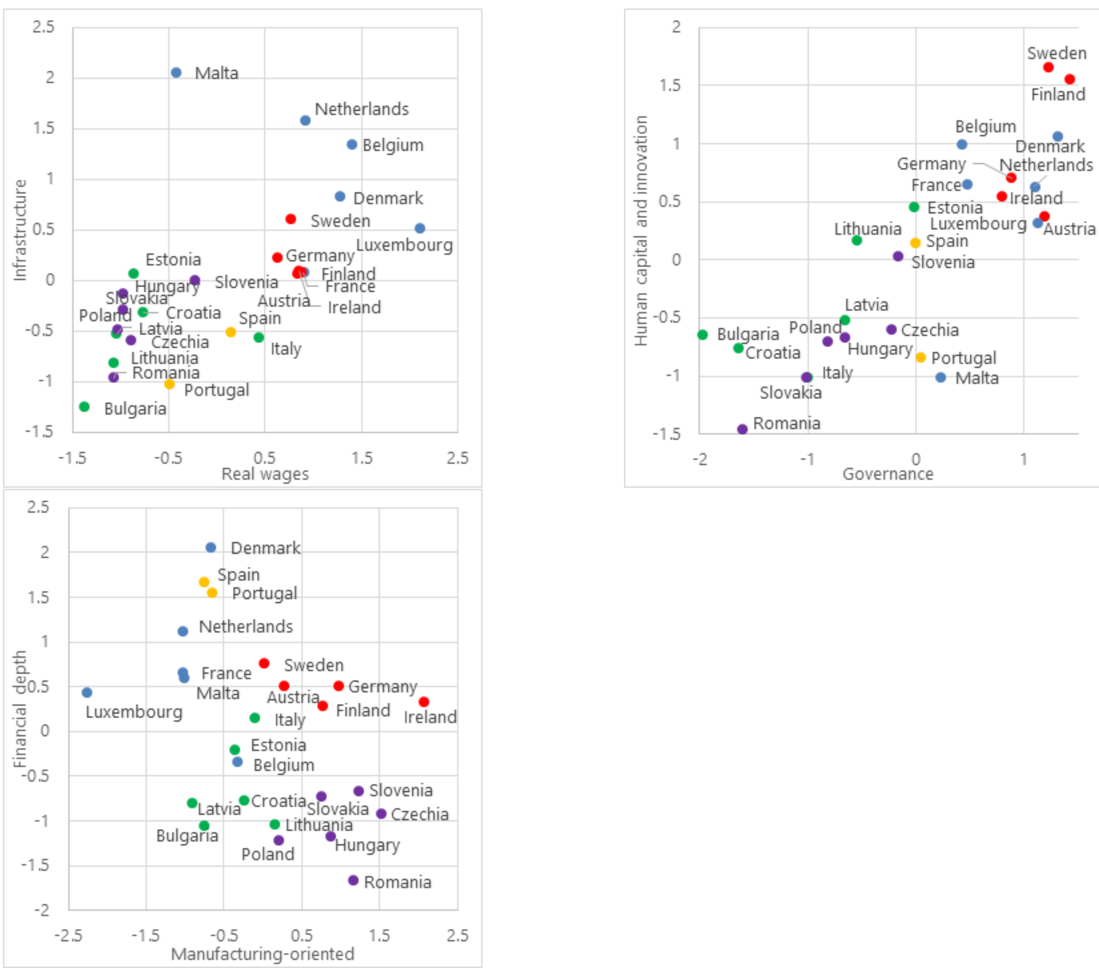
Sources: Eurostat, World Bank, OECD, IMF staff calculation.

[2] We are using Ward's method for hierarchical clustering, which minimizes the total within-cluster variance, based on a chosen measure of distance, in our case Euclidean distance (Ward, 1963).

[3] Average for the 2010–20 period have been used and the data has been preliminarily centralized and standardized.

1. The figure below shows the clusters in terms of variable pairs. Each identified cluster is represented in different color. Bulgaria belongs to the green cluster, together with Croatia, Estonia, Italy, Latvia and Lithuania. This group of countries is characterized by low wages and low levels of infrastructure, human capital and innovation, governance, and financial integration, while being relatively manufacturing-oriented. We can see that the green and purple clusters generally share similar GVC drivers except for the level of industrialization – the purple group has a higher share of manufacturing in GDP and somewhat lower level of highly educated population. The blue and red groups are also comparable but can be distinguished based on somewhat more developed infrastructure and lower industrialization in the blue group. Finally, Spain and Portugal form a group of their own, as they are characterized by subpar infrastructure and lower wages, but also by high rule-of-law scores and depth of financial markets.

Clustering of EU Countries Based on the Identified GVC Determinants



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

Note: The clusters are formed as follows:

- (green): Bulgaria, Croatia, Estonia, Italy, Latvia, and Lithuania.
- (purple): Czechia, Hungary, Poland, Romania, Slovakia, and Slovenia.
- (orange): Portugal and Spain.
- (blue): Belgium, Denmark, France, Luxembourg, Malta, and Netherlands.

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