The Impact of Financial Technology Development on Money Laundering Risks

Yifan Wang

School of Banking & Finance, University of International Business and Economics, Beijing, China

wangyifan_uibe2021@163.com

ABSTRACT. The rapid advancement of financial technology has introduced increased complexity into the global landscape of anti-money laundering. This study seeks to examine the influence of a country's financial technology development on money laundering risks, and whether such impact varies between developing and developed countries. To support our research, we collected data from a sample of 20 economies spanning the time frame of 2012 to 2022, and employed principal component analysis and lagged variables within a multiple linear regression framework. The results indicate that the development of financial technology initially increases money laundering risks in the short term but eventually leads to a reduction in these risks in the long term. Furthermore, this effect is more pronounced in developing countries compared to developed countries. These findings contribute novel insights to the research exploring the role of financial technology in the realm of anti-money laundering.

KEYWORDS: Financial technology development; Money laundering risks; Anti-money laundering

1 INTRODUCTION

The Financial Action Task Force (FATF) defines money laundering as the process by which criminals conceal the origins of illegally acquired funds to give them a misleading appearance of legitimacy. Money laundering progressively undermines the governance of the banking system, resulting in the corruption of financial markets. Simultaneously, it erodes public confidence in the global financial system and increases the risk and instability of the financial system. In general, these impacts ultimately reduce global economic growth rates [4]. According to the United Nations, criminal proceeds from money laundering make up an estimated 2% to 5% of global GDP annually, equivalent to approximately 1.6 to 4 trillion US dollars [20].

To address the consequences of money laundering on the global financial system and economies worldwide, different international measures have been put in place to combat this issue. In the United States, the Bank Secrecy Act (BSA) mandates that financial institutions must report currency transactions if they appear suspicious and exceed $10,000. Additionally, the FATF sets global standards for preventing money

A. Bhunia et al. (eds.), *Proceedings of the 2023 International Conference on Finance, Trade and Business Management (FTBM 2023)*, Advances in Economics, Business and Management Research 264,
https://doi.org/10.2991/978-94-6463-298-9_20

laundering and evaluates countries' adherence to these standards to ensure effective implementation.

The rapid advancement of financial technology (FinTech) has given rise to a complex global landscape concerning money laundering and anti-money laundering (AML) efforts. The Financial Stability Board (FSB) defines FinTech as technological innovation that enables the delivery of financial services. On one hand, FinTech improves the overall effectiveness of anti-money laundering (AML) efforts by enhancing regulatory efficiency for supervisory authorities and reducing compliance costs for financial institutions, thus mitigating the risk of money laundering. For instance, blockchain technology can assist financial institutions in meeting the Know Your Customer (KYC) principle more effectively and advancing AML compliance in the financial industry [22]. According to an analysis by a RegTech company, machine learning and big data technologies can enable financial institutions to decrease false positives by approximately 55% when identifying suspicious accounts, resulting in a substantial 42% reduction in AML compliance costs [21]. On the other hand, the advancement of FinTech has also expanded the repertoire of money laundering methods, making criminal activities more covert and challenging to detect and regulate. The quasi-anonymous and decentralized nature of cryptocurrencies (CCs) enables money launderers to transfer illicit funds swiftly, cost-effectively, and discreetly [5] [8]. In 2015, Bitcoin was implicated in 40% of confirmed illicit transactions in Europe [10].

Given the perspectives discussed above, the main research question addressed in this paper is the impact of FinTech development on a country's susceptibility to money laundering risk. While there is a substantial body of research on money laundering and anti-money laundering efforts, studies specifically examining the relationship between FinTech development and money laundering risk are limited. Previous investigations have primarily concentrated on the efficacy of money laundering regulations, risk evaluation, analysis of real-life money laundering cases, or the macro and micro implications of money laundering. While some studies have examined the relationship between FinTech and money laundering, they predominantly focus on specific technologies like blockchain and their implications for money laundering or anti-money laundering efforts. In contrast, this paper takes a comprehensive approach by considering the overall level of FinTech development in a country. By controlling for other factors that influence money laundering risk, such as economic development level and legal regulatory framework, we utilize empirical analysis using data from 20 countries spanning the period of 2012 to 2022. This analysis aims to understand the impact of FinTech development on money laundering risk. Furthermore, we explore whether there are variations in this influence between developing and developed countries.

