



DETERMINANTS OF ALTERNATIVE FINANCING DEVELOPMENT IN THE EUROPEAN UNION

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Abstract

Research background: Despite the growing significance of alternative finance (AF) in the European Union (EU), few studies have comprehensively analysed its drivers using recent panel data. Prior research often overlooks the combined impact of innovation, digitalisation, and regulatory conditions across the EU-27.

Purpose: This paper aims to discern the determinants that contribute to the development of AF within the EU.

Research methodology: The study employs panel regression analysis based on 162 observations across 27 EU countries, using indicators such as GDP per capita, the Global Innovation Index (GII), the Digital Economy and Society Index (DESI), the Index of Economic Freedom (IEF), and R&D expenditure. Model selection and robustness were ensured through the Breusch–Pagan LM test, the Hausman test, the Wooldridge test for autocorrelation, the Pesaran CD test for cross-sectional dependence, and the VIF for multicollinearity. K-means clustering was applied to identify countries with similar innovation and economic profiles.

Results: Innovation emerged as the strongest positive driver of AF, while GDP per capita had a limited positive influence. A negative relationship was found between AF and economic freedom, while digitalisation and R&D showed no significant effect.

Novelty: The study offers novel empirical evidence on AF determinants using a validated econometric model, revealing innovation as a more important driver than traditional economic or regulatory variables in the context of the EU.

Keywords: alternative finance, digitalisation, innovations, economic development

JEL classification: G19, O16, O52

Introduction

Advanced business funding guarantees sustainable development and enterprise attractiveness, fast technical development, and rapid digitalisation. One of the benefits of AF is its ability to provide enterprises with extended access to capital, which is vital for the post-pandemic recovery and in conditions of uncertainty. AF, encompassing instruments like peer-to-peer lending, crowdfunding, and other non-bank funding channels, has grown explosively in recent years. Globally, the average annual growth rate of crowdfunding exceeded 200% before 2017, and even during the COVID-19 pandemic, the sector showed resilience (Ziegler et al., 2021). Using AF tools allows going beyond traditional sources of financing, such as bank loans, and tapping new opportunities in the capital market. These help attract investment, expand and enhance financial partnerships, and improve financial resource efficiency. The most crucial factor for initiating, developing, and stimulating the growth of businesses and small and medium-sized enterprises (SMEs) is the availability of financial resources. SMEs have specific needs and face challenges different from those of large enterprises. The importance of non-traditional AF is increasing in both developed and transition economies. It is important for ensuring financial stability and the successful development of enterprises in the contemporary economic environment.

AF has become a critical funding source for start-ups and SMEs in the EU. It supports recovery post-COVID, particularly when conventional lenders tightened credit. This context makes an EU-focused study of AF development especially timely, as policymakers seek to harness digital finance innovations to support economic growth and financial inclusion. Despite the rapid rise in AF, there is a paucity of research on the determinants of AF development in EU countries, using recent panel data and multifaceted indicators. Most existing cross-country studies analyse global samples or specific regions, often with limited variables (Bilan et al., 2019; Bednarz et al., 2017; Claessens et al., 2018). This suggests a potential gap in understanding how digital readiness and regulatory conditions affect AF, especially within the EU, where digitalisation policies and regulatory frameworks have evolved rapidly in recent years.

This paper addresses the above gap by providing a novel empirical analysis of the drivers of AF development across the EU-27 over 2017–2022. The paper aims to identify the determinants of AF development within the EU. Methodologically, the paper contributes a rigorous panel econometric approach combined with a clustering analysis, yielding new insights into both the magnitude and the patterns of AF development. We offer both econometric evidence of determinants and a comparative segmentation of countries, which

together yield practical insights for policymakers. This paper is novel in empirically assessing how digitalisation, innovation, the institutional environment, and macro-financial factors influence the development of AF across all EU-27 countries during the post-pandemic period, using a rigorously validated panel econometric framework.

The paper is organised into distinct sections as follows: the initial section provides a comprehensive review of the literature about the elements under investigation; section 2 delineates the research methodology employed in the study; section 3 presents the findings obtained through the research; Section 4 provides discussion and summaries with the limitations of the conducted study; and, ultimately, section 5 provides conclusions drawn from the research along with directions for future research directions.

