CHAPTER VIII

# ECONOMIC GROWTH AND LOGISTICS PERFORMANCE: A DATA-DRIVEN ANALYSIS

**Muhammed BENLİ[1] & Fatih GÜNEŞ[2]**

[1]*(Assoc. Prof.), Bilecik Şeyh Edebali University,*
*E-mail: muhammed.benli@bilecik.edu.tr*
*ORCID: 0000-0001-6486-8739*

[2]*(Graduate Student), Bilecik Şeyh Edebali University,*
*E-mail: fatihgunes96@hotmail.com*
*ORCID: 0009-0005-0056-1961*

## 1. Introduction

The effectiveness and reliability of logistics systems are essential for economic growth and prosperity in today's worldwide economy. The interconnection of markets is supported by the movement of information, goods, and services both domestically and internationally, making trade and commerce easier. However, the significance of logistics extends beyond the mere transportation of goods and services. Logistics systems, encompassing transportation, warehousing, inventory management, and the intricate networks that connect producers with consumers, play a pivotal role in determining a country's competitive edge in the international market.

One crucial point that frequently arises when nations go on their developmental journeys is whether logistical performance and economic indicators—most notably GDP per capita—are causally related. The link in question bears significant consequences for policy formulation, allocation of resources, and strategic development agendas.

Based on both qualitative and quantitative data, the Logistics Performance Index (LPI), a benchmarking tool created by the World Bank, thoroughly assesses a nation's "friendliness" to logistics. However, GDP per capita, a widely used indicator, measures the average economic production per individual and provides insight into a country's overall life and financial health. An understanding of the interaction between these two variables provdes a glimpse into the mutually beneficial relationship between efficient logistics systems and general economic prosperity.

The relationship between GDP and the LPI is complex. While there is a strong inclination to consider logistics performance as a driver for economic growth, it is equally essential to recognize that a nation's GDP can influence its logistics capabilities. Countries with a higher GDP often have more financial resources to invest in critical infrastructure such as roads, ports, airports, and railways. Efficient infrastructure is a significant component of the LPI, as it directly affects the speed, reliability, and efficiency of transporting goods (Rodrigue, 2020). Furthermore, higher-income nations tend to adopt and implement the latest technologies faster (UNCTAD, 2021). In the logistics realm, this could mean advanced tracking systems, efficient warehouse management tools, and state-of-the-art shipping and delivery mechanisms, all of which can enhance a country's LPI score. Countries with higher GDPs also often have more sophisticated and efficient customs procedures due to better technological systems, training, and sometimes less corruption. Efficient customs operations mean faster clearance times and reduced costs, positively influencing the LPI (WTO/WCO, 2022). Moreover, a strong economy often translates to more significant demands for higher-quality services (Hoekman and Mattoo, 2008). As a result, logistics providers in wealthier nations might be more incentivized to offer top-tier services, further improving the LPI score. Also, developed economies with higher GDPs generally have a more established regulatory environment that can ensure that logistics operations are streamlined, transparent, and efficient. A conducive regulatory environment can foster better logistics practices, as reflected in the LPI (Jaller et al., 2020). Besides, a nation's wealth can often be directed towards better educational and training facilities. Regarding logistics, specialized training can improve the quality and efficiency of services, subsequently boosting the LPI (Shramenko et al., 2020). A higher GDP often correlates with a more competitive market environment. In such markets, logistics providers strive to outdo each other in terms of cost, quality, and efficiency, improving logistics performance overall (Aziz et al., 2015). Economies with higher GDPs also often have a complex industrial base that demands more sophisticated and integrated logistics services. This complexity can drive innovations and optimizations in the logistics sector, enhancing the overall LPI (Moldabekova et al., 2015; Magazzino et al., 2021).