The remaining sections of this paper are organized as follows: Section 2 presents a literature review on money laundering and FinTech. Section 3 describes the empirical methods employed in this study, including the proxies used for various variables and their respective data sources. The findings of the empirical analysis are presented in Section 4. Lastly, Section 5 provides a conclusion and policy recommendations based on the results of this study.

2 LITERATURE REVIEW

2.1 Money Laundering

The term "money laundering" was initially introduced during the Watergate scandal in 1973 when it was informally described as the process of transforming illicit funds into legal ones [18]. In 1988, the United Nations provided the first official definition of money laundering, stating that it involves disguising the origins, nature, location, ownership, or control of unlawfully obtained assets in order to make them appear legitimate, thereby creating the illusion of a legal source within the legitimate economy. The process of money laundering typically consists of three stages: placement, layering, and integration [9], and it is a complex process intended to obscure the true origin of the funds.

Unregulated money laundering implies the potential involvement of financial institutions in criminal activities, which severely erodes customer trust and confidence in the financial market [14]. Moreover, the substantial circulation of illicit funds can jeopardize the reputation and stability of the financial system, posing a significant threat to a country's domestic market security [6]. This is because the presence of illicit funds poses a danger to legitimate interests, and criminal activities have the potential to disrupt normal business operations [16]. Furthermore, money laundering can contribute to a rise in corruption and crime rates, resulting in problems such as price imbalances and inflation. Consequently, this can lead the public to question and become dissatisfied with their country's policies [6].

2.2 The link between FinTech and money laundering and anti-money laundering (AML)

In order to address the adverse effects of money laundering on the economic system and society, global initiatives are underway to continually enhance anti-money laundering measures and enhance their effectiveness. The FATF has consistently called for the integration of technology in identifying and analyzing money laundering activities [7]. Biometric recognition technology, for instance, can assist in verifying customer identities and enhancing payment transparency through authorized mobile payments, thereby supporting the prevention of money laundering and other illicit activities [17]. Blockchain technology facilitates real-time and transparent sharing of customer transaction information among financial institutions, and regulatory authorities can also participate in the blockchain network as nodes to access firsthand data [22]. In collaboration with the Bank of England, the Financial Conduct Authority (FCA) has implemented machine semantic learning technology to establish machine-readable regulation (MRR) and machine-executable regulation (MER), enabling digital regulatory reporting (DRR) for both regulatory authorities and financial institutions [11].

However, as FinTech continues to advance, money laundering techniques have also become increasingly intricate in order to evade detection and regulation. Money launderers have been utilizing crowdfunding platforms like Uber and Airbnb for cybercrime, taking advantage of their services to operate without incurring overhead costs and circumvent international regulations [19]. Moreover, the widespread adoption of automated payment platforms has made it easier for money launderers to conceal their identities, making it progressively more challenging to differentiate between illicit and legitimate transactions. In fact, it is estimated that the error rate of mistakenly categorizing innocent accounts as suspicious accounts in AML/CFT (Anti-Money Laundering/Combating the Financing of Terrorism) systems is approximately 95-99% [1]. Furthermore, the advent of FinTech has brought about a digital transformation that offers customers a range of remote and anonymous financial services. As a result, there has been a notable surge in the number of suspicious activity reports related to these services, as reported by the UK Treasury for the period between 2017 and 2020 [2]. Therefore, the objective of this article is to investigate the impact of FinTech development on a country's susceptibility to money laundering risk through empirical analysis using real data.

3 METHODOLOGY

3.1 Empirical model

The relationship between variables can be represented by following equations:

$$MLR_{i,t} = \beta_0 + \beta_1 FTD_{i,t} + \beta_2 FTD_{i,t-1} + \beta_3 FTD_{i,t-2} + \beta_4 GDP_{i,t} + \beta_5 FDI_{i,t} + \beta_6 CI_{i,t} + \beta_7 CPI_{i,t} + \beta_8 FAC1_{i,t} + \beta_9 FAC2_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$MLR_{i,t} = \beta_0 + \beta_1 FTD_{i,t} + \beta_2 FTD_{i,t-1} + \beta_3 FTD_{i,t-2} + \beta_4 GDP_{i,t} + \beta_5 FDI_{i,t} + \beta_6 CI_{i,t} + \beta_7 CPI_{i,t} + \beta_8 FAC1_{i,t} + \beta_9 FAC2_{i,t} + \beta_{10} FAC3_{i,t} + \varepsilon_{i,t} \tag{2}$$

Equation 1 represents the regression model applied to the entire sample and developing countries. Equation 2, on the other hand, represents the model specifically applied to developed countries. In both equations, FACn represents the principal component scores derived from the data of each respective group using the principal component analysis method.

