

## **METHODS FOR MEASURING FISCAL FRAUD AND EVASION**

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***Abstract:** Tax fraud and evasion are essential and perennial topics in the tax field, and have major effects on both global economies and public finances. In order for the fight to fight and the establishment of effective policies to protect public revenues to be effective, it is necessary to identify and measure the determining factors of fraud and evasion. In this article, we consider a justification approach that argues the necessity of studying the determinants, emphasizing the presentation of theoretical justifications and the discussion of methodological issues related to the measurement of these phenomena.*

**Keywords:** fiscal fraud, evasion, empirical studies, tax policies, econometric estimation models, value of tax fraud and evasion

**JEL Classification:** G28, G41

### **Introduction**

Fiscal fraud and evasion have been critical issues globally since ancient times. As soon as taxes are perceived as burdensome, people and businesses start looking for ways to avoid paying them. This behaviour challenges governments and institutions tasked with collecting revenue necessary for public services and infrastructure. Assessing the extent of fiscal fraud and evasion is difficult due to the covert nature of these activities and the variety of methods used to measure them. There are numerous indexes developed by international institutions to evaluate the level of fiscal fraud and evasion. These indexes differ significantly in their methodologies, the aspects of the economy they consider, and the degree of complexity they employ. Some focus on the underground economy, while others estimate the informal economy or the financial losses from activities in tax havens. Each index has its strengths and weaknesses, and they can produce markedly different results.

Synthesizing these indexes is crucial to understand their relative effectiveness in measuring fiscal fraud and evasion. A comprehensive analysis involves comparing the methodologies and results of these indexes to identify which ones provide the most accurate and reliable data. For instance, Schneider's underground economy estimates, the European Commission's Atlas of the Offshore World, and the World Bank's various informal economy measures each offer different perspectives and data sets. Evaluating these can reveal the most robust indicators and help policymakers make informed decisions. Ultimately, improving the assessment of fiscal fraud and evasion through better indexes can help governments design more effective tax policies and enforcement strategies. Simplifying tax systems, enhancing transparency, and fostering a culture of compliance are essential steps toward reducing fiscal fraud and evasion and securing the necessary revenues for sustainable development.

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The remainder of the paper is structured as follows. Section 2 present a synthesis of the literature on this topic. Section 3 describes the data and the methodology used. Section 4 presents the results, while the last section concludes.

### **Literature review**

Despite the importance of fiscal fraud and evasion, there is a surprisingly small number of empirical studies addressing the determinants of these phenomena. The main obstacle is the difficulty in quantifying these illicit fiscal activities. The major reason for this measurement challenge is their hidden and illicit nature, making them difficult to observe. Consequently, there are no precise data for these variables, unlike other economic indicators. This significant shortcoming hinders academic research, which typically relies on highly reliable data. Therefore, some researchers (Khlif & Achek, 2015; Tsakumis et al., 2007) consider fiscal fraud and evasion practically unknown and almost impossible to determine accurately, forcing researchers to use approximate values as proxies for real values. Some studies go further, using perceptions of these phenomena or subjective estimates from public authorities. The overarching idea here is that no measure has proven superior to another, leaving it to researchers to choose which one to use (Schneider & Enste, 2000).

