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The influence of digital technology in combating money laundering

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Abstract

In current context of accelerated evolution and spreading of digital technology there is acknowledge significant effects in what about economic and financial crime but also about preventing and combating that. In this paper we analyze the meaning of correlation between digital technology and money laundering risk and how strong this dependencies is using data for 162 countries in 2012-2020 time period. Applying econometric methods and models, independent variables as percent of individuals using internet and technology adoption and also important control variables our research provides empirical evidence for existence of a significant impact of digital technology on money laundering.

We find clear evidence for the entire sample that increase digital technology leads to decrease in the risk of money laundering. Our findings are further confirmed in high-income countries and low-income countries in what means percent of internet users and in low-income countries in what concern technology adoption. Regarding GDP, even if it is not significant, it has a positive sign in developed countries and it has a negative value in developing countries, meaning that, rich countries are more liable to commit money laundering crimes than poor countries.

The paper may prove useful to governments, investors, and decision makers in different markets who must acknowledge the role of technology in combating money laundering.

Keywords: money laundering, digital technology, internet, Anti money laundering index

Jel Codes: E26, O17, O32, H26, K42

1. Introduction

Money laundering, in the current context, of the unprecedented evolution of technology, of conducting transactions especially in the electronic, virtual environment, anywhere in the world, at high speed, poses a major risk to the integrity, proper functioning, reputation and stability of society in terms of the financial system.

Technology-based innovations are beginning to radically change the financial industry. FATF, the international body responsible for combating money laundering and terrorist financing, has already undertaken a large amount of work to understand the risks and vulnerabilities of new payment products and services and to ensure that Anti Money Laundering (AML) and Combating the Financing of Terrorism (CFT)) remain up-to-date as new technologies emerge. One of the key priorities is to develop a partnership with the FinTech and RegTech community to support innovation in financial services, while maintaining transparency and mitigating the associated risks.

FinTech broadly refers to the use of new and emerging digital technologies in the financial sector for any of the purposes of a wide variety of actions. Initially, FinTech was primarily concerned with applying technology-based innovations to deliver new customer-oriented financial products and services - for example, mobile payment solutions, online marketplace loans, algorithmic savings and investment tools, payments in virtual currency, capital raising (crowd financing) and asset takeover, remote check settlement, mobile banking. FinTech now also includes the use of new and emerging technologies to provide automated mid-office and back-office functions, such as the use of algorithms, big data and machine learning, as well as analysis for clearance, settlement, securities, derivatives, wholesale financing and payments, as well as very importantly, activities to comply with legal regulations.

The digital transformation of society is introducing new Fintech for payments, funds transfer, and other financial transactions. Criminals are using and abusing financial technologies for fraud, extortion, money laundering, and financing activity in the criminal underground. The investigation of Fintech and digital payment activity needs to be recognized as a new technical sub-discipline of the digital forensics landscape. The digital forensics community is well positioned to provide research for practitioners to enhance investigations involving Fintech and technical financial activity.

RegTech is subsequently FinTech and refers to the use of new technologies to meet regulatory requirements more efficiently than existing capabilities. The new technologies known as RegTech are, but are not limited to, AI, machine learning, big data, and advanced cognitive algorithms that address customer identification and verification requirements and broader AML / CFT compliance requirements.

Meetings organized by the FATF, discussed the current state of interaction of traditional financial institutions with the FinTech and RegTech industries, the impact that financial innovations and technologies have or are expected to have on reshaping the provision and delivery of financial services, significant trends and developments in FinTech and RegTech and how the financial services landscape might look in the near future, including peer-to-peer transfers, crowdfunding, distributed registry technology or blockchain-based services , analysis tools, customer knowledge utilities and digital identity.

Many studies have concluded that digital technology has two sides in relation to money laundering: a positive effect by ensuring compliance in the fight against money laundering through new innovative digital techniques used to detect criminals, and a negative effect on increasing crime through new channels of information and communication technology and through already widespread cryptocurrencies.

First stand concern the prevention of money laundering, various authors (Amoore and de Goede, 2005; de Goede, 2008; Levi and Wall, 2004; Sadgali et al., 2019; Zoldi, 2015) find that investments in high technologies in the form of data mining, artificial intelligence, machine learning and risk profiling are used to track the flow of illicit funds in areas such as money laundering and terrorist financing, thus reducing the volume of money laundering offenses.

However, as a second point of view many recent studies find that their modern use does not have a positive effect, but rather has attracted fraudsters and criminals to the misuse of technology in order to obtain financial benefits, in the form of cybercrime (Ali et al., 2019); (McAfee, 2018); (Ryman-Tubb et al., 2018).

Starting to the aforementioned studies, in this paper, we focus to empirically explore the effect of digital technology on money laundering.

The relationship between digitalization and money laundering is empirical tested on a sample of 162 countries, for the period 2012-2020. The results show that the increase in the percent of internet users and technology adoption level leads to a decrease in the risk of money laundering.

