International Journal of *Financial Studies*

MDPI

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Digital Credit and Its Determinants: A Global Perspective

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Abstract: Digital credit has gained much attention from academic researchers, practitioners, and policymakers worldwide. This study empirically evaluates the determinants of digital credit using cross-country data from 2013 to 2019. The conventional ordinary least square regression with fixed effects estimator is used to investigate the factors affecting the growth of digital credit. Our study highlights that the regulatory frameworks of anti-money laundering and terrorist financing, the economy's innovative capacity, and financial development are significant factors affecting the development of digital credit, especially fintech credit. However, the findings indicate that only the innovation capacity is more critical to the expansion of bigtech credit. Nonetheless, our results provide some important implications for market participants and the authorities in promoting digital credit. Accordingly, this study contributes to the literature on the growth of digital credit when considering the critical roles of money laundering and terrorist financing frameworks and innovation capacity.

Keywords: digital credit; money laundering; terrorist financing; innovation capacity; financial development

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Citation: Le, Tu D. Q., Thanh Ngo, and Dat T. Nguyen. 2023. Digital Credit and Its Determinants: A Global Perspective. *International Journal of Financial Studies* 11: 124. https://doi.org/10.3390/ijfs11040124

Academic Editor: Zied Ftiti

Received: 31 August 2023
Revised: 29 September 2023
Accepted: 20 October 2023
Published: 25 October 2023

1. Introduction

The global financial system has witnessed significant transformation in past decades. Although conventional banks and financial institutions maintain a primary funding source for firms and households in most countries and the role of capital markets is critical in some cases, new digital lending platforms have recently materialized. Digital credit models may include invoice trading, peer-to-peer and balance sheet lending, and equity crowdfunding or funding (Bazarbash and Beaton 2020). These credit forms, expedited by online platforms rather than traditional lenders, are considered debt-based alternative finance (Wardrop et al. 2015), fintech credit (Claessens et al. 2018), total alternative credit when accounting for both bigtech credit and fintech credit (Cornelli et al. 2023), or marketplace lending (Bazarbash and Beaton 2020). Digital credit has attracted practitioners, academics, and policymakers as many countries have witnessed remarkable growth in digital credit (Cornelli et al. 2023); however, several authorities are relatively sceptical about promoting digital credit because of the lack of a rigorous regulatory framework (Claessens et al. 2018; Bazarbash and Beaton 2020). Accordingly, our study attempts to investigate the drivers of digital credit when considering the importance of money laundering and terror financing risks and to answer the research question "What are the key determinants of digital credit?".

Several studies have concentrated on different dimensions of digital credit using micro-data levels (De Roure et al. 2016, 2021; Freedman and Jin 2017; Jagtiani and Lemieux 2019; Berg et al. 2019; Cheng and Qu 2020; Sheng 2021). However, several studies using cross-country exist (Claessens et al. 2018; Cornelli et al. 2023; Nguyen et al. 2021; Le 2022b; Le et al. 2021). We continue exploring the determinants of digital credit using aggregated data levels. Most studies in this perspective have focused on the effects of financial development and financial literacy (Oh and Rosenkranz 2020), financial inclusion (Le 2022a), economic conditions, and technological infrastructures (Bazarbash and Beaton 2020; Claessens et al. 2018; Cornelli et al. 2023), or the efficiency of the global banking system (Le et al. 2021). Additionally, recent studies have emphasized money laundering and terrorist financing risks (ML/TF) as one critical concern related to digital credit growth (Allen et al. 2021; Soudijn 2019), as well as different adoption stages of central bank digital currency (Le et al. 2023).

Most studies have provided an overall view of the anti-money laundering and terror financing (AML/TF) frameworks regarding the emergence of fintech. Schwarz et al. (2021) comprehensively explained how fintech should be subject to AML/TF measures. Akartuna et al. (2022a) additionally identified several ways fintech modernizes ML/TF methods. These studies proposed some significant recommendations for implementing a sound AML/TF framework for the growth of fintech. Sarmento and Viegas (2022), analyzing the responsibility of different entities for fighting ML/TF globally and in Portugal, suggested that new innovative solutions address the associated fintech risks in collaboration with the private sector.