1. Literature review

There is no universally accepted definition of AF. According to AF is funded from external sources, excluding bank loans or capital raised through stock and bond markets. Ziegler et al. (2021) state AF is digital funding that has emerged outside existing banking systems and traditional capital markets on the Internet. This online AF ecosystem comprises various lending, investment, and non-investment models, enabling individuals, businesses, and other organisations to raise funds through a digital online market. Peterhoff et al. (2014) consider AF for SMEs as a means of accessing financial capital from sources other than traditional banks, including crowdfunding, peer-to-peer (P2P) lending, factoring, leasing, venture capital, angel investors, and government grants and loans. Segal (2016) suggests that alternative online financing is a financial and technical innovation. The emergence and development of this mechanism would be possible with the modern development of information and communication technologies. Some definitions highlight the direct link between those seeking funds and potential backers, often facilitated by online platforms (Baeck et al., 2014). AF is inherently interdisciplinary and involves financing channels outside formal institutions, relying on social, business, and virtual networks (Allen, Qian, 2023). These include trade credits, family lending, cooperatives, private equity, and digital platforms like P2P and crowdfunding.

There are two perspectives on AF. The first perspective views AF as a substitute for traditional banking. Recent theories explore the generic advantages of AF, such as relationships, reputation, tax benefits, and others. This approach highlights the informational and monitoring advantages of alternative credit suppliers over banks. Trade credit, for example, allows suppliers to leverage private data on buyer behaviour (Petersen, Rajan, 1997). Their study found that

small firms rely more on trade credit when traditional financing is unavailable, making it a last-resort financing method. The conventional perspective posits that AF is a second-best option, influenced by information asymmetry and moral hazard. On the contrary, the generic-advantage approach examines the competitiveness of AF vis-à-vis bank loans under identical market conditions, free of information asymmetry or market failure. Therefore, AF can be considered the primary choice in many scenarios. So (Allen et al., 2019) sought to develop a model that identifies optimal options by allowing different funding sources to compete within a single structure, thereby directly addressing the comparative competitiveness of AF. They model how implicit benefits and enforcement costs of repayment affect credit allocation, costs, and renegotiation. The optimal solution explains that financing accompanied by implicit benefits can, in many instances, lead to lower financing costs, greater managerial effort, and superior economic outcomes for the borrower and the lender.

Nguyen and Rugman's (2015) examined how internal equity financing, such as income retention and reinvestment, influences the performance of multinational subsidiaries in developing economies. Their findings show that UK subsidiaries rely heavily on internal funding, which positively impacts performance, possibly through tax-related strategies. However, this may be related to tax strategies. According to the classification proposed by the Cambridge AF Centre, the main types of AF are P2P consumer lending, P2P business lending, P2P/Marketplace Property Lending, balance sheet business loans, invoice trading, equity-based crowdfunding, non-financial overview ("reward-based crowdfunding"), real estate crowdfunding, profit sharing crowdfunding, donation-based crowdfunding, debt-driven debt-based securities (Ziegler et al., 2021). AF is developing unevenly worldwide. To identify the primary drivers of its rapid development, let us focus on the most crucial factors. Scholars explored various determinants of AF development, and the aggregated indicators they employed are presented in Table 1.

Due to the available data, we decided to select only a few and focus on the following: the economic development of a country (measured by GDP per capita), innovation (measured by the Global Innovation Index – GII, with an additional focus on R&D), digitisation (measured by the Digital Economy and Society Index – DESI, as it is the primary indicator for digitalisation levels in EU countries), and regulatory influence (measured by the Economic Freedom Index).

Table 1. Determinants of AF development

Determinants of AF Development	Indicators	Authors			
		Paslari (2023)	Bilan et al. (2019)	Claessens et al. (2018)	Tan et al. (2021)
The state of the economy	GDP per capita		+	+	+
	International Country Risk Guide				+
	Lerner Index			+	
Regulatory Impact	Economic Freedom Index	+	+		
	Index of Regulatory Restrictions on Direct Foreign Investment	+			
	Regulatory Impact Assessment (RIA) by the OECD methodology		+		
	Normalised Regulatory Stringency Index			+	
	Ease of Doing Business Score				+
Social Capital	Social Capital (component of Global Competitiveness Index)	+			
Innovations	Global Innovation Index	+	+		
Technical development. Information technology and Internet access infrastructure	World Digital Competitiveness Ranking	+			
	ICT Development Index		+		
Financial Institutions Access and Depth. Financial Inclusion	The share of the population (aged 15+) using loans from traditional financial intermediaries		+		
	Financial Development Index	+			+
	Global Competitiveness Index (GCI) – 8, the component of “Financial Market Development”		+		
	The share of the population (aged 15+) who do not have a bank account		+		

Source: compiled by the authors based on Bilan et al. (2019); Claessens et al. (2018); Paslari (2023); Tan et al. (2021).