On the other hand, LPI encapsulates various elements of a country's logistics proficiency, including infrastructure, customs efficiency, tracking, timeliness, and the quality of logistics services. A strong LPI score indicates that a nation has a robust logistics backbone, which can substantially impact its economic growth in several ways. Efficient logistics systems reduce the time and cost of moving goods across borders (Wiederer, 2013). This ease of trade can increase exports and imports, enhancing a country's trade balance and overall economic growth. Countries with a high LPI score are more attractive to foreign investors. Efficient logistics systems signal a conducive environment for business, reducing operational complexities and costs (Kovács et al., 2017). This can lead to higher levels of FDI, which in turn can spur economic growth. Furthermore, efficient logistics operations can lower the costs of transporting goods (Yekimov, 2023). These savings can translate to competitive pricing for consumers and higher profit margins for businesses, stimulating economic activity. A high LPI score also often corresponds to reliable supply chains (Aboul-Dahab and Ibrahim, 2020). Reliable logistics systems ensure that businesses can maintain lean inventories, reduce stockouts, and minimize holding costs. Such efficiencies can boost the productivity and profitability of businesses. Moreover, an efficient and expanding logistics sector can lead to job creation, both directly within the logistics industry and indirectly in sectors that rely on logistics, such as manufacturing, agriculture, and retail (Maggi et al., 2008). Effective logistics systems allow for a broader distribution of goods, ensuring that consumers, even in remote areas, can access to a diverse range of products. This increased market access can stimulate demand and consumption, driving economic growth. A competitive logistics sector, reflected in a high LPI score, can foster innovation (Soosay and Hyland, 2004; Kamali, 2018). Logistics companies in such environments might invest in new technologies and innovative solutions to improve their services further, leading to a ripple effect of technological advancement and economic growth. Efficient logistics systems can also provide a buffer during economic downturns. In the face of external shocks, countries with strong logistics can adapt more swiftly, sourcing goods from alternative locations or leveraging their logistics capabilities to pivot to new markets or sectors (De Leeuw and Wiers, 2015; Sarimsakov and Gaffarov, 2019). Moreover, countries that perform well in LPI are often better positioned in the global market. Efficient logistics can enhance the competitiveness of domestic industries by reducing production and distribution costs, making them more attractive internationally (Shpileva and Serhii, 2019).

It is important to note that while there is a general trend of higher GDPs correlating with better logistics performance, this is not an absolute rule. Several factors, including governance, policies, geographical challenges, and historical contexts, can play a role. However, understanding the influence of GDP on logistics performance can be crucial for policymakers, businesses, and stakeholders aiming to optimize logistics systems and, by extension, boost economic growth. Similarly, the LPI provides more than just a measure of logistics performance; it offers a lens into a nation's economic potential. While a strong LPI score alone does not guarantee growth, it does lay a foundational infrastructure that, when coupled with other conducive factors like sound governance, skilled labor, and market demand, can substantially drive economic progress.

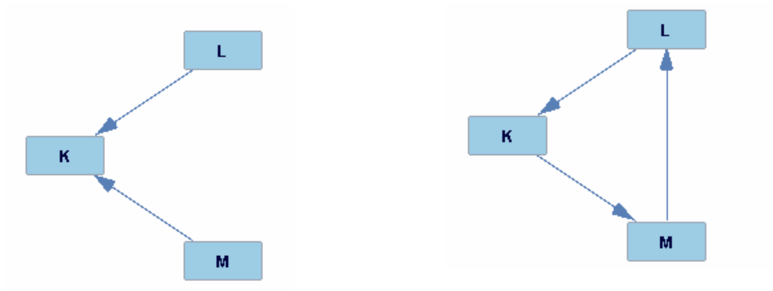
As discussed, although there is a known association between GDP per capita and logistics performance, more sophisticated analytical techniques are needed to determine a causal relationship. This paper uses the Directed Acyclic Graphs (DAGs) method to explore this complex web. The ability of DAGs to both describe and infer causal structures from data offers a sophisticated framework for analyzing the directionality and nature of the link between GDP per capita and logistical performance. This study aims to provide a complete understanding of the potential influence of nations' economic standing on logistics systems by analyzing data for 2019 from both developed and developing nations.

This study aspires to provide stakeholders and policymakers with practical insights and clarify academic curiosities by thoroughly examining this causation paradigm. After all, comprehending the mechanisms underlying advancement is not merely theoretical but also essential in a global community aiming for sustainable economic growth and development.

## 2. Directed Acyclic Graphs

In the economic literature, parameters and structure of economic models are often identified based on economic theory and researchers' intuition-driven studies. However, theory often fails to provide sufficient information to define the causal structure between the variables under study and can be said to be quite heterogeneous. Additionally, since the causal structure is theoretically determined by the statistical properties of the data, the observational data-based causal structure cannot be determined by theory-driven models, leading to incorrect causal inferences (Kwon & Bessler, 2011). Therefore, rather than "deductive causality" arising from innate ideas or assumed behaviors' mathematics, "inductive causality" that helps create causal graphs based on observational data and conditional independencies between variables can contribute to accurate determinations of relationships between variables (Li et al., 2013; Benli, 2019).