The rest of the paper is organized as follows. The next section 2 designs the literature review made by using both VosViewer soft and a critical analysis. Section 3 highlights the results and discussions of the main empirical findings. The paper ends with the conclusions including a summary and a brief discussions of policy implications, limitations and the avenues for future research.

2. Literature review

The rise of digitalization has been widely attributed to the removal of borders and the liberalization of trade. In the digital world, various innovations such as working from home, mobile banking, and shopping for food have become common. (Kaygin, Topcuoglu and Ozkes, 2019). The rise of virtual platforms has allowed criminal organizations to expand their operations by allowing them to carry out various crimes, such as money laundering. They can use various platforms such as video game consoles and virtual reality headsets to carry out their crimes. (Ramos, Funderburk and Gebelein, 2018). Despite many new regulations and anti-money laundering requirements, it is now possible to open an offshore account. New payment technologies such as mobile banking and smart cards have also changed the way businesses operate. This has raised the concerns of tax authorities in identifying tax evaders. (Haughey and Byrne, 2010)

With the advent of technology companies, new rivals have emerged for traditional banks. Although these companies offer a variety of services, they are not regulated by central banks and pose a risk to consumers due to the lack of oversight to ensure their stability. (Murshudli and Loguinov, 2019)

Remaining in the same register of modern technologies, another innovative product that came to the attention of researchers in the field of economic and financial crime is cryptocurrencies. Due to the fact that cryptocurrencies do not require financial institutions, cryptocurrencies completely bypass the financial sector (Brenig et al., 2015). Until recently (2018), anti-money laundering regulations were ineffective in the case of cryptocurrencies. In the elaborated studies, Șcheau et al., (2020) but also Albrecht et al., (2019) claim that cryptocurrencies such as bitcoin, Ethereum and Monero have become the currency of choice for many drug traffickers and extortionists. Criminal networks have been favored by them due to pseudo-anonymity or total anonymity. Because of this the rise of digital currencies has been controversial and has raised various concerns. One of these concerns is the lack of proper monitoring of transactions due to their nature. (Neagu, 2019) but also some researcher conclude that virtual currencies have the potential to support various types of AML frameworks in banking. However, the use of generic case examples is not very helpful when developing such frameworks. (Naheem, 2019)

Although the impact of technology and the internet is visible, the effects are being

felt on all levels, but few studies on new technologies in relation to money laundering have been conducted and published in journals with an impact factor. Our assertion is supported by the number of articles, studies, books identified in the Web of Science following the searches for the associations of terms money laundering and technology, cryptocurrencies, internet, digital.

Thus, from the 2017 papers published on Web of Science (February 2022) on money laundering, in correlation with the technology or terms related to it, by the search field title, author, keywords and abstract, the following were identified:

- 72 papers address the issue of money laundering in connection with the Internet;
- 109 works following the correlation of the terms money laundering - digital;
- 227 works on the money laundering-technology relationship.

The processing with the VosViewer program of the 227 articles, previously mentioned, resulted in 74 frequently used terms, grouped in 3 clusters (Figure 1) according to the number of occurrences and relevance of the words connected in these articles (at least 10 occurrences).

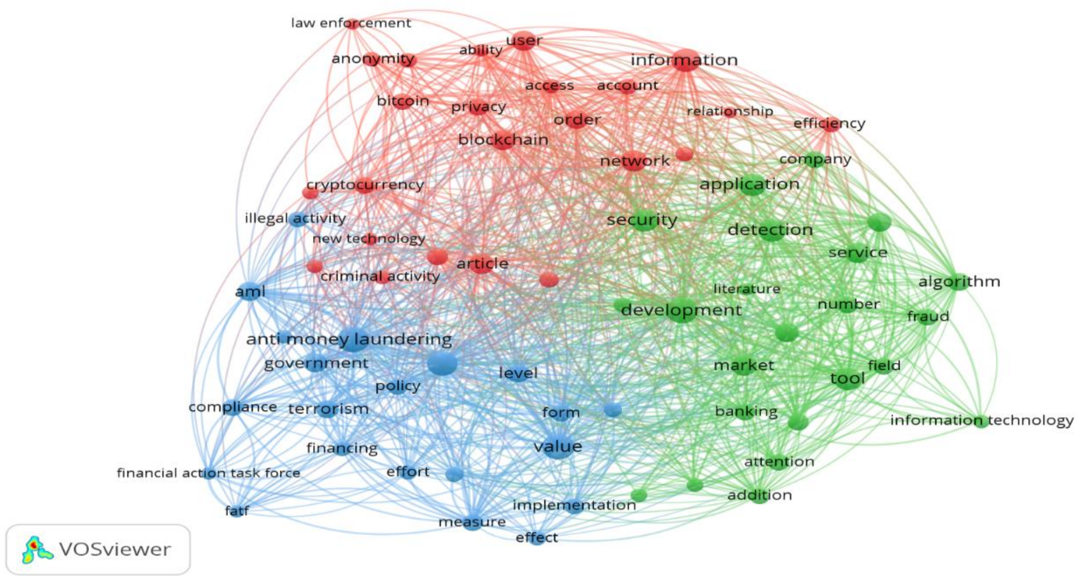

Figure.1 Map of terms used in articles on money laundering and technology
Source: own processing

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From the point of view of the distribution of word used over time, the map shows that in recent years (market with yellow) we find the most common uses for terms blockchain, bitcoin, anonymity, cryptocurrency **(Figure 2)**.