1.1. Economic development of the country

The importance of GDP as a determinant of AF development is evidenced by its important role as a comprehensive indicator of a nation's economic health and prosperity. A country's GDP can influence access to and usage of AF mechanisms. Higher GDP means greater economic power and resource availability, potentially providing input in creating an enhanced financial ecosystem (Chander, Chand, 2019). Some scientists concluded that GDP positively affects venture capital and private equity. Others consider GDP a direct determinant of AF development (Bilan et al., 2019). GDP can influence individuals' and enterprises' risk-taking behaviour and a country's behavioural finance. Nations with higher GDP levels generally

exhibit a heightened financial literacy among the population (Lusardi, Oggero, 2017), broader company investing opportunities, and increased investor confidence. This interconnection underscores the multifaceted role of GDP as a determinant of various aspects of AF, including the structure of financial ecosystems, risk appetite, economic behaviour, and the investment landscape within a given country.

1.2. Innovation

Innovation activities encompass a spectrum of scientific, technological, organisational, financial, and commercial endeavours designed to actualise or facilitate the implementation of innovations (OECD/Eurostat, 2005). Innovation is a primary driver of economic progress. They also progressively reshape the financial sector by introducing revolutionary technologies and platforms that enhance the efficiency of business capital mobilisation. Therefore, it is reasonable to show in our study that a country's level of innovation development influences the volumes of AF. Since innovation is a key driver of digitalisation and innovative financial technologies, our study focuses on two indicators characterising this phenomenon. First, a country's level of innovation, often measured by the Global Innovation Index (GII), is essential for determining AF volume. The GII assesses a country's innovation capabilities and outcomes. It provides insights into various dimensions, such as institutions, human capital, research, infrastructure, market sophistication, and technology outputs. Countries with higher GII scores tend to have more developed ecosystems for AF, supported by advanced technological infrastructure, an innovation culture, and supportive regulatory frameworks. They typically possess advanced digital and technological infrastructures, which are very important for supporting digital finance platforms and transactions. Mulas et al. (2015) highlight the importance of digital infrastructure in enabling the digital economy, including the creation of digital capital. Countries with high levels of innovation tend to have sophisticated markets ready to invest in new technologies and start-ups. Lee et al. (2015) found that market conditions critically affect access to finance for innovative firms. The expansion of P2P lending and crowdfunding has enabled direct capital raising from a broad investor base. Agrawal et al. (2015) provide evidence that crowdfunding platforms extend the geography of finance, enabling capital raising from a broader base of investors and increasing the volume of capital raised digitally. Secondly, research and development (R&D) is essential as a driver of innovation, as investments in research enable the creation of new ways of thinking and their practical implementation. A high level of R&D expenditure is typically associated with

well-developed innovation ecosystems. For instance, authors investigated that increased R&D expenditure is the channel through which financing affects SMEs' innovation (Hu et al., 2024).

1.3. Digitisation

The rise of alternative financial channels is the most visible outcome of the digitalisation of the entrepreneurial finance ecosystem (Bertoni et al., 2022). New financial technologies enhance access to financing by opening opportunities for new types of projects and attracting new categories of investors (Bollaert et al., 2021). Mikalef and Parmiggiani (2022) developed a conceptual framework for digital transformation, showing that digitalisation leads to achieving particular economic, social, and environmental performance. The level of development of digital technologies varies across countries, so specific indicators have been developed to monitor states' progress in this area. In the EU, this is the DESI, which includes measurements in four sub-dimensions: Human capital, Connectivity, Integration of digital technology, and Digital public services.