The dependent variable MLRi,t is the money laundering risk indicator for country i in year t, and the level of FnTech development in each country is denoted by FTD, while FTDi,t-1 and FTDi,t-2 represents the lagged terms of FTDi,t. Control variables that capture the factors influencing money laundering risk include the level of economic activity, financial development, crime, and corruption. The economic level is controlled using per capita GDP, denoted by GDPi,t, and FDIi,t is defined as financial development level. CIi,t represents the crime level, and CPIi,t is measured as the level of corruption. The coefficients of the variables are represented by β terms, and the residual term is denoted as εi,t.

3.2 Data description and variables measurement

The data utilized in this study comprises panel data from 20 countries, spanning the period from 2012 to 2022. Multiple sources were employed to gather this data. The dependent variable is represented by the Basel AML Index, created by the Basel Institute on Governance, which serves as a proxy for the money laundering risk scores of different countries. The index ranges from 0 to 10, with 0 indicating the lowest risk level of money laundering. It is constructed using data from 18 public sources, including prominent organizations such as the Financial Action Task Force (FATF), Transparency International, World Bank, and World Economic Forum. The Basel AML Index is recognized as a "leading indicator of money laundering risk" by The Economist.

The primary independent variable, the level of FinTech development, is quantified using the number of FinTech companies, following the methodology employed by Xueyan Xie and Xiaoyang Zhu [23]. The data regarding the number of FinTech companies is obtained from the Crunchbase platform, which offers supplementary resources such as details on investment and financing activities, as well as real-time industry trends.

Furthermore, several control variables are included in this study. The financial development level of each country is measured using the financial development index (FDI), which is scored from 0 to 1, with 0 indicating the lowest level of financial development. Per capita GDP serves as an indicator of the economic level and is obtained from the IMF database. Both the financial development index and per capita GDP are sourced from the IMF database. The level of crime is measured using the crime index from the NUMBEO platform, ranging from 0 to 100, with 0 indicating the lowest level of crime. The level of corruption is assessed using the corruption perceptions index (CPI) provided by Transparency International, which ranges from 0 to 1, with 0 indicating the highest level of corruption. Table 1 provides an overview of the measurements and data sources for each variable.

Table 1. Variable descriptions and data sources

Variable	Variable measurement	Data source
Money laundering risk (MLR)	Basel AML Index	Basel Institute on Governance
Financial technology development (FTD)	Number of FinTech companies	Crunchbase
Economic level (GDP)	Per capita GDP	IMF
Financial development (FDI)	Financial development index	IMF
Crime level (CI)	Crime index	NUMBEO
Corruption level (CPI)	Corruption perceptions index	Transparency International

4 EMPIRICAL RESULTS

4.1 Summary statistics

Table 2 presents the descriptive statistics of the variables. The average AML index for the entire sample is 5.30, with a mean of 5.86 for developing countries and 4.74 for developed countries. These figures suggest that the global money laundering risk is at a moderate level, while the overall money laundering risk in developing countries surpasses that of developed countries.

The average number of FinTech companies in the entire sample is 580, with a mean of 192 in developing countries and 969 in developed countries. These statistics reveal that the level of FinTech development in developed countries surpasses that in developing countries significantly.

Furthermore, the average per capita GDP in the entire sample amounts to $25,296, with a mean FDI of 0.62, a mean crime index of 44.64, and a mean CPI of 52.85. In developing countries, the average per capita GDP is $5,425, with a mean FDI of 0.41, a mean crime index of 51.18, and a mean CPI of 33.43. On the other hand, in developed countries, the average per capita GDP reaches $45,166, with a mean FDI of 0.83, a mean crime index of 38.16, and a mean CPI of 72.28.