Our study contributes to the existing literature in several ways. Most studies use a qualitative approach to outline and examine the possible relationship between money laundering and terrorist financing risks and the development of digital credit (Oxford Analytica 2021; Singh and Lin 2021; Simser 2013; Akartuna et al. 2022b). There need to be more empirical studies. To the best of our knowledge, this is the first attempt that empirically investigates this link. In addition, this matter of ML/TF risks is often missing in prior empirical studies that attempted to investigate the determinants of digital credit growth. Therefore, considering ML/TF in our study is critical because fintech firms providing financial services that are not compliant with AML/TF laws will face difficulty when scaling up (Duhaime 2019). In addition, we also investigate the significance of the economy's innovative capacity using the Global Innovation Index as a broader measure and the development of the financial market in explaining the growth of digital credit.

The findings argue that digital credit is more developed in nations with stringent regulations on anti-money laundering and terrorist financing. More importantly, our findings agree with early studies' view that developing a rigorous legal framework is critical to promote fintech credit worldwide (Allen et al. 2021; Soudijn 2019). Given the shorter examination period, our results indicate that anti-money laundering and terrorist financing frameworks hardly impact the growth of bigtech credit. Perhaps, lending activities are not a primary focus of bigtech firms. Furthermore, our findings also suggest that innovation capacity plays a critical role in expanding all forms of digital credit. Additionally, the negative relationship between financial development and digital credit demonstrates that digital credit may not be a substitute for conventional financial systems. This supports the early findings of Cornelli et al. (2023) and Claessens et al. (2018). The same conclusions still hold for both developed and developing countries.

The remainder of the present study is organized as follows: Section 2 outlines relevant studies on digital credit. Section 3 presents the data and methodology used in this study. Section 4 discusses our main findings, while Section 5 concludes the study.

2. A Brief Overview of Relevant Literature

The literature on digital credit can be divided into two strands. The first strand is to investigate the effect of digital credit on the conventional financial market, especially the banking sector. Several studies using firm-level and aggregated data have attempted to examine the impacts of fintech credit (e.g., peer-to-peer lending) on commercial banks' lending (Buchak et al. 2018; Tang 2019; De Roure et al. 2021; Sheng 2021; Hodula 2021), bank efficiency or profitability (Le et al. 2021; Nguyen et al. 2021), household and firm credit (Le 2022b), economic growth (Song and Appiah-Otoo 2022), and income inequality (Hodula 2023).

The second strand is to examine the factors that influence the development of digital credit. It is important to note that our study does not focus on adopting fintech services regarding the user side using a qualitative approach (Rehman et al. 2023; Hu et al. 2019; Nugraha et al. 2022) because it goes beyond the scope of this study.

The expansion of digital credit is broadly associated with demand and supply sides (Cornelli et al. 2023). On the demand side, the state of the economy will influence the demand for alternative credit from households and firms, especially small- and medium-sized firms (Claessens et al. 2018). When incumbent banking products and services become costly and the coverage of conventional banks is low, this may induce the growth of digital credit (Le et al. 2021). On the supply side, financial regulation and institutional characteristics may significantly affect the development of digital credit. For example, more stringent banking regulations will inhibit the penetration of fintech and bigtech firms (Le et al. 2021; Cornelli et al. 2023). Most empirical studies using cross-country data in this strand have pointed out several key determinants of fintech credit. Bazarbash and Beaton (2020) showed that higher economic development could boost digital credit because higher income per capita raises (1) borrowers' repayment capacity and (2) there is a greater supply of funding for fintech credit as any small investors can participate in lending transactions over online platforms. However, Cornelli et al. (2023) and Claessens et al. (2018) argued that the positive relationship becomes less crucial and even slightly adverse at greater levels of development. In addition, there is a consensus view that the development and quality of the financial market matter for the expansion of digital credit. Rau (2020) and Navaretti et al. (2017) indicated a positive association between crowdfunding volume and financial depth. However, several studies have demonstrated the opposite findings, and the effect of financial development may depend on different types of digital credit and components of financial development. For example, financial development has been found to have no impact on total marketplace lending (Bazarbash and Beaton 2020) or peer-to-peer lending, regardless of advanced and emerging countries (Oh and Rosenkranz 2020). More specifically, Bazarbash and Beaton (2020) highlighted that financial development positively affects consumer marketplace lending, while negatively impacting business marketplace lending. Mixed findings have also been found when observing financial development components. Nonetheless, Le (2022b) emphasized that fintech credit tends to expand more in developing countries where the level of financial development is lowered. Furthermore, it is acknowledged that information technology infrastructure is a critical prerequisite for expanding digital credit. Several studies have suggested that the growth of new digital lending is significantly affected by fixed broadband subscriptions (Oh and Rosenkranz 2020) and internet users (Bazarbash and Beaton 2020).