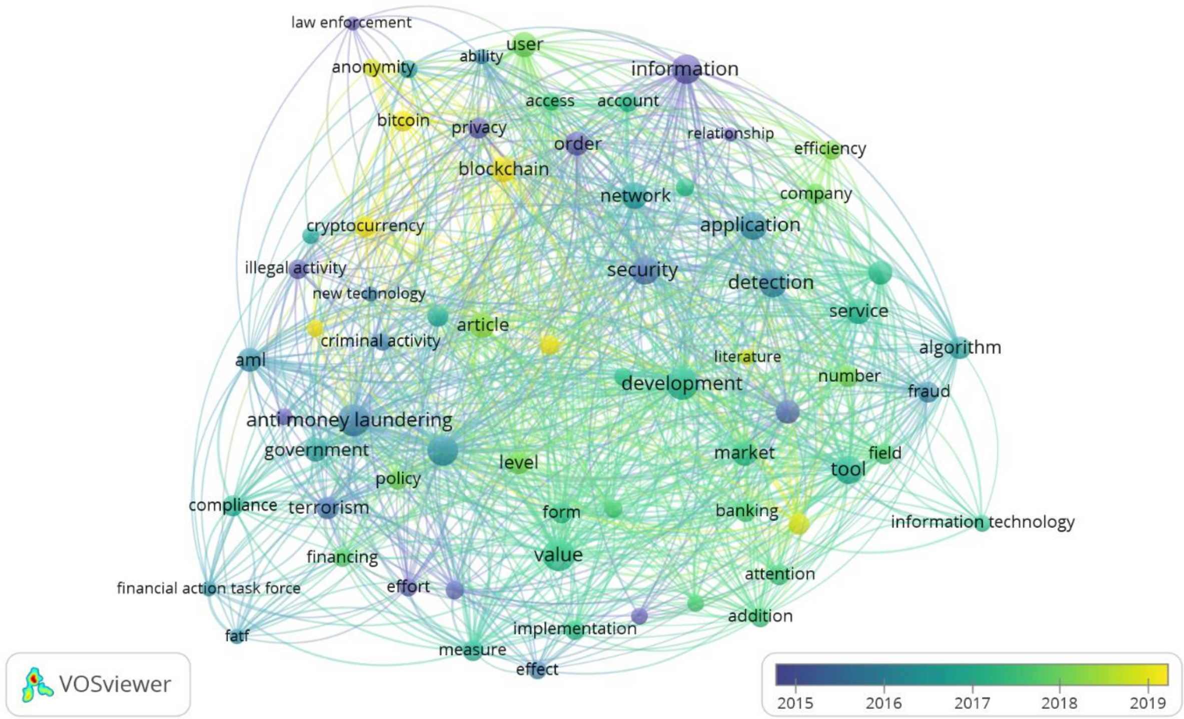

Figure 2. Map of time distribution of term used in articles on money laundering and technology
Source: Own processing

The influence of technology expressed through proxies like research and development expenses, as % of GDP, the score of technology adoption and high-technology exports, on the level of economic and financial crime – an index build by the authors as an arithmetic average score of corruption, shadow economy and money laundering- was studied on a sample of 185 countries from 2012 to 2015. It has seen that the size of the crime in low income nations is significantly higher than in high income nations. The authors find evidence that technological change has reduced the size of financial and economic crime. Further, research and development spending is associated with a reduction in crime in low income countries. (Achim et al., 2021)

Since the transition from a state-owned economy to a digital format has taken place, the study of money laundering has become more prevalent. It has been revealed that the rise of digital economy has brought about the profitability of money laundering. (Reznik et al., 2020) Also it is reveal there has been an increase in the number of patent applications for artificial intelligence-related inventions in the last couple of years and once AI-related patents are included in the overall patenting activities, they contribute to the productivity of companies, this effect being mainly concentrated in the SMEs and services industries (Damioli, Van Roy & Vertesy, 2021).

Due to the various changes in the global financial market and the rise of cross-border organized crime, money laundering has become more sophisticated. It is therefore important to analyze the risks associated with this industry and determine its future dynamics. (Lyeonov et al., 2020)

Analyzing the determinants of anti-money laundering (AML) compliance in 155 countries from 2004 to 2016. It was finding that although the number of countries with adequate AML compliance has improved over the years, it is still not enough to improve the overall compliance. The key factors that influence the level of compliance are bank concentration, regulatory quality, and technology. (Mekpor, Aboagye and Welbeck, 2018). In the same register the use of text mining and data analysis in business intelligence tools can help fight against money laundering and terrorism financing. But, despite the advantages of data mining and intelligence, implementing these applications have privacy concerns (Federici, 2007)

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Considering the presented aspects, in our study we analyzed the following hypothesis:

Hypothesis. *Increasing the level of digital technology decrease the risk of money laundering.*

3. Data and methodology

The profile studies show that there is a correlation between money laundering and technology. Starting from this premise, we set out to investigate the meaning of the correlations /dependencies between these variables and how strong these correlations are.