Based on the aforementioned results, it is evident that developed countries exhibit notably higher levels of economic and financial development when compared to developing countries. Furthermore, developed countries also demonstrate considerably lower levels of crime and corruption in comparison to their developing counterparts.

Table 2. Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
Full sample					
MLR	212	5.296037	0.8312929	3.52	7.18
FTD	220	580.3773	1314.815	6	8818
GDP	220	25296	21453.36	1109	76398
FDI	200	0.6216497	0.2430783	0.2042413	0.9333178
CI	219	44.64155	12.17801	5.7	77.9
CPI	220	52.85455	21.04565	24	87
Developing countries					
MLR	105	5.86006	0.6554711	4.55	7.18
FTD	110	192.1727	279.8805	6	1429
GDP	110	5425.064	3869.84	1109	15974
FDI	100	0.4131295	0.1590233	0.2042413	0.7408382
CI	109	51.17982	10.37793	23.9	77.9
CPI	110	33.42727	4.592493	24	43
Developed countries					
MLR	107	4.742557	0.5741853	3.52	6.026746
FTD	110	968.5818	1758.076	51	8818
GDP	110	45166.94	10620.12	25754	76398
FDI	100	0.8301699	0.0751189	0.6697968	0.9333178
CI	110	38.16273	10.23648	5.7	64.9
CPI	110	72.28182	10.34641	42	87

4.2 Correlation results

Table 3 presents the results of the correlation analysis conducted between the variables. We observe that money laundering risk exhibits a negative correlation with the development of FinTech, economic and financial development, while displaying a positive correlation with levels of crime and corruption. Furthermore, the development of FinTech shows a positive correlation with economic and financial development. Additionally, economic development demonstrates a positive correlation with the development of the financial sector while displaying a negative correlation with crime and corruption.

Table 3. Correlation results

	MLR	FTD	GDP	FDI	CI	CPI
MLR	1.000					
FTD	-0.276***	1.000				
GDP	-0.662***	0.454***	1.000			
FDI	-0.617***	0.355***	0.855***	1.000		
CI	0.295***	0.064	-0.446***	-0.491***	1.000	
CPI	-0.657***	0.293***	0.927***	0.835***	-0.567***	1.000

*** Shows significance at the 0.01 level

4.3 Diagnostic tests

We perform a White's test to investigate heteroscedasticity [3] in our regression model. The null hypothesis of the test assumes no heteroscedasticity, while the alternative hypothesis suggests the presence of heteroscedasticity. The results strongly reject the null hypothesis at a significance level of 5%, indicating the presence of heteroscedasticity in the regression model. As we are using panel data in the regression analysis, we address this issue by employing clustered robust standard errors in subsequent regression analysis.

The presence of autocorrelation in our regression model is examined using the Wooldridge test [15], with the null hypothesis assuming no autocorrelation. The results reveal that when the significance level is set at 0.01, we do not have sufficient evidence to reject the null hypothesis. However, when the significance level is set at 0.05, we reject the null hypothesis, suggesting the presence of a certain degree of autocorrelation. In order to address this issue, we introduce lagged variables into the model with a lag order of 2, which represents the values from the previous two periods.

To evaluate the presence of multicollinearity in our model, we utilize the Variance Inflation Factor (VIF) test, as outlined by Lavery et al. [13]. The results reveal that while the average VIF value remains below 10, the maximum VIF value slightly exceeds this threshold, indicating the presence of mild multicollinearity. To address this issue, we employ Principal Component Analysis (PCA) to derive several principal components and their corresponding scores within each group of data. Subsequently, we include these component scores as explanatory variables in each regression model to mitigate the problem of multicollinearity.

In addition, we employ the Hausman test [12] to investigate the potential endogeneity issue within the model. The results of the test show that we do not have sufficient evidence to reject the null hypothesis, indicating the absence of an endogeneity issue.

4.4 Regression results

The objective of this article is to examine the influence of FinTech development on money laundering risk and analyze potential disparities in this impact between developing and developed countries. Table 4 presents the regression outcomes pertaining to these research objectives. Models 1-3 offer regression results for the complete sample, developing countries, and developed countries, respectively.