Along with these essential determinants, several perspectives have also been examined, such as financial literacy (Oh and Rosenkranz 2020), financial inclusion (Le 2022a; Bazarbash and Beaton 2020), the characteristics and conditions of the banking system (e.g., banking efficiency, banking concentration, a regulatory stringency for the banking sector, profitability) (Claessens et al. 2018; Cornelli et al. 2023; Le et al. 2021), and country institutional characteristics and financial crises (Cornelli et al. 2023).

However, FATF (2021) reported two primary risks related to digital credit, namely money laundering (ML) and terrorist financing (TF). Several qualitative studies have also reemphasized the critical roles of anti-money laundering and terrorist financing frameworks in expanding digital credit (Allen et al. 2021; Soudijn 2019). Our study contributes to the existing literature by providing empirical evidence of the association between ML/TF risks and the development of digital credit. Our main hypothesis is formed as follows:

H_0: *Money laundering and terrorist financing risks have no impact on the development of digital credit.*

H_1: *Money laundering and terrorist financing risks significantly reduce the development of digital credit.*

3. Data and Methodology

3.1. Data

Our data were gathered from various sources. The data on digital credit were primarily obtained from the databases provided by Cornelli et al. (2020) and the Cambridge Centre for Alternative Finance, covering 101 countries from 2013 to 2019. The data on ML/TF risks were extracted from the Basel AML Index database deposited at the Basel Institute on Governance, covering 110 nations between 2012 and 2021. The data on financial development (FD) and its components (e.g., FI and FM) were collected from the Financial Development Index dataset (Svirydzenka 2016), while data on inflation and economic conditions were acquired from World Development Indicators (WB 2020). Additionally, financial freedom ($FREE$) information was derived from the Heritage Foundation database. This index is constructed using five criteria and ranges between 0 and 100, where greater values mean greater financial freedom (Mercieca et al. 2007). Finally, the innovation capability (GII) data were obtained from the Global Innovation Index co-published by World Intellectual Property Organization, INSEAD, and Cornell University. After matching these databases, an unbalanced sample of 81 countries[1] with 371 observations at a maximum between 2013 and 2019 was obtained.

In brief, Table 1 shows that three measures of digital credit had a higher value of standard deviation, implying a substantial difference in digital credit among countries. The same results were also true for the cases of technological infrastructure (e.g., GII and $INTERNET$) and overall economic and institutional development ($GDPPC$).

Table 1. Descriptive statistics of the variables used in our regression.