3.1.Description of variables

Dependent variable: money laundering
For the purpose of our study, we use a sample of 162 countries, for the period 2012-2020. As there are no data on the volume of money laundering, the dependent variable used in the research was the Basel AML index, an index calculated annually since 2012 by the Basel Institute. The index is largely based on perception-based indicators and unlike financial risk models based exclusively on statistical calculations, the Basel AML Index assesses structural factors by quantifying regulatory, legal, political and financial indicators that influence countries' vulnerability to ML / TF. According to the 2020 report, the Basel AML Index uses a composite methodology based on 16 relevant indicators for assessing ML / TF country risk. We include in our sample only those countries for which AML index was calculated at least two times, for the purpose of comparability of this index in time.

Independent variable: digital technology
Digitalization is defined as Integration of digital technologies into everyday life by the digitization of everything that can be digitized (Ochs and Riemann, 2018). In our paper we use as proxy percent of individuals using the internet, data being provide from World Bank for 2012-2020 period and technology adoption, data being provided from World Economic Forum for the period 2012-2018 and using own processing (the least square method) to obtain values for 2019-2020 period.

A panel data is conducted using the Eviews statistical software. The presentation of the rest of variables is made in the table 1.

Table 1. Describing variables

Variables	Way of expressing	Calculation	Sources
Dependent variables			
Money laundering	AML Index (Risk of money laundering)	The score is provided by Basel AML Index determined starting with 2012 for the world countries. The score ranges from 0 (low risk level) to 10 (high risk level) in money laundering/ terrorist financing	Basel Institute on Governance (2012-2020)
Independent variables			
Digital technology	Internet	Individuals using the Internet (% of population). Internet users are individuals who have used the Internet (from any location) in the last 3 months.	International Telecommunication Union (ITU) https://www.itu.int/en/ITU-D
	Technology adoption	Weighted score of technological readiness (technological adoption and ITC use) which ranges between 1 to 7, from least to most agile company to adopt existing technologies to enhance the productivity of its industry.	World Economic Forum (2020)
Control variables			
Economic development	GDP(Gross Domestic Products) per capita	The level of economic development is measured used GDP per capita (GDP). GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Initial data was in current U.S. dollars and was rescale.	World Bank Group https://databank.worldbank.org/
Tax burden	Fiscal freedom	Fiscal freedom from Index of business freedom. The score ranges from 0 to 100, where 0 is the least fiscal freedom and 100 is the maximum degree of fiscal freedom.	Heritage Foundation 2020
Education	Education Index	It is a component part of the Human Development Index. Education index has been measured by combining average adult years of schooling with expected years of schooling for students under the age of 25, each receiving 50% weighting.	Human Development Index http://hdr.undp.org/en
Innovation	GII (Global Innovation Index)	The index is computed by taking an average of the scores in two sub-indices, the Innovation Input Index and Innovation Output Index, which are composed of five and two pillars respectively.	Global Innovation Index https://www.globalinnovationindex.org
Cybersecurity	GCI (Global Cybersecurity Index)	Global Cybersecurity Index (GCI) is a composite index of indicators, which monitors the level of cyber security and takes values between 0 and 1.	International Telecommunication Union (ITU) https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx

Source: own processing

The paper further uses the World Bank's classification of countries based on their level of economic development. It then groups them into two groups: low income states and high income states.

3.2.The model

We estimate panel regression models that are focused on estimating the money laundering measured through AML index as a function of various variables, above mention.

The general form of our model is:

$$\text{Money laundering (AML)}_{it} = \beta_0 + \beta_1 \text{Digital technology}_{it} + \beta_{(j)2}\text{Controls (j)}_{it} + C_i + \varepsilon_{it}$$

Where,

- Money laundering $(AML)_{it}$ is the dependent variable for the country i and period t;
- Digital $technology_{it}$ is Internet for country i in year t, first and then Technology adoption for country i year t;
- $Controls(j)_{it}$ is the j-th control variable for country i in year t –Economic development (GDP per capita), Tax burden, Education, Innovation (GII) and Cybercrime (GCI);
- β0 is intercept;
- β_1 is the regression coefficient that will indicate the extent to which the independent variable Internet and Technology adoption is associated with the dependent variable Money laundering, if β1 is found to be statistically significant;
- $\beta_{(j)2}$ the regression coefficient for the j-th variable in the vector of controls; j denotes the ranges, for the vector of control variables;
- i countries from panel date;
- t period of time (2012-2020);
- ε_{it} is the residual or prediction error for country i at year t.