In all three sample groups, we observe positive regression coefficients for the main explanatory variable. However, for model 2, the coefficient of the lagged variable at period 1 is negative, while for models 1 and 3, the coefficient of the lagged variable at period 2 is negative. Notably, all of these results demonstrate statistical significance. From these findings, we can deduce that the development of FinTech initially increases money laundering risks in the short term, but eventually leads to a decrease in money laundering risks in the long term.

In the short term, the rapid advancement of technology can create opportunities for money launderers to exploit regulatory loopholes before they are detected by regulators. This enables them to engage in criminal activities utilizing sophisticated technology, thereby elevating the risk of money laundering. However, in the long term, regulators can continually learn from monitoring and investigating money laundering cases, leveraging advanced FinTech tools to enhance anti-money laundering measures and strengthen regulatory frameworks. As a result, the criminal activities of money launderers become increasingly exposed, leading to a reduction in the risk of money laundering.

By comparing model 2 and 3, we can discern that the impact of FinTech development on money laundering risks is more pronounced in developing countries than in developed countries. This discrepancy arises due to the fact that developed countries generally possess more robust anti-money laundering regulatory systems and higher levels of FinTech development compared to their developing counterparts. Consequently, the money laundering risks in developed countries are better controlled and are less prone to significant fluctuations. Conversely, developing countries still require strengthening of their anti-money laundering frameworks. Technological advancements enable money launderers to exploit loopholes with greater ease, while also providing regulators with increased opportunities for progress. Consequently, money laundering risks in developing countries are more likely to experience pronounced fluctuations.

Table 4. The impact of financial technology development on money laundering risks

	Full sample MLR$_{i,t}$	**Developing** MLR$_{i,t}$	**Developed** MLR$_{i,t}$
FTD$_{i,t}$	0.00267***	0.00579***	7.05e-05***
	(2.59e-10)	(3.80e-10)	(7.39e-11)
FTD$_{i,t-1}$	3.06e-09***	-2.43e-09**	2.62e-10**
	(7.60e-10)	(1.06e-09)	(8.88e-11)
FTD$_{i,t-2}$	-2.43e-09***	2.84e-09*	-7.42e-11**
	(4.86e-10)	(1.34e-09)	(7.39e-11)
GDP$_{i,t}$	4.55e-05***	-0.000559***	1.16e-05***
	(6.13e-06)	(1.09e-05)	(1.19e-05)
FDI$_{i,t}$	2.249***	-5.817***	-
	(1.35e-07)	(2.25e-07)	
CI$_{i,t}$	0.168***	-0.0824***	0.0389***
	(1.04e-08)	(1.91e-09)	(5.93e-10)
CPI$_{i,t}$	0.00970***	0.268***	0.00172***
	(3.57e-09)	(9.77e-09)	(1.29e-09)
FAC1$_{i,t}$	-2.302***	-0.522***	-0.137***
	(1.28e-07)	(5.91e-08)	(1.74e-08)
FAC2$_{i,t}$	-4.223***	3.574***	-0.639***
	(1.96e-07)	(8.69e-08)	(1.12e-08)
FAC3$_{i,t}$	-	-	0.556***
			(4.20e-09)
Constant	-6.674***	5.577***	2.624***
	(2.92e-07)	(1.74e-07)	(9.59e-08)
Observations	174	87	87
R-squared	1.000	1.000	1.000
Prob-value	0.000	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5 Robustness test

To verify that the impact of financial technology on money laundering risk is not random, this study examines the robustness of the conclusions by introducing a new control variable.

Based on the literature on money laundering, it has been found that education level can also have an impact on the money laundering risk [15]. Therefore, in this study, we include education level as a new control variable to conduct a robustness test. To measure the education level of a country, we chose the mean years of schooling for adults aged 25 years, which is one of the indicators in the United Nations Development Programme's Human Development Index (HDI). By incorporating this variable into the regression equation, we obtain the following new regression model. Equation 3 represents the regression model for the entire sample, while Equation 4 represents the model specifically for developing and developed countries.