Variables	Mean	Std	Min	Max	No. Obs
FIN ($US)	11.29	31.16	0.00	181.54	515
BIG ($US)	20.88	51.96	0.01	260.10	115
TOTAL ($US)	12.82	40.55	0.00	414.44	530
AFIN (%)	4.92	10.87	0.00	71.27	389
ML	5.49	1.21	2.51	8.39	548
GII	39.48	12.66	14.55	68.40	607
FD	0.41	0.26	0.03	0.98	622
FI	0.48	0.24	0.06	1.00	622
FM	0.34	0.29	0.00	0.95	622
INF (%)	3.55	4.03	0.01	29.51	614
GDPGR (%)	3.78	2.69	0.00	27.99	628
GDPPC ($,000)	18.56	22.03	0.22	117.26	628
FREE	56.14	18.10	10.00	90.00	619
ROA (%)	1.59	1.19	0.01	7.29	465
INTERNET (%)	55.97	30.12	1.80	99.15	623

Notes: The dependent variables are winsorized at the 1% and 99% level. FIN = the volume of fintech credit per capita ($US); BIG = the volume of bigtech credit per capita ($US); TOTAL = the sum of fintech and bigtech credit per capita ($US); AFIN= the ratio of the volume of fintech credit volume to the total domestic credit by financial sector; ML = a broad index for money laundering and terrorist financing risk; GII = the innovation index; FD = financial development index; FI = financial institution index; FM = financial market index; INF = inflation rate; $GDPGR$ = annual economic growth rate; $GDPPC$ = GDP per capita ($GDPPC$); $FREE$ = financial freedom index; ROA = banking return on assets; $INTERNET$ = share of internet users over the population.

3.2. Methodology

Following Cornelli et al. (2023) and Le (2022b), the following baseline model is constructed:

$$DIGCRE_{i,t} = \alpha + \beta_1 ML_{i,t-1} + \beta_2 GII_{i,t-1} + \beta_3 X_{i,t-1} + \mu_k + \tau_t + \pi_{k,t} + \varepsilon_i \quad (1)$$

where $DIGCRE_{i,t}$ is digital credit in country i at year t as measured by the natural logarithm of fintech credit per capita (FIN). We also use the natural logarithm of big tech credit per capita (BIG) and the natural logarithm of total alternative credit per capita ($TOTAL$), where total alternative credit is the sum of fintech credit and bigtech credit (Cornelli et al. 2020). All explanatory regressors take a value of one year lagged to mitigate the endogeneity problem. Fixed effects are also controlled by including geographic region and year dummy indicators. The sample is classified into seven geographic regions: Latin America and the Caribbean, East Asia and the Pacific, Europe and Central Asia, Middle East and North Africa, South Asia, Sub-Saharan Africa, and North America. Our regressions are estimated using fixed effects estimation, with and without dually clustering on geographic region and year for robustness. ε_i is an error term.

$ML_{i,t-1}$ represents a broad index for money laundering and terrorist financing risk. This index was constructed using five dimensions: the quality of the anti-money laundering and combating terrorist financing frameworks, public transparency and accountability, financial transparency and standards, legal and political risks, and bribery and corruption. A greater value for this index implies higher risk. $GII_{i,t-1}$, a broad index measured by the average of the innovation input and output sub-index scores is used to evaluate countries' innovation ecosystems. For control variables, we included the financial development index (FD), inflation rate (INF), annual economic growth rate ($GDPGR$), overall economic and institutional development as proxied by GDP per capita ($GDPPC$), squared GDP per capita ($SQGDPPC$), and financial freedom index ($FREE$) (Claessens et al. 2018; Cornelli et al. 2023).

4. Discussions

4.1. The Results of a Baseline Model

Table 2 presents the Pearson pairwise correlation matrix among variables used in this study. More specifically, the highest correlation coefficient was 0.77, which was between FD and GII. The relatively lower levels of correlation among independent variables imply that multicollinearity should not be of concern (ElBannan 2015).

Table 2. Correlation matrix among variables.