4. Results and discussions

4.1. Descriptive statistics

The results of analyzes are based on three dimensions: descriptive statistics, correlation analysis and econometric modeling of the links between dependent variables and independent variables.

The main descriptive statistics of our variables are presented in Table 2. For our sample, AML index has an average value of 5.513271 points ranging from 1.77 (Finland, 2017) to 8.61 point (Iran, 2016). The lowest levels of the money laundering risk reside among the European countries (Finland, Estonia, Norway, Slovenia, Sweden) and New Zealand. Then, the highest levels of money laundering risk are found in Iran, Afghanistan, Cambodia, Tajikistan.

Table 2. Descriptive statistics

Variables	Mean	St. dev	Minimum	Maximum
AML Index	5.51	1.19	1.77	8.61
Internet	58.29	27.34	1.05	100.00
Technology	4.74	0.59	2.60	6.19
GDP per capita	18789.24	22450.06	315.77	123514.20
Tax burden	76.95	12.84	37.20	99.90
Education	0.70	0.15	0.20	0.94
Innovation	38.38	11.54	17.24	68.40
Cybersecurity	0.49	0.27	0.02	1.00

Source: own processing

In the same time, the average level of individuals using internet is about 58.29 percent, ranging from 1.05 percent (Niger, 2012) up to 100.00 (United Arab Emirates, 2020). The highest levels of internet users are found in United Arab Emirates, Barhrain, Qatar, Kuwait and North European countries and the lowest are found in the great majority of African countries.

Also, the average level of technology adoption is about 4.74 point, ranging from 2.60 point (Yemen, 2018) up to 6.19 point (Sweden, 2012). The highest levels of technology adoption are found in United Arab Emirates (6.11), Qatar (6.10), Singapore (6.08). Opposite, the lowest levels of technology adoption are found in Yemen, Mauritania, Myanmar, Venezuela.

In order to estimate the sign of relation between money laundering and the level of digital technology we analyzed the correlation between dependent variable and the two independent variables which consider in our model but also control variables (table 3 and 4) and plot money laundering against each internet and technology adoption (Figures 3, 4).

Table 3 and 4 acknowledge a strong negative correlation between internet and technology by one hand and money laundering on the other hand. From this kind of analyses one it acknowledge there are a negative correlation between money laundering and control variables consider in our model with one exception, tax burden.

Table 3. Correlation between AML, Internet and other variables

Correlation	AML INDEX	INTERNET	GDP	TAX BURDEN	EDUCATION	GII	GCI
AML_INDEX	1.000000						
INTERNET	-0.648438	1.000000					
GDP	-0.461648	0.690039	1.000000				
TAX_BURDEN	0.307555	-0.246894	-0.450154	1.000000			
EDUCATION	-0.677381	0.825407	0.612086	-0.284860	1.000000		
GII	-0.573590	0.637370	0.691913	-0.467810	0.654510	1.000000	
GCI	-0.504125	0.618616	0.449519	-0.260719	0.539523	0.438842	1.000000

Source: Own processing

Table 4. Correlation between AML, Technology and other variables

Correlation	AML INDEX	TECHNOLOGY	GDP	TAX BURDEN	EDUCATION	GII	GCI
AML_INDEX	1.000000						
TECHNOLOGY	-0.527833	1.000000					
GDP	-0.472941	0.723016	1.000000				
TAX_BURDEN	0.304003	-0.346076	-0.451129	1.000000			
EDUCATION	-0.674678	0.542044	0.631316	-0.301905	1.000000		
GII	-0.569392	0.666356	0.693281	-0.455984	0.658696	1.000000	
GCI	-0.489225	0.491376	0.437920	-0.264725	0.510031	0.416703	1.000000

Source: Own processing

The negative (indirect) correlations between AML index and both independent variables consider, mean that an increase of Internet and Technology adoption leads to a decrease of money laundering risk.

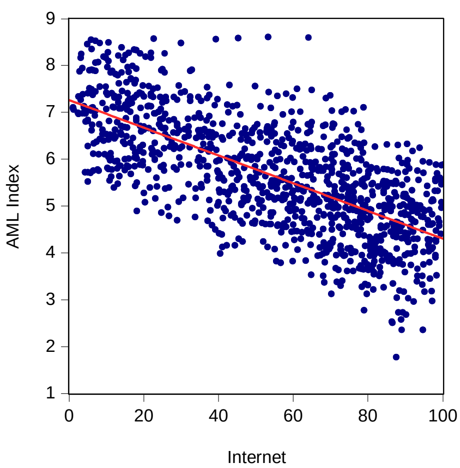

Figure 3. Plots of Money laundering (AML index) against individuals using internet as % of population (Internet)
Source: own processing