The academic literature on fiscal fraud and evasion generally distinguishes between two types of approaches: micro-direct and macro-indirect (Khlif & Achek, 2015; Gemmill & Hasseldine, 2012). The micro-direct approach primarily uses data from taxpayers, numerical information from surveys and inspections to estimate values of tax non-compliance. In contrast, the macro-indirect approach tries to evaluate the size of the underground economy based on macroeconomic assumptions and models (Schneider, 2018). As previously noted, fraud and evasion cannot be directly observed because they are largely connected to the underground economy. A major difficulty in empirical applications is quantifying these concepts as numerical variables. However, there are estimation approaches through reports, some with an international character, such as the Global Competitiveness Report (GCR). Researchers extract data from these reports for empirical studies (Schwab, 2018). These reports rely on surveys estimating individuals' perceptions, including regarding fiscal fraud and evasion. For almost two decades, applied research has used these data. For example, Riahi-Belkaoui's 2004 study analyzed the relationship between global tax compliance and factors influencing fiscal morality using individuals' perceptions evaluated through GCR reports. The GCR survey study also defined a compliance score, trying to capture the level of tax obligation adherence at the country level. This score is scaled from zero (low compliance) to six (high compliance). Using these numerical values, Richardson (2006) utilized GCR estimates as proxy variables for fiscal fraud and evasion. Specifically, Richardson focused on measuring the connections between tax compliance and factors characterizing fiscal morality. Using information from nearly 50 countries and econometric estimation models, the study concluded that economic factors do not have the most significant effects on fraud and evasion levels. Factors such as education, primary income type, fairness, and fiscal morality were identified and tested through hypotheses. The econometric models showed that lower fiscal complexity and higher wage income levels, population fairness, and fiscal morality significantly reduce fraud and evasion statistically. Richardson's 2006 study provided more robust results by testing hypotheses through three proxy variables for tax evasion. The article used two different scales for declarative variables from surveys. The first was a Likert scale variable, scaled from 1 (strongly disagree) to 7 (strongly agree), representing average values from 2002 to 2004. The second variable was scaled from 0 (common) to 10 (unusual) for the same period. Data used came from surveys conducted by the World Economic Forum (WEF) through the GCR reports for 2002, 2003, and 2004 (Khlif & Achek, 2015). Both scores underwent mathematical transformations to obtain scalar values of fiscal fraud and evasion.

In a subsequent article, Richardson (2008) used standardized information from the WEF-GCR. This time, a third proxy variable was added alongside the two previously used. This variable was based on national survey questions about underreporting income and the underground economy. This item was evaluated on a scale from 1 (total underground business less than five percent) to 9 (total underground business over seventy percent). Subsequent opinions on Richardson's studies consider survey-based estimation methods as micro-direct approaches to estimating tax fraud and evasion. Despite being used in fiscal literature, there are opposing views on using aggregated scores from international report surveys. Critics argue that survey responses depend on respondents' willingness to answer questions accurately, affecting data quality (Khlif & Achek, 2015). Fuest & Riedel (2009) and Gabor (2012) also express doubts about the accuracy of responses from individuals engaging in fraud or evasion. Other criticisms (Schneider, 2018; Khlif & Achek, 2015) concern the formulation of survey questions, which can influence responses and thus numerical estimates of fraud and evasion. There may also be differences in attitude when responding to surveys between taxpayers in developed and emerging economies.

Tsakumis et al. (2007) build on previous studies on the determinants of fraud and evasion, using various proxy variables for these phenomena and the underground economy. They define the underground economy as the size of legal market production hidden from public authorities. National culture is extensively analyzed by Tsakumis and colleagues, who argue that it is relevant for understanding intentional evasion in different countries, using data from 50 countries.

Empirical observations from some studies (e.g., Khlif & Achek, 2015) highlight that countries with larger underground economies (as a proportion of national income) are associated with lower tax compliance. Subsequent studies (Pozdnyakova et al., 2019) use macroeconomic-inspired methods, such as dynamic multiple-indicators multiple-cause (DYMIMIC). This methodology, a derivation of a structural equation model, uses a latent variable representing the underground economy's size. Researchers believe this model can be adapted to not only explain behavior but also predict future values of the underground economy. Beyond these approximations, other approaches, both micro-direct and macro-indirect, appear in applied research (Gemmell & Hasseldine, 2012; Khlif & Achek, 2015).

Micro-direct approaches include tax audits as a method for estimating the value of tax fraud and evasion. However, this methodology has drawbacks, as it only refers to the fraction of the underground economy identified by public authorities, which may represent a smaller or larger proportion of the unknown real value.

Macro-indirect approaches reveal a diversity of techniques for estimating fiscal crime. The literature (Schneider, 2018; Khlif & Achek, 2015) identifies at least five macroeconomic methodologies for estimating fraud and evasion: (1) the discrepancy between expenditure and national income statistics; (2) the discrepancy between official and real labour force; (3) the transaction method; (4) the currency demand method; and (5) the physical input method. Each of these methodologies offers different insights and faces unique challenges in accurately capturing the extent of fiscal fraud and evasion. The complexity and hidden nature of these activities require a combination of approaches to achieve more reliable estimates (Schneider & Enste, 2013).