Directed Acyclic Graphs (DAGs) are commonly used in causal modeling and can be defined as directed graphs (digraphs) that do not contain directed cycles. The ordered pair (V, E), where V is a collection of vertices (variables or nodes), and E is a set of directed edges (arrows) linking the vertices, is used to represent a directed graph (DG) or digraph. Adjacent variables are connected by the edges. Take the directed graph G = (V, E) as an example, where V = {K, L, M} and E = {(L, K), (M, K)}. G is shown in Figure 1(a), where there are no cycles because starting and ending at the same vertex is not conceivable. As a result, G is known as a DAG. Whereas E' = {(L, K), (K, M), (M, L)} and V = {K, L, M}, G' = (V, E') is not acyclic. G' is depicted in Figure 1(b), and it has cycles because there is a path from L to K that returns via M to L. Since circular graphs cannot be identified, we limit our attention to acyclic graphs in this work (Li et al., 2013; Benli, 2018).




(a) (b)

**Figure 1.** Example of Directed Graphs

Several strategies, including PC (Partial Correlation), GES (Greedy Equivalence Search), and FCI (Fast Causal Inference) algorithms, are presented in the machine learning literature for DAG identification (Soremekun and Malgwi, 2012). We employ the PC method in this study since it is the most used algorithm in the literature.

In order to create directed graphs, Spirtes et al. (2000) created the PC method, which integrated the concept of d-separation (directional separation)[1]. An undirected graph with connections between every variable is the first step in this process. Then, iteratively, it removes edges with a stepwise testing process, evaluating zero correlation or zero partial (conditional) correlation with Fisher's

[1] The definition of d-separation can be found in Pearl (1995).

z-test. The idea of sepset is used to identify the final directed edges[2] (Benli, 2018).

The PC algorithm's edge inclusion/exclusion and edge direction correctness can be less dependable based on Monte Carlo simulations, especially when working with small sample sizes (Sprites et al., 2000; Awokuse and Bessler, 2003; Demiralp and Hoover, 2003; Zhang et al., 2006). Higher significance levels (e.g., 0.2 for sample sizes below 100 and 0.1 for sample sizes between 100 and 300) are suggested by Sprites et al. (2000) as a potential solution to this problem, which may improve performance in such scenarios (Awokuse & Bessler, 2003; Soremekun and Malgwi, 2012, also mentioned in Zhang et al., 2006; Benli, 2018).

We choose a 30 percent significance level due to the relatively modest number of observations in our dataset (40 developing and 36 developed nations). This choice also allows for a clear and unambiguous directed ordering of most variables in our analysis. We use the TETRAD VII software, which gives us access to the PC method and its expansions, to do the estimations in this work. In addition to LISREL, EQS, and AMOS, MIM and WinMine are also useful tools for predicting DAGs from data. A thorough study of three software programs that carry out DAG estimates can be found in Haughton et al. (2006).

**3. Data**

The variables frequently utilized in the body of current literature served as the basis for the selection of indicators in this study. We use cross-sectional data for 2019 (the most recent data available for the majority of countries) and five indicator variables in our research. The following variables are the focus of the empirical analysis: Logistics performance index (1=low to 5=high), GDP per capita (constant 2015 US$), gross fixed capital formation (% of GDP), trade (% of GDP), foreign direct investment net inflows (% of GDP), and research and development expenditure (% of GDP). The analysis covers 40 developing countries and 36 developed countries. For each particular set of nations, and for all countries, we build a DAG to investigate any changes or shifts in the direction of effects in various contexts. Table 1 lists the definitions and data sources of the variables included in the analysis, while Table 2 presents the list of the countries studied (39 developing and 35 developed).

[2] The conditioning variable(s) linked to the eliminated edges between two variables are referred to as the sepset. The sepset becomes an empty set when these edges are eliminated because there is no longer zero-order conditioning information (Awokuse & Bessler, 2003).

**Table 1.** Definitions and Data Sources for the Variables Used in the Analysis

| Variable | Symbol | Definition | Data Source |
|---|---|---|---|
| Income | *Real_GDP_PC* | GDP per capita (constant 2015 US$) | The Worldbank (WB) – World Development Indicators (WDI) |
| LPI | *LPI* | Logistics performance index: Efficiency of the customs clearance process (1=low to 5=high) | WB - WDI |
| Foreign Direct Investment | *FDI* | Foreign direct investment, net inflows (% of GDP) | WB - WDI |
| Trade Openness | *TRADE* | The sum of exports and imports of goods and services (% of GDP) | WB - WDI |
| R&D Expenditure | *R & D* | Research and development expenditure (% of GDP) | WB - WDI |
| Domestic Investment | *INV* | Gross fixed capital formation (% of GDP) | WB - WDI |