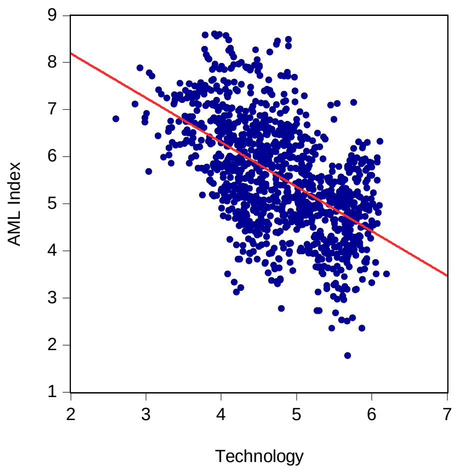

Figure 4. Plots of Money laundering (AML index) against technology adoption (Technology)
Source: own processing

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One can notice that also Figures 1 and 2 reflect negative correlations between money laundering (expressed by AML Index – the risk ok money laundering) and digital technology (expressed by individuals using internet as percent of entire population and by Technology adoption).

4.2. Empirical results

The results are built using the estimation multiple regression technique. At first we explicit money laundering (AML) as a function of individual using internet (Internet) or Technology adoption (Technology), the variables of interest. Then, the other independent variables are added for obtaining a Pooled-OLS regression. Because all these indexes contain data measured through different methods we use their standardized values in order to obtain homogenous data that would be subject to aggregation.

Table 5 estimates money laundering as a function of Internet and other valid control variables for the sample of 162 worldwide countries, respectively the Internet coefficient is negative and significant for OLS model. As the value of Internet increases with 1%, money laundering (AML index) decreases by 0.15 units.

Table 5. Regression results in OLS model for Money laundering (AML index) as function of Internet and other variables

Dependent Variable: AML_INDEX

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERNET	-0.151388	0.031021	-4.880172	0.0000
GDP	0.147115	0.035628	4.129220	0.0000
TAX_BURDEN	0.124534	0.037293	3.339316	0.0009
EDUCATION	-0.286595	0.034954	-8.199105	0.0000
GII	-0.171322	0.030701	-5.580405	0.0000
GCI	-0.080652	0.019031	-4.237911	0.0000
C	83.11445	3.570474	23.27827	0.0000
R-squared	0.526849	Mean dependent var		54.69788

Source: Own processing

Based on the results, we can see that probabilities are equal to 0, so results are significant for any level of acceptance. From the point of view of the model goodness-of-fit, the R-squared is equal to 0,5268 and indicates that the dependent variable Money laundering (AML Index) depends in proportion 52, 68 % from the independent variables studied. In this way, the state researched hypothesis is accepted, meaning that increasing Internet (Individuals using the Internet) determine decreasing of Money laundering measured through AML index.

In what concern the other variables, one can see for all of them there are influence of money laundering at an acceptance level of 10%. Thus education and innovation has a negative influence on money laundering which is in line with studies that conclude that more intelligent and informed people are more likely to solve problem through regulated route that through illegal behavior (Salahodjaev, 2015) and also human capital improves the institutional environment (Galeser et al., 2004). GDP and Tax burden accordingly to the propose model have a positive influence on money laundering.

For consolidated our results in Table 6 we estimate, on separate columns, the multiple regression for independent variable Internet through Fixed Effects Model (FEM) and the Random Effects Model (REM).

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Table 6. Regression results in FEM and REM models for Money laundering (AML index) as function of Internet and other variables

Dependent Variable: AML INDEX

	FEM		REM	
Variable	Coefficient	Prob.	Coefficient	Prob.
INTERNET	-0.057017	0.0652	-0.069609	0.0143
GDP	-0.116195	0.1742	-0.061270	0.2671
TAX_BURDEN	0.257971	0.0270	0.171466	0.0113
EDUCATION	-0.058239	0.6069	-0.311085	0.0000
GII	-0.019083	0.4796	-0.046134	0.0659
GCI	-0.061446	0.0003	-0.059314	0.0002
C	47.76328	0.0001	73.21544	0.0000
R-squared	0.900511		0.210337	

Source: Own processing

Both models in table 6 confirm our hypothesis, thus Internet has a significant and indirect influence on money laundering for a level of acceptance 10% similar to OLS model.

Beside Internet, in FEM model tax burden and cybersecurity are also significant in relation to money laundering. Three variables (GDP, education and innovation) are not significant in this model.

In what concern the R-squared in FEM model the values is 0.90, that means the dependent variable money laundering (AML Index) depends in proportion of 90 % from the independent variables studied. Comparing the results with the first model, OLS, we can say that in this case the independent variables influence in a higher proportion AML, but also it should be taken into consideration that here four control variables are not significant for our model.

In REM model there are five variables with a significant influence on money laundering from which internet, education, innovation and cybersecurity has an negative influence (the increase of this variable determine a decrease of money laundering risk) and tax burden has a positive influence confirm thus OLS model. One variables (GDP) is not significant in relation with AML index in REM model. R-squared are smaller compared to other models (OLS – 0.52 and FEM – 0.90).