Out of the revised literature, we have synthesized the most commonly used indexes for measuring fiscal fraud and evasion:

1. Estimation of the Shadow Economy by Medina & Schneider (2019) and Schneider & Asllani (2022);
2. Estimation of losses from offshore activities of companies in various countries, such as those conducted by the European Commission, OECD, or EUTAX Observatory (Vellutini et al., 2019, Alstadsæter et al., 2023, Atlas of the Offshore World, 2024);
3. Estimates based on various indicators and indices constructed from information in the Global Competitiveness Report (GCR) by the World Economic Forum, such as those by Schwab (2018) or Mazurenko et al. (2023);

4. World Bank estimates of the Informal Economy, which, again, attempt to estimate the level of the informal economy from various perspectives (World Bank – Informal Economy Database, 2024, based on Elgin et al., 2021).

**Data and Methodology**

The data are panel data for a sample of 104 countries worldwide, generally covering the period from 2015 to 2020, to compare the results obtained across various proxy variables used in the analysis. By using multiple proxies to measure fiscal fraud and evasion, we aim to evaluate the robustness of the results and determine which of these proxies are more effective from the perspective of the present research. Table 1 present the variables that we selected as proxies for fiscal fraud and evasion.

Although we mention the Shadow Economy of Medina & Schneider (2019), its last update for world countries is for 2017. Consequently, we have been obliged to drop this variable from our analysis.

Table 1. Variables used as proxies for fiscal fraud and evasion

Variable	Variable Name	Variable Description	Period
CTRL	Corporate Tax Revenue Lost	The Corporate Tax Revenue Lost indicator estimates the percentage of tax revenues lost by a country due to profit transfers made by companies to tax havens, out of the total taxes collected from companies. Source: Atlas of the Offshore World, <a href="https://atlas-offshore.world/dataset/global-profit">https://atlas-offshore.world/dataset/global-profit</a>	2015 - 2020
LP	Lost Profits	Lost Profits estimate the actual amounts of money countries have lost in a given year due to corporations transferring profits to tax havens. Measured in billion USD. Source: Atlas of the Offshore World, <a href="https://atlas-offshore.world/dataset/global-profit">https://atlas-offshore.world/dataset/global-profit</a>	2015 - 2020
TRL	Tax Revenue Lost	The Tax Revenue Lost indicator estimates the total amounts lost by the sample countries due to profit transfers to tax havens. Measured in billion USD. Source: Atlas of the Offshore World, <a href="https://atlas-offshore.world/dataset/global-profit">https://atlas-offshore.world/dataset/global-profit</a>	2015 - 2020
OFW	Offshore Financial Wealth	The Offshore Financial Wealth indicator estimates the value of all types of investments such as stocks, bonds, mutual fund shares, bank deposits, etc., that households hold in banks outside their country of residence. It can be measured as a percentage of the country's GDP (the variant considered in this analysis) or in billion USD. Source: Atlas of the Offshore World, <a href="https://atlas-offshore.world/dataset/offshore-financial">https://atlas-offshore.world/dataset/offshore-financial</a>	2015 - 2020
IE_EDG	Informal Economy EDG	The Informal Economy estimated by the Dynamic General Equilibrium (DGE) Model, which estimates the informal output obtained in a national economy as a percentage of the country's GDP. Source: <a href="https://www.worldbank.org/en/research/brief/informal-economy-database">https://www.worldbank.org/en/research/brief/informal-economy-database</a>	2015 - 2020
IE_MIMIC	Informal Economy	The Informal Economy estimated by Multiple Indicators Multiple Causes (MIMIC) Models, which	2015 - 2020

	MIMIC	estimate the informal output obtained in a national economy as a percentage of the country's GDP. Source: <a href="https://www.worldbank.org/en/research/brief/informal-economy-database">https://www.worldbank.org/en/research/brief/informal-economy-database</a>	
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*Source: authors' construction*