**Table 2.** Countries Studied

| Developed | | Developing | |
|---|---|---|---|
| Australia | Lithuania | Argentina | Mexico |
| Austria | Luxembourg | Armenia | Moldova |
| Belgium | Malta | Belarus | Mongolia |
| Bulgaria | New Zealand | Bosnia and Herzegovina | Montenegro |
| Canada | Norway | Brazil | North Macedonia |
| Croatia | Poland | Burkina Faso | Oman |
| Cyprus | Portugal | Chile | Pakistan |
| Czechia | Romania | China | Russian Federation |
| Denmark | Slovak Republic | Colombia | Rwanda |
| Estonia | Slovenia | El Salvador | Serbia |
| Finland | Spain | Georgia | Singapore |
| France | Sweden | Guatemala | South Africa |
| Germany | Switzerland | Hong Kong SAR, China | Thailand |
| Greece | United Kingdom | Iran, Islamic Rep. | Tunisia |
| Hungary | United States | Israel | Turkiye |
| Iceland | | Kazakhstan | United Arab Emirates |
| Ireland | | Korea, Rep. | Uruguay |
| Italy | | Kyrgyz Republic | Uzbekistan |
| Japan | | Mali | Vietnam |
| Latvia | | Mauritius | |

## 4. Findings

This section contains our discussion of the DAG analysis's findings. As a starting point, we first provide the results for the case of all countries. We set a thirty percent significance level, giving our analysis a clear directed ordering. Figure 2 shows the pattern produced by the PC algorithm.

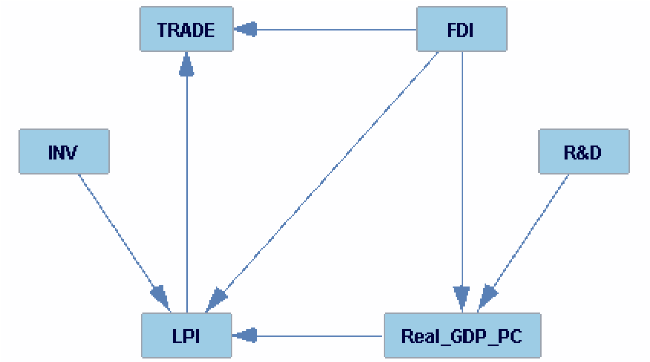



**Figure 2.** The Directed Graph at a 30% Significance Level (Whole Sample)

Examining the pattern that the PC algorithm produced indicates that *Real_GDP_PC*, *FDI*, and *INV* have directed effects on *LPI*, which directly triggers *TRADE*. The PC algorithm also illustrates a pathway from *FDI* and *R & D* to *LPI* through the intermediary of *Real_GDP_PC*.

Nonetheless, the 74-country model shown in Figure 2 may represent a variety of reactions; high-income countries may react differently to these variables than do less developed ones. As such, we perform a similar analysis with subgroups of 35 developed and 39 developing nations.

Figure 3 displays the DAG pattern generated by the PC for developing nations. The PC algorithm's output reveals that *Real_GDP_PC* has a directed impact on *LPI*. Through the intermediary of *Real_GDP_PC*, the PC algorithm also shows a path from *TRADE* and *R & D* to *LPI*.

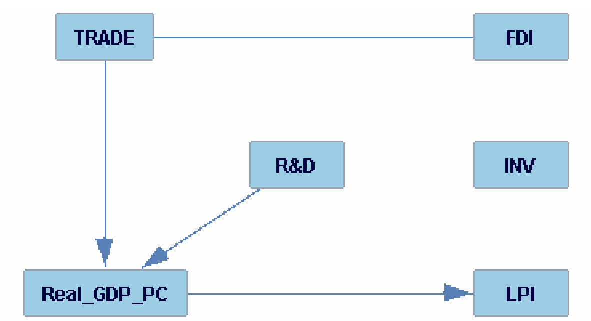



**Figure 3.** The Directed Graph at a
30% Significance Level (Developing Countries)

Figure 4 displays the DAG pattern generated by the PC algorithm for developed countries at a 30 percent significance level for edge removal. Similar to the findings from the analysis of developing countries, *Real_GDP_PC* has a directed impact on *LPI*. Furthermore, *R & D* has a directed effect on *LPI*, while it indirectly affects *LPI* through its impact on *Real_GDP_PC*, which is also the intermediary in the causal path from *INV* to *LPI*.