As we previous mention we use the World Bank's classification of countries based on their level of economic development and groups them into two groups: low-income states (developing countries) and high income states (developed countries). Table 7 estimates AML index for the two subsamples of high income level (55 countries) and low income countries (107 countries) as a function of Internet and other control variables.
Both models was tested by Hausman Test being accepted at a level of significance by 5 % respectively 10%

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Table 7. Regressions results for Money laundering (AML index) as function of Internet and other variables for developed and developing countries

Dependent Variable: AML INDEX

	Developed countries		Developing countries	
Variable	Coefficient	Prob.	Coefficient	Prob.
INTERNET	-0.157245	0.0573	-0.088293	0.0249
GDP	0.112186	0.1098	-0.067851	0.2269
TAX_BURDEN	0.181710	0.0804	0.127920	0.3718
EDUCATION	-0.213632	0.0017	-0.217434	0.0061
GII	-0.021515	0.5647	-0.073835	0.0614
GCI	-0.109572	0.0002	-0.020194	0.4433
C	73.46884	0.0000	68.59944	0.0000
Weighted R-squared	0.184194		0.083341	

Source: Own processing

The results show that in both developed and developing countries as the value of Internet increases with 1%, money laundering (AML index) decreases by 0.15 units in high-income states and by 0.08 units in developing countries our hypothesis being confirm. A very important and interesting aspect is the fact that the value of the coefficient for the variable Internet is slightly higher in developed countries, it being almost double. So we can conclude that the impact of Internet on money laundering is more pronounced in developed countries compared to developing countries. Other variable with significant and indirect influence in both sample on AML index is education, as expected.

The proportion in which money laundering depends of the regression variables is smaller than in entire sample - r square is 0.1841 points in high-income countries model and only 0.0833 point for developing countries. Regarding GDP, even if it is not significant, we can make a remark on the sign of this variable. It has a positive sign in developed countries and a minus in developing countries, meaning that as we expect, rich countries are more inclined to commit money laundering crimes than poor countries. However, we remain skeptical about the results because they are not statistically significant Regarding Technology adoption table 8 estimates money laundering as a function of Technology adoption and other valid control variables through OLS model. When technology adoption increase with one value-unit, money laundering (AML index) decreases by 0.18 units.

Table 8. Regression results in OLS model for Money laundering (AML index) as function of Technology adoption and other variables
Dependent Variable: AML_INDEX

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TECHNOLOGY	-0.183365	0.032886	-5.575756	0.0000
GDP	0.162569	0.036446	4.460523	0.0000
TAX_BURDEN	0.083516	0.035957	2.322681	0.0204
EDUCATION	-0.407692	0.027579	-14.78287	0.0000
GII	-0.124785	0.030553	-4.084253	0.0000
GCI	-0.090087	0.017523	-5.141035	0.0000
C	95.09983	3.580386	26.56134	0.0000
R-squared	0.524134	Mean dependent var		54.71456

Source: Own processing

The amount of variance in money laundering explained by Technology adoption and other control variables is of 52.41%. Technology adoption has an indirect relationship with the money laundering, in line with our expectations.

In what regard all other variables our findings are in line with those obtained when digital technology is expressed through Internet, for the same analyzed full sample (Table 3).

Fixed Effects Model (FEM) and Random Effects Model (REM) are used for consolidated our results and can be seen in table 9.

Table 9. Regression results in FEM and REM models for Money laundering (AML index) as function of Technology adoption and other variables

Dependent Variable: AML INDEX

	FEM		REM	
Variable	Coefficient	Prob.	Coefficient	Prob.
TECHNOLOGY ADOPTION	-0.050668	0.3103	-0.126613	0.0015
GDP	-0.041469	0.6437	-0.012950	0.8267
TAX BURDEN	0.196601	0.0893	0.136392	0.0447
EDUCATION	-0.066542	0.5607	-0.367353	0.0000
GII	0.020894	0.4466	-0.000136	0.9958
GCI	-0.091632	0.0000	-0.090484	0.0000
C	51.49032	0.0001	82.00856	0.0000
R-squared	0.883712		0.200104	

Source: Own processing

As it can see only REM model confirm our hypothesis, thus technology has a significant influence on money laundering for a level of acceptance 10%.

In FEM model, technology and other four variables are not significant in relation to money laundering in our regression. Only tax burden and innovation are significant and confirm the sense of influence from OLS model (tax burden – a positive influence on AML and innovation a negative influence).

REM model confirm most of the relation from main model. Thus technology, education and cybersecurity are significant and has and indirect (negative) influence, tax burden is significant and has a direct, positive influence on AML index and GDP and also innovation are not significant in this model.

The influence of technology adoption on AML index is investigated for the subsamples of high-income states and low-income states as a function of Technology adoption and other control variables.
In developed countries the model is not being validate with random effect or through fixed effects or technology adoption is statistically insignificant (table 10).