$$MLR_{i,t} = \beta_0 + \beta_1 FTD_{i,t} + \beta_2 FTD_{i,t-1} + \beta_3 FTD_{i,t-2} + \beta_4 GDP_{i,t} + \beta_5 FDI_{i,t} + \beta_6 CI_{i,t} + \beta_7 CPI_{i,t} + \beta_8 MYS_{i,t} + \beta_9 FAC1_{i,t} + \beta_{10} FAC2_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$MLR_{i,t} = \beta_0 + \beta_1 FTD_{i,t} + \beta_2 FTD_{i,t-1} + \beta_3 FTD_{i,t-2} + \beta_4 GDP_{i,t} + \beta_5 FDI_{i,t} + \beta_6 CI_{i,t} + \beta_7 CPI_{i,t} + \beta_8 MYS_{i,t} + \beta_9 FAC1_{i,t} + \beta_{10} FAC2_{i,t} + \beta_{11} FAC3_{i,t} + \varepsilon_{i,t} \tag{4}$$

Table 5 presents the comparison of three samples before and after the inclusion of the new control variable. It is observed that, across all samples, the coefficients of FTDi, t, FTDi,t-1, and FTDi,t-2 remain unchanged in terms of their positive or negative signs. Furthermore, the results indicate that the main explanatory variable, FTDi, t, remains statistically significant at the 1% level in all samples. Moreover, in the full sample, the results for FTDi, t-1 and FTDi, t-2 are also significant at the 5% level.

These results provide further support for the initial findings, reinforcing the robustness of the previous conclusions regarding the impact of financial technology on money laundering risk. This strengthens the validity and reliability of the study's overall findings.

Table 5. Results of the robustness test

	Full sample		**Developing**		**Developed**	
	(1)	(4)	(2)	(5)	(3)	(6)
	$MLR_{i,t}$	$MLR_{i,t}$	$MLR_{i,t}$	$MLR_{i,t}$	$MLR_{i,t}$	$MLR_{i,t}$
$FTD_{i,t}$	0.00267***	0.00242***	0.00579***	0.00225***	7.05e-05***	4.79e-05***
	(2.59e-10)	(7.61e-10)	(3.80e-10)	(2.50e-10)	(7.39e-11)	(0)
$FTD_{i,t-1}$	3.06e-09***	3.64e-09**	-2.43e-09**	-9.80e-11	2.62e-10**	6.91e-11
	(7.60e-10)	(1.49e-09)	(1.06e-09)	(5.32e-10)	(8.88e-11)	(6.72e-11)
$FTD_{i,t-2}$	-2.43e-09***	-1.90e-09**	2.84e-09*	2.54e-10	-7.42e-11**	-0
	(4.86e-10)	(8.26e-10)	(1.34e-09)	(2.82e-10)	(7.39e-11)	(0)
$GDP_{i,t}$	4.55e-05***	4.28e-05***	-0.000559***	1.55e-05***	1.16e-05***	8.60e-06***
	(6.13e-06)	(1.35e-05)	(1.09e-05)	(3.34e-05)	(1.19e-05)	(1.27e-05)
$FDI_{i,t}$	2.249***	2.339***	-5.817***	-	-	-
	(1.35e-07)	(1.37e-07)	(2.25e-07)			
$CI_{i,t}$	0.168***	0.155***	-0.0824***	0.00475***	0.0389***	0.0378***
	(1.04e-08)	(1.22e-08)	(1.91e-09)	(2.06e-10)	(5.93e-10)	(8.19e-10)
$CPI_{i,t}$	0.00970***	0.00822***	0.268***	0.0422***	0.00172***	0.00140***
	(3.57e-09)	(4.82e-09)	(9.77e-09)	(2.57e-09)	(1.29e-09)	(1.48e-09)
$MYS_{i,t}$	-	0.330***	-	0.0973***	-	0.159***
		(6.94e-09)		(5.34e-09)		(3.64e-09)
$FAC1_{i,t}$	-2.302***	-3.043***	-0.522***	-0.804***	-0.137***	-0.561***
	(1.28e-07)	(1.51e-07)	(5.91e-08)	(1.55e-08)	(1.74e-08)	(2.08e-08)
$FAC2_{i,t}$	-4.223***	-3.895***	3.574***	0.102***	-0.639***	-0.481***
	(1.96e-07)	(2.39e-07)	(8.69e-08)	(2.15e-08)	(1.12e-08)	(1.30e-08)
$FAC3_{i,t}$	-	-	-	0.781***	0.556***	0.568***
				(5.38e-09)	(4.20e-09)	(3.88e-09)
Constant	-6.674***	-9.244***	5.577***	2.973***	2.624***	0.868***
	(2.92e-07)	(3.67e-07)	(1.74e-07)	(1.04e-07)	(9.59e-08)	(8.49e-08)
Observations	174	174	87	87	87	87
R-squared	1.000	1.000	1.000	1.000	1.000	1.000
Prob-value	0.000	0.000	0.000	0.000	0.000	0.000