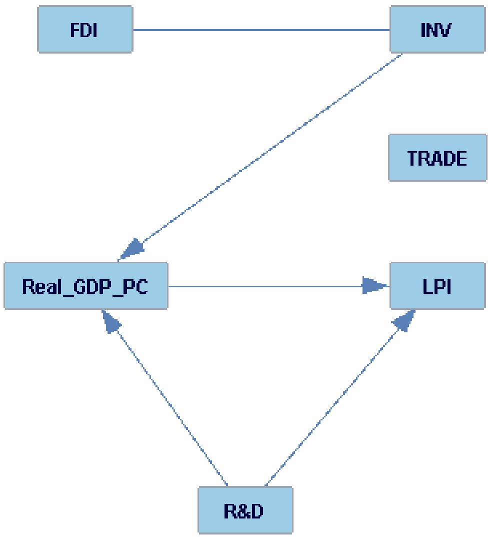



**Figure 4.** The Directed Graph at a 30% Significance Level (Developed Countries)

Furthermore, the DAG estimated using the PC algorithm reveals no association between other variables under consideration. In other words, *FDI* and *TRADE* are considered marginally independent as they have no common cause with other variables in the system. This also contradicts the findings for developing nations, where *TRADE* is a direct contributor to *Real_GDP_PC*, and there is a causal path from *TRADE* to *LPI* via *Real_GDP_PC*. The same argument can also be made for *INV* as it has an indirect effect on *LPI* through *Real_GDP_PC* in the case of developed countries, while it can be considered marginally independent in the case of developing countries.

### 5. Conclusion

The nexus between national economic indicators and the LPI has often been perceived as multifaceted and intricate. By employing DAGs as a methodological tool, this study has successfully deciphered this complexity across 74 nations, segmented into developed and developing categories.

Our findings reveal that the economic stature of nations, as denoted by GDP per capita, foreign direct investment, and domestic investment, plays a paramount role in determining their logistics performance. Notably, the causal pathways influencing LPI exhibit variations based on a country's development status. For instance, in developing countries, income per capita manifests as a linchpin in LPI determination, serving as a conduit for influences from other factors like trade and R&D expenditure. This suggests that improving income levels in these countries might be a keystone for enhancing logistical competencies.

Conversely, in developed nations, the tapestry is slightly different. While per capita income continues influencing LPI, R&D expenditure emerges as another direct and influential factor. This dual influence, both direct and indirect through its effect on income per capita, implies that fostering research and innovation can serve as a catalyst for logistical advancement in developed nations.

In essence, the study's findings underscore the need for a nuanced approach to logistics policymaking that is cognizant of a country's economic backdrop. As nations navigate the challenges of globalization and strive for economic and logistical optimization, it becomes imperative to tailor strategies to their unique economic landscapes. By doing so, nations can not only enhance their logistical performance but also fuel broader economic growth and development.

## REFERENCES

Aboul-Dahab, K., & Ibrahim, M. A. (2020). Investigating the efficiency of the logistics performance index (LPI) weighting system using the technique for order of preference by similarity to ideal solution (TOPSIS) method. *International Journal of Science and Research*, *9*, 269-277.

Awokuse, T. O. and Bessler D. A., (2003), Vector autoregressions, policy analysis and directed acyclic graphs: an application to the U.S. economy, *Journal of Applied Economics, 6,* 1–24.

Aziz, Z. A., Razak, R. C., Yaacob, M. R., & Rahim, R. C. (2015). Logistics resources as a source of competitive advantage for logistics service providers. *Nigerian Journal of Botany, 2*(10):105-111.

Benli, M. (2018). Causal structure of export-productivity nexus in Turkey. *Journal of Management and Economics Research, 16*(1), 194-203.

Benli, M. (2019). Yabancı portföy yatırımı-iktisadi büyüme ilişkisi: Yönlendirilmiş döngüsüz graflar analizi. *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi,* (53), 59-72.

De Leeuw, S., & Wiers, V. C. (2015). Warehouse manpower planning strategies in times of financial crisis: evidence from logistics service providers and retailers in the Netherlands. *Production Planning & Control*, *26*(4), 328-337.

Demiralp, S. and Hoover, K.D., (2003), Searching for the causal structure of a vector autoregression, *Oxford Bulletin of Economics and Statistics, 65*, 745-67.

Haughton, D., Kamis, A. and Scholten, P., (2006), A review of three directed acyclic graphs software packages: MIM, Tetrad and WinMine, *The American Statistician, 60*(3), 272-286.