FIN									
0.35 ***	BIG								
0.92 ***	0.80 ***	TOTAL							
−0.56 ***	−0.07	−0.43 ***	ML						
0.65 ***	0.42 ***	0.58 ***	−0.64 ***	GII					
0.45 ***	0.43 ***	0.41 ***	−0.38 ***	0.77 ***	FD				
0.54 ***	−0.06	0.46 ***	−0.61 ***	0.69 ***	0.54 ***	FREE			
−0.03	0.18 *	0.01	0.16 ***	−0.05	−0.1 **	−0.03	GDPPC		
−0.44 ***	−0.28 ***	−0.36 ***	0.33 ***	−0.43 ***	−0.32 ***	−0.34 ***	−0.05	INF	
−0.24 ***	−0.14	−0.21 ***	0.33 ***	−0.34 ***	−0.29 ***	−0.32 ***	0.1 **	0.09 **	GDPGR

Notes: The dependent variables are winsorized at the 1% and 99% level. FIN = volume of fintech credit per capita ($US); BIG = volume of bigtech credit per capita ($US); TOTAL = sum of fintech and bigtech credit per capita ($US); AFIN= ratio of the volume of fintech credit volume to the total domestic credit by financial sector; ML = a broad index for money laundering and terrorist financing risk; GII = innovation index; FD = financial development index; FI = financial institution index; FM = financial market index; INF = inflation rate; $GDPGR$ = annual economic growth rate; $GDPPC$ = GDP per capita ($GDPPC$); $FREE$ = financial freedom index. *, **, *** Significance at 10%, 5%, 1% levels, respectively.

Additionally, Table 3 shows that the variance inflation factor (VIF) values of most independent variables are small. However, VIF values of GII are greater than 5, but still acceptable (Vittinghoff et al. 2005; O'brien 2007; Hair et al. 2013).

Table 3. VIF results.

Variables	FIN	BIG	Total
ML	2.06	2.81	2.08
GII	5.18	5.56	5.14
FD	2.83	4.19	2.85
FREE	2.41	1.72	2.35
GDPPC	1.08	1.11	1.08
INF	1.35	1.56	1.32
GDPGR	1.16	1.54	1.16

Table 4 reports our baseline regression results. The negative coefficients on ML imply that digital credit (e.g., fintech credit and total alternative credit) is more developed in countries where money laundering and terrorist financing risks are lower. Thus, the null hypothesis is rejected. This somewhat supports the early suggestions of Duhaime (2019) that compliance with anti-money laundering and combating terrorist financing (AML/TF) laws is essential for the growth of fintech offering financial services. Additionally, several studies have recognized potential ML/TF risks associated with fintech (Nikkel 2020; Horn et al. 2020), so digital credit is perhaps less developed in several countries where AML/TF frameworks are relatively not strong and less adaptive (Claessens et al. 2018). The same results still remain when considering total alternative credit as a sum of fintech and bigtech credits. However, the finding shows insufficient evidence of the relationship between money laundering and terrorist financing risks and the development of bigtech credit. For big tech firms, lending only accounts for a small fraction, while their primary focus is non-financial activities (Cheng and Qu 2020). Therefore, bigtech providing financial services may not greatly suffer money laundering and terrorist financing laws.

The coefficients of GII are positive and significant, implying that innovative capability is critical to the growth of digital credit. Feyen et al. (2021) demonstrated that digital innovation contributes to enhancements in systems' connectivity, computing cost and power, and newly usable and generated data. This, thus, reduces transaction costs and promotes the emergence of new digital lending models and new entrants. Additionally, FD is negatively and significantly associated with digital credit in most models, suggesting that digital credit is more prevalent in nations where the financial market is less developed. This is comparable with the findings of Le (2022a), who argued that fintech credit concentrates on financing smaller corporate borrowers who face difficulty in accessing capital from traditional lenders or raising funds via stock markets in emerging markets. Additionally, Cornelli et al. (2023) advocated that digital lending serves underbanked areas or the low-credit market segment as a complement to traditional bank credit.

For the control variables, the positive coefficients on $GDPPC$ in both models highlight a positive association between fintech and bigtech credit and a nation's overall economic and institutional development. However, the negative coefficients on $SQGDPPC$ imply that this relationship may become less crucial and slightly adverse at greater levels of development. Nonetheless, this is comparable with the early findings of Claessens et al. (2018) and Cornelli et al. (2023). INF is negatively and significantly related to fintech credit, indicating that once the inflation rate increases, banks may demand higher interest rates on loans (Pervan et al. 2015; Perry 1992). Thus, borrowers may seek a better rate offered by digital lending platforms.