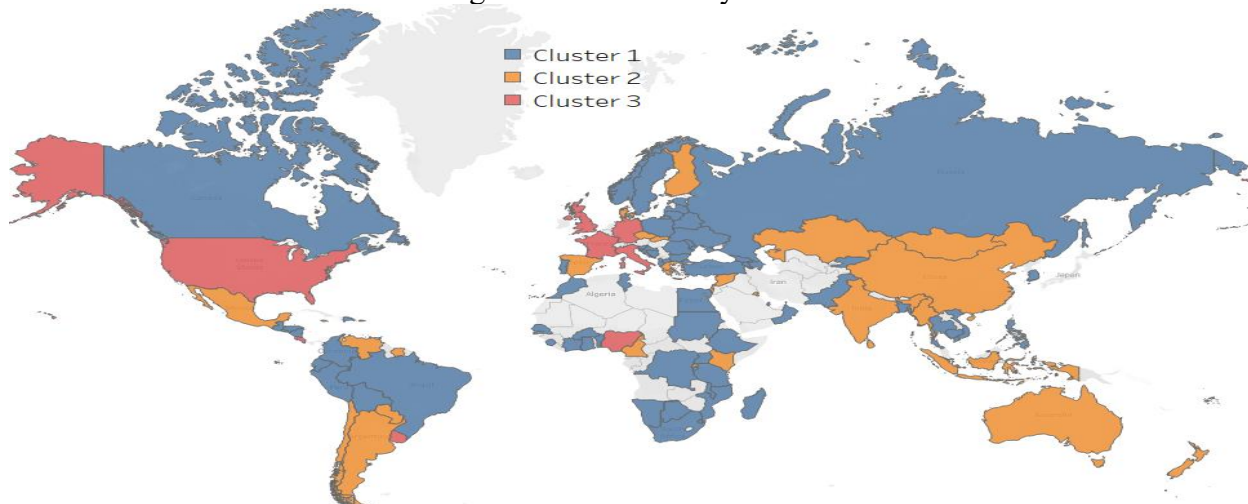
To assess the efficiency of the considered proxies in the evaluation of fiscal fraud and evasion, along with the stability and robustness of this assessment, we employ the cluster analysis. This allows us to emphasize specificities related to the studied topic for groups of countries in the sample. Moreover, as we are dealing with countries, we opted for applying the clusterization process from a spatial perspective. Out of the clustering methods, we chose the k-means method implemented in Tableau for data grouping. This method fits our data because all variables used in the analysis are quantitative variables, for which descriptive statistics can be estimated. The procedure automatically selects the number of clusters into which the sample is divided by calculating the means for each group and the distances between cluster means, on one hand, and between the actual values of the countries in each cluster and the cluster mean, on the other hand. The cluster mean is referred to as the centroid. The process starts with an initial variable automatically chosen by the procedure as the first step, dividing the sample into two clusters. The estimation procedure is iterative, sequentially selecting new variables that are introduced into the analysis and used for clustering until an optimal division is reached in terms of the aforementioned distances - within clusters and between clusters. The distances are estimated using the Euclidean distance, one of the most well-known methods for estimating a standardized distance.

Analyses have been conducted in Tableau 2024.1.

**Results**

The cluster analysis conducted on the sample of 104 countries initially revealed 3 clusters. These are presented in figure 1. Cluster 1 consists of 68 countries (the majority), including both developed countries like Canada and Nordic countries (Sweden, Norway) and most Eastern European countries, Russia, Turkey, most African countries, and South American countries. Cluster 2 consists of 28 countries, including Australia, China, Finland, Denmark, Greece, Israel, as well as less developed countries like Jamaica, Mongolia, and Paraguay. Cluster 3 consists of 8 countries: the USA, Costa Rica, France, Germany, Italy, Nigeria, the United Kingdom, and Uruguay.

Figure 1. Cluster analysis results



*Source: authors' construction in Tableau 2024.1*

On average, during the analyzed period, countries in the first cluster recorded the lowest values for losses incurred from the transfer of corporate profits from the countries where they were generated to tax haven jurisdictions, as shown in table 2 – 7.52% of tax revenue lost due to offshore operations as a share of total tax revenue, \$2.91 billion average profits lost through their transfer to tax havens, and \$0.49 billion total revenue lost due to these transfers. Citizens of these countries rank mid-level in terms of their financial wealth in tax havens, with an average share of 13.48% of GDP. However, the informal economy is the highest, with informal output estimates showing values of 32.43% of GDP for IE\_EDG and 36.75% for IE\_MIMIC.