Hoekman, B., & Mattoo, A. (2008). Services trade and growth. Opening markets for trade in services: Countries and sectors in bilateral and WTO negotiations, 21-58.

Jaller, M., Otero-Palencia, C., & Yie-Pinedo, R. (2020). Inventory and fleet purchase decisions under a sustainable regulatory environment. In *Supply Chain Forum: An International Journal* (Vol. 21, No. 1, pp. 53-65). Taylor & Francis.*g markets for trade in services: Countries and sectors in bilateral and WTO negotiations*, 21-58.

Kamali, A. (2018). Innovative and smart technologies in logistics. *CiiT International Journal of Artificial Intelligent Systems and Machine Learning, 10*(10), 216-222.

Kovács, G., Varga, Z., & Mihalik, M. (2017). Optimal formation of logistics networks. In *Vehicle and Automotive Engineering: Proceedings of the JK2016, Miskolc, Hungary* (pp. 391-403). Springer International Publishing.

Kwon, D. and Bessler, D., (2011), Graphical methods, inductive causal inference, and econometrics: a literature review. *Computational Economics*, 38, 85–106.

Li, Y., Woodard, J.D. and Leatham, D.J., (2013), Causality among foreign direct investment and economic growth: a directed acyclic graph approach. *Journal of Agricultural and Applied Economics, 45*(4), 617–637.

Magazzino, C., Alola, A. A., & Schneider, N. (2021). The trilemma of innovation, logistics performance, and environmental quality in 25 topmost logistics countries: A quantile regression evidence. *Journal of Cleaner Production*, *322*, 129050.

Maggi, E., Mariotti, I., & Boscacci, F. (2008). The indirect effects of manufacturing internationalisation on logistics. A focus on the industrial districts of Veneto. *International Journal of Logistics Economics and Globalisation*, *1*(2), 205-224.

Moldabekova, A., Philipp, R., Reimers, H. E., & Alikozhayev, B. (2021). Digital technologies for improving logistics performance of countries. *Transport and Telecommunication Journal*, *22*(2), 207-216.

Pearl, J. (1995). Causal diagrams for empirical research. *Biometrika, 82*(4), 669-688.

Rodrigue, J. P. (2020). *The geography of transport systems.* Routledge.

Sarimsakov, A. & Gaffarov, M. (2019). Advantages of logistics guarantee system. *Bulletin of Science and Practice*, *5*(5), 344-347.

Shpileva, V., & Serhii, T. E. N. G. (2019). Logistics as a strategy of increasing competitiveness in international markets. *Bulletin of the Cherkasy Bohdan Khmelnytsky National University. Economic Sciences*, (3).

Shramenko, N., Muzylyov, D., Shramenko, V., & Mazyliuk, P. (2020). Directions for quality assurance of specialists training in logistics and transport spheres from a competence approach perspective. In *New Technologies, Development and Application III 6* (pp. 605-611). Springer International Publishing.

Soosay, C. A., & Hyland, P. W. (2004). Driving innovation in logistics: case studies in distribution centres. *Creativity and Innovation Management*, *13*(1), 41-51.

Soremekun O., and Malgwi, C., (2012), Exploring the relationship between foreign direct investment and mobile technology in Africa: an application of directed acyclic graphs. *Case Studies in Business, Industry and Government Statistics, 5*(1), 58-66

Spirtes, P., Glymour, C. and Scheines, R., (2000). *Causation, prediction, and search.* Cambridge, MA: MIT Press.

United Nations Conference on Trade and Development (UNCTAD) (2021). Technology and Innovation Report 2021. https://unctad.org/page/technology-andinnovation-report-2021.

Wiederer, C. (2013). Logistics Infrastructure Along the Belt and Road Initiative Economies. *Production and Operations Management*, *22*(2), 236-252.

World Trade Organization (WTO) / World Customs Organization (WCO) (2022). The role of advanced technologies in cross-border trade: A customs perspective. https://www.wcoomd.org/-/media/wco/public/global/pdf/topics/facilitation/instruments-and-tools/tools/wco-wto-paper/role-of-advanced-tech_en.pdf?la=en

Yekimov, S. (2023). Improving the efficiency of the transport and logistics sector. In *E3S Web of Conferences* (Vol. 376). EDP Sciences.

Zhang, J., Bessler, D. and Leatham, D., (2006), Does consumer debt cause economic recession? evidence using directed acyclic graphs. *Applied Economics Letters*, 13, 401 – 407.