Furthermore, $FREE$ is generally negative and statistically significant in the two models, emphasizing that digital credit is growing in markets where government interference in the conventional financial system increases. As local and international traditional lenders face significant restrictions, this creates a huge opportunity for the growth and penetration of new digital lending activities. Digital credit models have generally been constructed based on decentralized forms, where individual lenders and institutional investors directly select borrowers and projects according to their risk appetite to finance in a marketplace. In the special case of bigtech credit, bigtech firms lend to a substantial number of potential borrowers efficiently and effectively based on their large existing user base (Cornelli et al. 2023). When $FD * FREE$, an interaction term between financial development and the degree of financial freedom, is included in the model, the negative coefficient suggests that digital credit is more developed in the markets where there are a higher level of government interference in conventional financial systems and less developed financial markets. This could be explained by supply-side factors. For example, a greater level of government interference in allocating credit to households and unbanked people with a lower degree of financial development reduces firms' access to credit; digital credit is seen as an alternative source of financing for them (Le 2022a) because these forms of credit are more flexible than traditional credit and the ease and speed of receiving the loan decision is higher (Cornelli et al. 2023).

Table 4. The results of the baseline regression model.

DIGCRE	FIN	BIG	TOTAL	TOTAL
ML	−0.007 *** (0.002)	0.009 (0.007)	−0.006 ** (0.002)	−0.005 * (0.003)
GII	0.174 *** (0.019)	0.121 *** (0.032)	0.149 *** (0.027)	0.162 *** (0.026)
FD	−1.496 *** (0.349)	0.918 (0.723)	−1.323 *** (0.449)	1.873 (1.149)
FREE	−0.014 (0.011)	−0.062 *** (0.02)	−0.034 *** (0.012)	−0.006 (0.016)
*FD*FREE*				−0.053 *** (0.016)
GDPPC	0.0001 *** (0.00003)	0.0004 *** (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
SQGDPPC	−0.000 *** (0.000)	−0.000 *** (0.0000)	−0.000 * (0.0000)	−0.000 (0.0000)
INF	−0.099 *** (0.028)	−0.002 (0.042)	−0.113 *** (0.029)	−0.104 *** (0.029)
GDPGR	0.018 (0.039)	−0.248 (0.179)	−0.032 (0.049)	−0.056 (0.053)
CONST	−6.001 *** (1.042)	−3.243 (4.375)	−0.749 (1.471)	−2.887 * (1.617)
Obs	363	93	371	371
R-squared	0.671	0.709	0.387	0.399
Geographic regions fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	No	No

Notes: Robust standard errors in parentheses are dually clustered geographic region and year. *, **, *** Significance at 10%, 5%, 1% levels, respectively. The dependent variables are winsorized at the 1% and 99% level. FIN = volume of fintech credit per capita ($US); BIG = volume of bigtech credit per capita ($US); TOTAL = sum of fintech and bigtech credit per capita ($US); ML = a broad index for money laundering and terrorist financing risk; GII = innovation index; FD = financial development index; INF = inflation rate; $GDPGR$ = annual economic growth rate; $GDPPC$ = GDP per capita ($GDPPC$); $FREE$ = financial freedom index; $FD * FREE$ = interaction term between FD and $FREE$.

4.2. The Results of Robustness Checks

For robustness checks, we first examined the determinants of digital credit when observing the components of financial development. Then, we used the alternative measures of our main interest variables. Last, we investigated the factors determining digital credit in the subsamples.

The second column of Table 5 indicates that the role of financial institutions (FI) is more critical in explaining the growth of fintech credit, especially financial institutions depth (FID) (e.g., bank credit) and financial institution access (FIA) (e.g., bank branches and ATMs). The negative relationship between financial institutions and digital credit is found in the case of fintech credit not bigtech credit. Nonetheless, this is somewhat in line with the early findings of Cornelli et al. (2023). More importantly, when including bank profitability in the original model, the positive coefficient on ROA reemphasizes the suggestion of Claessens et al. (2018) and Le et al. (2021) in cross-country, that fintech credit is complementary to the conventional banking systems, or Zhang et al. (2019) in China.