Table 2. Cluster characteristics

Cluster	Volume	CTRL (%)	LP (mld. USD)	TRL (mld. USD)	OFW (%)	IE_EDG (%)	IE_MIMIC (%)
Cluster 1	68	7.52	2.91	0.49	13.48	32.43	36.75
Cluster 2	28	8.34	6.60	1.59	18.49	22.05	19.99
Cluster 3	8	20.97	45.90	13.18	10.24	24.22	23.1

*Source: authors' estimations in Tableau 2024.1*

Countries in the second cluster have significantly higher values than those in the first cluster when estimating losses from various offshore activities. They have a CTRL of 8.34% compared to 7.52% for Cluster 1. Losses from profits transferred to tax havens are, on average, nearly three times higher than in the first cluster, amounting to approximately \$6.6 billion average annual losses during the analyzed period. A similar ratio between Cluster 1 and Cluster 2 is observed in total revenues lost: \$1.59 billion for Cluster 2 compared to \$0.49 billion for Cluster 1. Cluster 2 has the highest financial investments in tax havens, averaging nearly 18.5% of annual GDP. Interestingly, these countries rank at the opposite end when quantifying the informal economy, with the lowest shares in GDP: 22.05% and 19.99%, respectively.

Cluster 3 has the fewest countries but exhibits offshore activities nearly three times greater than Clusters 1 and 2 in terms of lost tax revenues. The ratio significantly increases, with average profits lost through transfers to tax havens being over 15 times greater than Cluster 1 and nearly 7 times greater than Cluster 2. Similarly large differences are seen in total revenues lost. Interestingly, however, these countries have the fewest financial investments in tax havens, averaging only 10.24% of annual GDP. In terms of the informal economy, Cluster 3 ranks second.

However, table 3, that presents the results of the variance analysis shows that OFW, the variable estimating the offshore financial wealth, is not significant in the clustering process. The p-value = 0.378 > 0.05.

Table 3. Analysis of Variances for the cluster analysis

Variable	F-statistic	p-value	Between Sums of Squares		Within Sums of Squares	
			Value	DF	Value	DF
CTRL	35.6	0.000	2.233	2	3.168	101
IE_MIMIC	23.22	0.000	2.092	2	4.549	101
LP	17.76	0.000	0.599	2	1.704	101
TRL	16.87	0.000	0.458	2	1.372	101
IE_EDG	9.85	0.000	0.884	2	4.53	101
OFW	0.9837	0.378	0.047	2	2.424	101

*Source: authors' estimations in Tableau 2024.1*

As a result of these findings, we ran the clustering analysis again, this time without OFW. Results are presented in table 4 and visually in Figure 2. The confirmation of the variables' efficiency in the clustering process is shown in table 5, where all p-value values are observed to be below the critical threshold of 5%. This time, the analysis identifies 4 effective clusters.

Countries in Cluster 1 from figure 2 are predominantly Asian countries - India, China, etc., as well as Australia and New Zealand. Interestingly, this group is dispersed across all continents. The 28 countries in Cluster 1 lost, on average, approximately 8% of their tax revenues due to transfers to tax havens. They rank second in all proxies related to tax havens. For instance, the profit losses due to transfers to tax havens are estimated to be nearly \$6 billion annually on average during the analyzed period, while the total revenue lost amounted to approximately \$1.43 billion. The informal economy is, on average, the second lowest, after that of Cluster 4 when analyzed through the lens of IE\_EDG, and the lowest when estimated through IE\_MIMIC.

Table 4. Cluster characteristics without OFW

Cluster	Volume	CTRL (%)	LP (mld. USD)	TRL (mld. USD)	IE_EDG (%)	IE_MIMIC (%)
Cluster 1	28	7,9758	5,9849	1,4263	22,218	21,31
Cluster 2	66	7,4455	2,9871	0,50591	32,575	36,997
Cluster 3	7	18,76	12,122	3,4583	29,933	16,197
Cluster 4	3	22,233	100,06	28,611	11,659	30,559