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5 CONCLUSION AND POLICY RECOMMENDATIONS

The advancement of financial technology is occurring at an unprecedented rate and is being extensively utilized across various sectors of the socio-economic sphere. However, technological innovation has always presented a dual nature. While regulators are leveraging these technological advancements to identify new methods for anti-money laundering and enhance the AML system, money launderers continuously exploit more technologically advanced means to elude regulation and engage in criminal activities. Nonetheless, it is reassuring to observe that money laundering risks have generally decreased in various countries worldwide over the past decade, as suggested by the available data. This decline can be attributed to various factors, and this article aims to investigate whether FinTech also plays a role in this downward trend.

This paper adopts a multivariate linear regression model incorporating lagged variables and principal component analysis. It utilizes data from 20 countries across six continents, covering an extensive period of nearly 11 years. Our findings provide evidence to indicate that in the short term, the utilization of advanced technology by money launderers may lead to an increase in money laundering risks within countries. However, in the long term, the integration of financial technology can benefit regulators in enhancing anti-money laundering frameworks and improving the effectiveness of anti-money laundering measures, consequently resulting in a decrease in money laundering risks. Furthermore, the impact of FinTech on money laundering risks is more pronounced in developing countries relative to developed countries. The article systematically validates these significant impacts and ensures the credibility of the conclusions through a series of rigorous tests and evaluations.

The research findings have significant implications for policymakers. Anti-money laundering regulatory authorities should fully capitalize on the opportunities presented by advances in FinTech to explore more effective methods in combating money laundering. This entails promptly addressing regulatory loopholes and harnessing the potential of FinTech in anti-money laundering endeavors. It is also essential to exercise caution in relation to the risks associated with technological advancements. Close monitoring of how money launderers exploit FinTech is crucial, along with the implementation of targeted measures to address these issues, ultimately aiming to mitigate global money laundering risks. Furthermore, developed economies should consider ways to further empower financial technology as a more potent tool within their robust anti-money laundering frameworks. By doing so, they can bolster their efforts to combat money laundering effectively.

Indeed, this study is subject to certain limitations. It somewhat lacks precision in measuring the level of financial technology development and restricts its sample to only 20 countries. Future researchers could overcome these limitations by constructing a distinctive financial technology index or exploring more comprehensive proxy methods. Additionally, expanding the sample to include more countries and employing more optimized models would contribute to further research in this area. Despite these limitations, this study offers empirical evidence that aids in assessing the impact of financial technology development on money laundering risks and adds to the body of research in the field of anti-money laundering.