Table 5. Results of the robustness checks.

DIGCRE			**FIN**		**AFIN**
ML	−0.009 *** (0.002)	−0.008 *** (0.002)	−0.013 *** (0.003)	−0.008 *** (0.002)	−0.0002 ** (0.0001)
GII	0.148 *** (0.021)	0.172 *** (0.022)	0.089 *** (0.029)		0.005 *** (0.002)
FD				−0.365 (0.304)	−0.092 *** (0.027)
FI	−1.116 *** (0.376)				
FM	0.000 (0.0000)				
FID		−1.683 *** (0.364)			
FIA		−0.261 * (0.136)			
FIE		0.316 (0.297)			
$ROA_{t\text{-}5}$			0.17 ** (0.064)		
INTERNET				0.041 *** (0.007)	
CONST	−4.696 *** (1.273)	−6.318 *** (1.224)	0.577 (2.006)	−2.021 * (1.07)	0.134 * (0.043)
Obs	363	363	113	368	290
R-squared	0.662	0.68	0.696	0.62	0.166
Control variables	Yes	Yes	Yes	Yes	Yes
Geographic regions fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	No

Notes: Robust standard errors in parentheses are dually clustered geographic region and year. *, **, *** Significance at 10%, 5%, 1% levels, respectively. The dependent variables were winsorized at the 1% and 99% level. $AFIN$ = ratio of fintech credit volume to the total domestic credit by the financial sector. FIN = volume of fintech credit per capita ($US); ML = a broad index for money laundering and terrorist financing risk; GII = innovation index; FD = financial development index; FI = financial institution index; FM = financial market index; FID = financial institutions depth; FIA = financial institutions access; FIE = financial institutions efficiency; ROA = banking return on assets; $INTERNET$ = share of internet users over the population. Control variables include financial freedom, GDP per capita, squared GDP per capita, inflation rate, and economic growth rate.

Following Bazarbash and Beaton (2020) and Cornelli et al. (2023), we replaced GII with the share of internet users over the population ($INTERNET$). The fifth column of Table 5 indicates the vital role of internet coverage in the development of fintech credit, because these platforms are operating online without the need for physical branches. The data shown in the last column of Table 5 reemphasize a negative relationship between digital credit and money laundering and terrorist financing risk when digital credit is alternatively measured by the ratio of the volume of fintech credit to the total domestic credit provided by the financial sector ($AFIN$).

Table 6 highlights that money laundering and terrorist financing risks tend to have vital roles in the expansion of fintech credit in developed and developing countries. As result of the large amount of missing data on bigtech credit, we could not include the bigtech credit variable in a separate model. When observing the total alternative credit (bigtech and fintech credit) ($TOTAL$), the findings indicate that the significantly negative relationship between ML and $TOTAL$ is only found in the case of developed countries. When including other independent variables, the coefficient of ML becomes insignificant, though negative. This finding should be interpreted with caution because of the reduced number of observations. Nonetheless, financial development and innovation capacity are seemingly more critical factors affecting the development of fintech credit in developing countries.

Table 6. Results of robustness checks using sub-samples.

	Developed Countries			Developing Countries	
DIGCRE	**FIN**	**FIN**	**TOTAL**	**FIN**	**FIN**
ML	−1.078 *** (0.178)	−0.923 ** (0.201)	−0.782 *** (0.177)	−0.005 ** (0.003)	−0.001 (0.004)
GII		0.104 *** (0.02)	0.136 *** (0.023)		0.239 *** (0.033)
FD		−0.829 ** (0.32)	−1.187 *** (0.332)		−2.012 *** (0.563)
CONST	5.178 *** (0.922)	0.134 * (0.043)	−0.623 *** (2.087)	−1.336 *** (0.452)	−8.385 *** (1.464)
Obs	191	185	185	203	178
R-squared	0.469	0.539	0.525	0.347	0.556
Control variables	No	Yes	Yes	No	Yes
Geographic regions fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses are dually clustered geographic region and year. *, **, *** Significance at 10%, 5%, 1% levels, respectively. The dependent variables were winsorized at the 1% and 99% level. FIN = volume of fintech credit per capita ($US); TOTAL = sum of fintech and bigtech credit per capita ($US); ML = a broad index for money laundering and terrorist financing risk; GII = innovation index; FD = financial development index. Control variables include financial freedom, GDP per capita, squared GDP per capita, inflation rate, and economic growth rate.