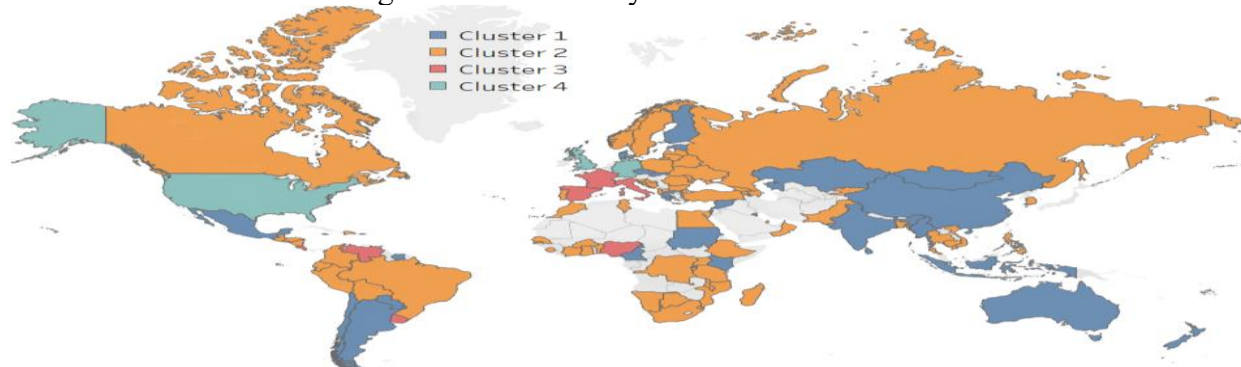
*Source: authors' estimations in Tableau 2024.1*

Cluster 2, consisting of 66 component countries, largely overlaps with cluster 1 from the initial clustering analysis. It exhibits the lowest values of losses from offshore activities, hence, consequently, the lowest level of tax fraud and evasion from this perspective. Similar to the first clustering analysis, it also has the highest level of informal economy, regardless of the proxy used.

Cluster 3 is made up of 7 different countries spanning across Europe (Italy, France, Spain), Latin America, and Africa, varying in levels of development. It represents the second group with the highest levels of tax fraud and evasion (see table 4). It holds the same position based on IE\_EDG, but interestingly, it has the lowest level of informal economy if analyzed through IE\_MIMIC.

Cluster 4 comprises only 3 countries: USA, UK, and Germany. These countries annually report tax losses three times higher on average than clusters 1 and 2. Corporate profit transfers from these countries to tax havens average over 100 billion USD, nearly 20 times higher than cluster 1 and nearly 50 times higher than cluster 2. Similar proportions apply to total revenue losses due to offshore activities. The positioning of this cluster in terms of informal economy is entirely opposite for the two indicators, having the lowest level for IE\_EDG but the second highest for IE\_MIMIC.

Figure 2. Cluster analysis results without OFW



*Source: authors' construction in Tableau 2024.1*

Table 5 confirms that the clustering process is effective, with all variables recording null hypothesis acceptance probabilities much lower than the critical threshold of 0.05 (5%), thereby confirming their effectiveness in grouping the countries in the sample.

Table 5. Analysis of Variances for the cluster analysis without OFW

Variable	F-statistic	p-value	Between Sums of Squares		Within Sums of Squares	
			Value	DF	Value	DF
CTRL	24.85	0.000	2.362	3	3.168	100
LP	24.12	0.000	1.233	3	1.704	100
TRL	22.12	0.000	0.91	3	1.372	100
IE MIMIC	16.32	0.000	2.227	3	4.549	100
IE EDG	8.458	0.000	1.149	3	4.53	100

*Source: authors' estimations in Tableau 2024.1*

### Conclusions

The goal of the current research was to synthesize and compare the most used proxies for the assessment of fiscal fraud and evasion. Based on the specialized literature, we selected the most commonly used proxies for estimating fiscal fraud and evasion, and attempted to compare them to assess the stability and similarity of the results obtained based on these proxies, in order to evaluate their robustness. Results indicate that the subjectivity we identified makes its influence felt.

We have demonstrated how countries in the sample are clustered based on the proxy variables used to estimate tax fraud and evasion. Once again, we highlighted the discrepancies in the "performance" of various countries, sometimes even contrasting based on different variables. Developed countries such as the USA and Germany stand out for their highly intense offshore activities, placing them at the forefront of the global ranking for losses due to profit transfers to tax havens. These significant losses contribute to a high level of tax fraud and evasion. Paradoxically, despite these massive operations, they have the lowest shares of informal economy in their GDP, suggesting a high degree of formality and regulation in the rest of the economy. On the other hand, countries like Russia and Canada, although experiencing smaller losses from offshore activities, face a much more intense informal economy. This indicates that, although losses from profit transfers are lower, a significant portion of these countries' economies operates outside official regulations, thereby contributing to a high level of informal economy. This dynamic suggests fundamental differences in the structure and economic behaviour of these countries, highlighting the contextual importance in analyzing tax fraud and evasion phenomena.