1.4. Regulatory influence

Regulation ensures a level playing field in the AF sector. It sets standards and guidelines for platform operators, reduces information asymmetry and ensures market integrity. Regulatory oversight helps prevent fraud or unethical practices that could harm SMEs and investors and creates an environment in which AF can thrive while minimising the potential for market abuse. A clearly defined regulatory framework delineates the rights and responsibilities of all involved parties, ensuring transparency and fairness and, in turn, strengthening investor trust and encouraging more individuals and institutions to participate in AF. Rau (2017) shows that introducing explicit legal regulation increases crowdfunding volume. Philippon (2016) concludes that significant welfare gains in financial services are technologically feasible but unlikely without the entry of new firms facilitated by a regulatory approach that supports FinTech innovation. This approach could lead to a more efficient and inclusive financial system.

2. Research methodology

Based on the preceding analysis, we have formulated four hypotheses regarding the dependency of AF volumes on the quantitative and qualitative characteristics of the respective factors:

- Hypothesis 1: The volume of AF is directly influenced by the country's economic development level.
- Hypothesis 2: A country's innovativeness level directly influences AF volume.
- Hypothesis 3: The volume of AF is directly influenced by the country's level of digitalisation.
- Hypothesis 4: The volume of AF is directly influenced by the nature of the state's regulatory impact on the economy.

We tested hypotheses based on theoretical exploration to discern developmental trends, forecast the evolution of the AF market, and make relevant recommendations. Drawing on somewhat modified approaches by Claessens et al. (2018), Tan et al. (2021), Bilan et al. (2019), and Paslari (2023), we developed a model to determine the impact on AF volumes. We used a panel dataset of 162 longitudinal observations for 2017–2022 across 27 EU countries. We applied a panel regression model to examine our hypotheses, incorporating our dependent and independent variables. This model elucidates the relationship between the independent and dependent variables, illustrating how alterations in the independent variable can influence the dependent variable. Given the panel structure of our dataset (27 EU countries over 2017–2022, yielding 162 observations), we undertook several steps to ensure an appropriate econometric model was specified. First, we did the Breusch-Pagan LM test (Breusch, Pagan, 1980). It examines whether variance across entities (countries) is zero – i.e., unobserved country-specific effects are negligible. Next, we needed to choose between a fixed-effects (FE) and a random-effects (RE) model for the panel. We applied the Hausman specification test (Hausman, 1978) to assess whether the country-specific effects are correlated with the regressors. The null hypothesis of the Hausman test is that the RE estimator is consistent (and hence RE is appropriate), while the alternative is that RE is inconsistent and FE should be used. Our Hausman test results were significant at the 5% level, indicating that the coefficients differ systematically between FE and RE specifications. Consequently, the fixed-effects model was deemed appropriate. Table 2 exhibits the selected quantitative indices/indicators, meticulously chosen from an extensive array of metrics for the ultimate analysis.

These indicators were used for the panel regression analysis. The regression equation can be formulated using the coefficients derived from the analysis. In general, a multiple linear regression equation takes the following form:

$$\begin{aligned} \text{AF per capita} = & \beta_0 + \beta_1 \times (\text{GDP per capita}) + \beta_2 \times (\text{GII}) + \beta_3 \times (\text{DESI}) + \\ & + \beta_4 \times (\text{IEF}) + \beta_5 \times (\text{R\&D}) + \epsilon \end{aligned} \quad (1)$$

where:

AF per capita – the dependent variable,

β_0 – the intercept,

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ – the coefficients for the independent variables,

ϵ – the error term.

Table 2. List of variables used in the study

Variable name	Abbreviation	Description
AF per capita	AF per capita	Market volume of digital capital raising for each country in US dollars
GDP per capita	GDP per capita	A country's GDP divided by its total population
Global Innovation Index	GII	Global trends in innovation, education, infrastructure, and knowledge creation in the economy
Digital Economy and Society Index	DESI	Summarises indicators on Europe's digital performance and tracks the progress of EU countries
Index of Economic Freedom	IEF	The rule of law, regulatory efficiency, market openness, and tax burden
Research and development expenditure, Percentage of gross domestic product (GDP)	R&D	Measures a country's investment in research and development relative to its overall economic output, calculated as the total R&D expenditure divided by the GDP

Source: authors' compilation based on Statista (2023); World Bank Group (2023b, 2023a); Eurostat (2023); European Commission (2023); The Heritage Foundation (2023); World Intellectual Property Organisation (2023).