All in all, our empirical analysis provided the statistical evidence to support the alternative hypothesis H_1 that money laundering and terrorist financing risks significantly reduce the development of digital credit at an international level for both developed and developing countries, although the effect is stronger for the former group. Our results, therefore, strengthen the previous qualitative attempts to examine the roles of money laundering and terrorist financing, such as Soudijn (2019), Horn et al. (2020), and Allen et al. (2021), among others. Consequently, we argue that the stringency of the regulatory framework toward those risks is important for digital credit development.

5. Conclusions

This study investigated the critical factors affecting the development of digital credit across the globe from 2013 to 2019. Our findings indicate that digital credit tends to expand in countries with stringent regulations on anti-money laundering and terrorist financing (ML/TF). This reemphasizes that the continuing and adaptive development of regulatory frameworks against ML/TF risks, regardless of developed and developing countries, is crucial as the growth of digital credit has changed over time. Our study strongly recommends that authorities across the globe should introduce explicit provisions applied specifically to fintech firms. These should involve at least three crucial perspectives: registration requirements, know-your-customer checks, and ongoing supervising and monitoring.

Also, a negative relationship between the financial development index and the growth of digital credit suggests that digital credit may complement the conventional financial system. Nonetheless, this supports the view of Cornelli et al. (2023) and Le et al. (2021), that fintech credit should be encouraged in the future. Furthermore, national innovation capacity (e.g., internet coverage) was found to be a critical factor in promoting the expansion of digital credit. Together, our findings suggest that authorities should further focus on science and innovation investments and technological progress perspectives in promoting digital credit.

However, our study may suffer limitations. Given the negative impact of the COVID-19 pandemic on the global economy in general and the financial system in particular (Boubaker et al. 2022; Narayan et al. 2021; Hui and Chan 2022), future research may consider the impact of this health outbreak on the growth of digital credit once the data on digital credit become available. Furthermore, many central banks have engaged in central bank digital currency projects (Le et al. 2023). Thus, this perspective should be considered in future research when identifying the factors affecting the growth of digital credit.

Author Contributions: Conceptualization, T.D.Q.L. and T.N.; methodology and software, T.D.Q.L. and D.T.N.; validation, T.N.; formal analysis, D.T.N.; investigation, D.T.N. and T.D.Q.L.; resources, T.D.Q.L. and T.N.; data curation, T.D.Q.L. and T.N.; writing—original draft preparation, T.D.Q.L. and D.T.N.; writing—review and editing, T.N.; visualization, D.T.N.; supervision, T.N.; project administration, T.D.Q.L.; funding acquisition, T.D.Q.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the University of Economics and Law, Vietnam National University, Ho Chi Minh City, Vietnam.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is publicly available from the Cambridge Centre for Alternative Finance.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

[1] These countries include Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Burkina Faso, Cambodia, Canada, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Czech Republic, Denmark, Ecuador, Egypt, El Salvador, Estonia, Finland, France, Georgia, Germany, Ghana, Guatemala, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Kenya, Korea, Latvia, Lebanon, Liberia, Lithuania, Luxembourg, Malawi, Malaysia, Mali, Mexico, Mongolia, Morocco, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Russian Federation, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Tanzania, Thailand, Turkey, Uganda, United Arab Emirates, United Kingdom, United States of America, Uruguay, Vietnam, Yemen, Zambia.

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