Our results are fundamental for understanding the complex issue of fiscal (tax) fraud and evasion. This is highly important from the point of view of the policy making process. Different proxies used to measure the assessed aspect are based on different estimation methodologies and comprise different types of information. Consequently, constructing public policies devoted to reducing fraud and evasion must be done by fully understanding all these differences that may appear when using different proxies for estimating the same aspect.

### References

1. Alstadsæter, A., Godar, S., Latitude, A. C. L., Nicolaides, P., & Zucman, G. (2023). *Global tax evasion report 2024* (Doctoral dissertation, Eu-Tax Observatory).
2. Elgin, C., M. A. Kose, F. Ohnsorge, & S. Yu. (2021). *Understanding Informality. CERP Discussion Paper 16497*, Centre for Economic Policy Research, London.
3. Fuest, C., & Riedel, N. (2009). Tax evasion, tax avoidance and tax expenditures in developing countries: A review of the literature. *Report prepared for the UK Department for International Development (DFID)*, 44.



4. Gabor, R. (2012). Relation between tax evasion and Hofstede's model. *European Journal of Management, 12*(1), 61-72.
5. Gemmell, N., & Hasseldine, J. (2012). *The tax gap: a methodological review* (Vol. 20, pp. 203-231). Emerald Group Publishing Limited.
6. Khlif, H., & Achek, I. (2015). The determinants of tax evasion: a literature review. *International Journal of Law and Management, 57*(5), 486-497.
7. Mazurenko, O., Tiutiunyk, I., Cherba, V., Artyukhov, A., & Yehorova, Y. (2023). Shadow Tax Evasion and Its Impact on the Competitiveness of the Country's Tax System. *Public and Municipal Finance, 12*(2), 129-142.
8. Medina, L., & Schneider, F. (2019). *Shedding light on the shadow economy: A global database and the interaction with the official one*.
9. Riahi-Belkaoui, A. (2004). Relationship between tax compliance internationally and selected determinants of tax morale. *Journal of International Accounting, Auditing and Taxation, 13*(2), 135-143.
10. Richardson, G. (2006). Determinants of tax evasion: A cross-country investigation. *Journal of international Accounting, Auditing and taxation, 15*(2), 150-169.
11. Richardson, G. (2008). The relationship between culture and tax evasion across countries: Additional evidence and extensions. *Journal of International Accounting, Auditing and Taxation, 17*(2), 67-78.
12. Schneider, F. (2018). *Size, Causes and Consequences of the Underground Economy: an international perspective*. Routledge.
13. Schneider, F., & Asllani, A. (2022). *Taxation of the Informal Economy in the EU*. European Parliament, Subcommittee on tax matters (FISC).
14. Schneider, F., & Enste, D. H. (2000). Shadow economies: Size, causes, and consequences. *Journal of Economic Literature, 38*(1), 77-114.
15. Schneider, F., & Enste, D. H. (2013). *The shadow economy: An international survey*. Cambridge University Press.
16. Schwab, K. (2018). *The global competitiveness report 2018*. World Economic Forum Eds.
17. Tsakumis, G. T., Curatola, A. P., & Porcano, T. M. (2007). The relation between national cultural dimensions and tax evasion. *Journal of International Accounting, Auditing and Taxation, 16*(2), 131-147.
18. Vellutini, C., Casamatta, G., Bousquet, L., & Poniowski, G. (2019). *Estimating international tax evasion by individuals*. Publications Office of the European Union.
19. Atlas of the Offshore World (2024): <https://atlas-offshore.world/dataset> , last accessed at 17.04.2024.
20. World Bank (2024). World Bank Databank: <https://databank.worldbank.org/>, last accessed at 05.06.2024.
21. World Bank – Informal Economy Database (2024). <https://www.worldbank.org/en/research/brief/informal-economy-database>, last accessed at 17.03.2024.
22. OECD (2024). Base Erosion and Profit Shifting, <https://www.oecd.org/en/topics/policy-issues/base-erosion-and-profit-shifting-beps.html> , accesată ultima dată la data de 20.03.2024.