Table 10. Regressions results for Money laundering (AML index) as function of Technology adoption and other variables for developed countries

Dependent Variable: AML INDEX

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TECHNOLOGY ADOPTION	-0.005594	0.064965	-0.086103	0.9314
GDP	-0.050069	0.110330	-0.453817	0.6502
TAX BURDEN	0.482323	0.224477	2.148654	0.0324
EDUCATION	-0.119044	0.103879	-1.145986	0.2526
GII	0.002279	0.040331	0.056503	0.9550
GCI	-0.149559	0.025000	-5.982302	0.0000
C	38.06007	18.42281	2.065920	0.0396
R-squared	0.774984	Mean dependent var		53.70275

Source: Own processing

In developing countries OLS model with random effects are tested with Hausman Test, the level of significance accepted is 5%. Result obtained confirm the expectation regarding technology adoption in correlation with money laundering (table 11). As the value of Technology adoption increases with 1%, money laundering (AML index) decreases by 0.15 units in developing countries.

Table 11. Regressions results for Money laundering (AML index) as function of Technology adoption and other variables for developing countries
Dependent Variable: AML INDEX

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TECHNOLOGY ADOPTION	-0.150774	0.053167	-2.835826	0.0047
GDP	-0.003164	0.058186	-0.054382	0.9567
TAX_BURDEN	-0.016015	0.146175	-0.109559	0.9128
EDUCATION	-0.290521	0.077791	-3.734651	0.0002
GII	0.020352	0.040300	0.505016	0.6137
GCI	-0.076134	0.021576	-3.528585	0.0005
C	86.48110	12.24825	7.060692	0.0000
R-squared	0.077545	Mean dependent var		11.15557

Source: Own processing

Similar with entire sample results other variable with significant and indirect influence on AML index is education, and cybersecurity index.

The proportion in which money laundering depends of the regression variables is smaller than in entire sample - r square is 0.07 points for developing countries and also in contrast to the main results (entire sample), GDP is not statistically significant. Also making a comparison in what concern the variable Technology adoption we can see that in both developed and developing countries the coefficient is a negative one even if, in high income states, it is not statistically significant. Thus, we can conclude one more time that the increase of technology adoption leads to decrease money laundering risk.

Therefore, our results from OLS for Internet and Technology adoption, FEM for Internet, REM for Internet and Technology adoption and also for internet in developed and developing countries and technology adoption confirm in developed countries confirm our research hypothesis that a higher level of digital technology determines a decrease of dimension of money laundering.

Our results are in line with several researcher (Levi & Wall, 2004; Amoore & de Goede, 2005; de Goede, 2008; Sadgali et al., 2019; Zoldi, 2015) who find that high technological investments like data mining, artificial intelligence and risk profiling tools are used to trace illegal funds in areas such as terrorist financing, thus the money laundering phenomenon is contracted and could help prevent money laundering. (Couchoro et al., 2021). Despite the fact that criminals have been able to exploit new features, new communication and information technology for their money laundering activities, also new technology could be applied for increasing anti-money laundering efficiency (Tang and Ai, 2016).

Also Elgin and Oyvat (2013) find that capital investments into better internet usage rates decrease the dimensions of the shadow economies and according to Gnangnon (2020), the availability of the Internet in developing countries has a positive impact on tax reforms.

Regarding the influence of control variables we find clear evidence for the role exerted by education, innovation and cybersecurity upon the money laundering risk, not only in entire sample but in subsample too. Thus, in all model and sample, an increase on the level of education measured through education index determined a decrease of money laundering risk. A similar results shows that people with higher intelligence were less prone to money laundering (Lowe, 2017). The researchers also noted that well trained employees of banks can better detect suspicious transactions (Nikolaska and Simonovski, 2012).

Opposite to the large literature we find a positive and significant influences of economic development (GDP) for the entire sample. Some researcher also found that the boost in economic development has a positive impact on the level of incentives for people to break the law and get benefits. This conclusion supports the concept of the shadow economy. (Wu & Schneider, 2019).

For the tax burden of worldwide countries we obtain also positive and significant coefficients meaning that although high tax rates do not increase directly the crime levels, they can contribute to the increase of tax evasion. Other findings also highlight the positive coefficients of tax pressure on the tax evasion and shadow economy (Stankevičius & Vasiliauskaitė, 2014; Achim et al., 2020).

5. Conclusions

In this paper, we explore the impact of digital technology on the level of money laundering risk, using unbalanced panel data from 162 countries over the 2012–2020 time period and controlling for many other important variables. We find clear evidence for the entire sample that increase digital technology leads to decrease in the risk of money laundering. Our findings are further confirmed in high-income countries and low-income countries in what means percent of internet users and in low income countries in what about technology adoption.

Regarding the influence held by the control variables we find clear evidence about the roles of education, innovation and cyber security upon the AML index. In what concern of economic development and tax burden we may conclude that although there are common determinant factors of the money laundering phenomena, there also are influences and are related to the level of economic development of countries.

In what concern policy implications, on top of the many benefits of technology investments and development, one more may be certainly added: the reduction of economic and financial crime under the form of money laundering.

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Declaration of Competing Interest

The authors of this paper certify that there is no financial or personal interest that could have appeared to influence the work reported in this paper.

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