REFERENCES

1. Akartuna, E.A., Johnson, S.D., Thornton, A. (2022) Preventing the money laundering and terrorist financing risks of emerging technologies: An international policy Delphi study. Technological Forecasting & Social Change, 179: 121632. https://doi.org/10.1016/j.techfore.2022.121632.
2. Akartuna, E.A., Johnson, S.D., Thornton, A.E. (2022) The money laundering and terrorist financing risks of new and disruptive technologies: a futures-oriented scoping review. Security Journal. https://doi.org/10.1057/s41284-022-00356-z.
3. Ando, M., Hodoshima, J. (2007) A note on bootstrapped White's test for heteroskedasticity in regression models. Economics Letters, 97: 46-51. https://doi.org/10.1016/j.econlet.2007.02.017.
4. Buchanan, B. (2004) Money laundering—a global obstacle. Research in International Business and Finance, 18: 115–127. https://doi.org/10.1016/j.ribaf.2004.02.001.
5. Bryans, D. (2014) Bitcoin and money laundering: mining for an effective solution. Indiana Law Journal, 89: 441-472. https://www.repository.law.indiana.edu/ilj/vol89/iss1/13.
6. Bučiūnas, G., Gaidelys, V. (2008) Money Laundering and its Economic Impacts in the Context of the Fight Against Terrorism. Engineering Economics, 3: 26-33. https://www.ceeol.com/search/article-detail?id=952942.
7. Canhoto, A.I. (2021) Leveraging machine learning in the global fight against money laundering and terrorism financing: An affordances perspective. Journal of Business Research, 131: 441–452. https://doi.org/10.1016/j.jbusres.2020.10.012.
8. Campbell-Verduyn, M. (2018) Bitcoin, crypto-coins, and global anti-money laundering governance. Crime Law Soc Change, 69: 283–305. https://doi.org/10.1007/s10611-017-9756-5.
9. Clark, N. (1996) The impact of recent money laundering legislation on financial intermediaries. Penn State International Law Review, 14: 467-503. http://elibrary.law.psu.edu/psilr/vol14/iss3/4.
10. EUROPOL (2015) The Internet Organised Crime Threat Assessment (IOCTA) 2015. https://www.europol.europa.eu/activities-services/main-reports/internet-organised-crime-threat-assessment-iocta-2015.
11. FCA (2023) Digital regulatory reporting. https://www.fca.org.uk/innovation/regtech/digital-regulatory-reporting.
12. Jeong, J., Yoon, B.H. (2007) The Effect of Pseudo-exogenous Instrumental Variables on Hausman Test. Communications in Statistics - Simulation and Computation, 39: 315-321. https://doi.org/10.1080/03610910903447833.
13. Lavery, M.R., Acharya, P., Sivo, S.A. & Xu, L.H. (2017) Number of Predictors and Multicollinearity: What are their Effects on Error and Bias in Regression?. Educational Foundations, Leadership and Policy Faculty Publications, 48: 27-38. https://doi.org/10.1080/03610918.2017.1371750.
14. Ofoeda, I., Agbloyor, E.K., Abor, J.Y. & Osei, K.A. (2022) Anti-money laundering regulations and financial sector development. International Journal of Finance & Economics, 27: 4085–4104. https://doi.org/10.1002/ijfe.2360.

15. Reganati, F., Oliva, M. (2018) Determinants of money laundering: evidence from Italian regions. Journal of Money Laundering Control, 2: 402-413. https://www.ceeol.com/search/article-detail?id=952942.
16. Steinko, A.F. (2012) Financial Channels of Money Laundering in Spain. The British Journal of Criminology, 52: 908–931. https://doi.org/10.1093/bjc/azs027.
17. Stanley, R.L., Buckley, R.P. (2016) Protecting the West, excluding the rest: the impact of the AML/CTF regime on financial inclusion in the Pacific and potential responses. Melbourne Journal of International Law, 17: 1-24. https://heinonline.org/HOL/P?h=hein. journals/meljil17&i=93.
18. Schneider, F., Windischbauer, U. (2008) Money laundering: some facts. Eur J Law Econ, 26: 387–404. https://doi.org/10.1007/s10657-008-9070-x.
19. Teicher, R. (2018) How Uber ghost rides are linked to online money laundering. The Next Web. https://thenextweb.com/contributors/2018/03/18/uber-ghost-rides-linked-online-money-laundering
20. Weeks-Brown, R. (2018) Cleaning up: countries are advancing efforts to stop criminals from laundering their trillions. Finance & Development, 55: 44-45.
21. Wass, S. (2017) Regtech could save banks £2.7bn on AML compliance. Global Trade Review (GTR). https://www.gtreview.com/news/global/regtech-could-save-banks-2-7bn-yearly-on-aml-compliance.
22. Wang, Y.R., Kim, D.K., Jeong, D.W. (2020) A Survey of the Application of Blockchain in Multiple Fields of Financial Services. Journal of Information Processing Systems, 16: 935-958. https://doi.org/10.3745/JIPS.04.0185.
23. Xie, X.Y., Zhu, X.Y. (2022) FinTech and capital allocation efficiency: Another equity-efficiency dilemma?. Global Finance Journal, 53: 100741. https://doi.org/10.1016/j.gfj.2022.100741.