Additionally, the model was tested for first-order autocorrelation using the Wooldridge test (Drukker, 2003). To detect potential multicollinearity, the Variance Inflation Factor (VIF) test was performed (Greene, 2018). Finally, the Pesaran CD (cross-sectional dependence) test was carried out to detect potential interdependence among countries in the panel (Pesaran, 2004). By applying these specifications and diagnostic procedures, the study ensures that the estimated model meets the econometric requirements for validity and provides reliable inferences for policy and academic interpretation.

To complement the panel regression and to identify groups of EU countries with similar profiles, we applied k-means clustering to the country-level indicators averaged over 2017–2022. Prior to clustering, variables were standardised (z-scores) to ensure comparability across different measurement scales. The k-means algorithm partitions observations into k clusters by minimising the within-cluster sum of squared distances to cluster centroids (Aldenderfer, Blashfield, 1984; Hartigan, Wong, 1979). The optimal number of clusters was selected using the elbow criterion by inspecting the reduction in total within-cluster sum of squares as k increases and choosing the point where additional clusters yield diminishing improvements

(Ketchen, Shook, 1996). We analysed time trends to examine how the scores changed over six years. This analysis involved calculating the average score for each cluster each year.

3. Results

A series of diagnostic tests was conducted to validate key econometric assumptions and to ensure the robustness and reliability of the panel regression results. These tests help determine the appropriate model specification and address potential issues such as autocorrelation, multicollinearity, and cross-sectional dependence – common challenges in macro-panel datasets. Table 3 summarises the purpose, outcomes, and implications of each test conducted in the study.

Table 3. Diagnostic test results

Test	Purpose	Result	Implication
Breusch-Pagan LM Test	Check if the panel model is preferred over pooled OLS	LM = 439.5102, p < 0.001	The panel model is appropriate
Hausman Test	Decide between Fixed Effects and Random Effects	Statistically significant → RE inconsistent	Use the Fixed Effects model
Wooldridge Test for Autocorrelation	Detect first-order autocorrelation in panel residuals	F = 0.0550, p = 0.8149	No autocorrelation detected → standard errors reliable
Variance Inflation Factor (VIF)	Assess multicollinearity among explanatory variables	All VIF < 5	No multicollinearity concerns
Pesaran CD Test	Detect cross-sectional dependence in panel data	CD = 3.0835, p = 0.0020	Cross-sectional dependence detected

Source: own calculations.

The diagnostic tests confirmed the suitability of the fixed effects panel model. The Breusch-Pagan LM test supported using panel data rather than pooled OLS, while the Hausman test indicated that fixed effects are more appropriate than random effects. The Wooldridge test showed no first-order autocorrelation, suggesting that a serial correlation does not bias the estimates. The Pesaran CD test confirmed cross-sectional dependence consistent with the economic integration of these countries. Finally, the VIF values indicated no issues with multicollinearity among the independent variables.

Descriptive statistics are computed over 162 country-year observations (EU-27, 2017–2022). The average amount of AF per capita was approximately USD 7.2 (ranging from USD 0.09 to USD 20.15). GDP per capita varied significantly (from USD 6,630 to USD 133,711). The average scores on the Global Innovation Index (GII), the Digital Economy and Society

Index (DESI), and the Index of Economic Freedom (IEF) were 47.8, 44.8, and 70.6, respectively, indicating different levels of innovation, digitalisation, and regulatory conditions. GII ranged from 34.1 to 63.8; DESI ranged from 13.9 to 59.8; IEF ranged from 55 to 82. Research and development (R&D) expenditure as a share of GDP averaged 1.65% and ranged from 0.46 to 3.5%. It had less dispersion than other indicators. These results confirm the presence of structural and institutional diversity in the EU, supporting the relevance of panel data methods for the analysis.

Analysing the explanatory variables considered significant for the dependent variable, AF per capita, began by examining correlation coefficients among the variables (Table 4). The analysis of explanatory variables deemed necessary for the dependent variable, AF per capita, begins with an examination of the correlation coefficients between variables.

Table 4. Correlation matrix

	AF per capita	GDP per capita	GII	DESI	IEF	R&D
AF per capita	1					
GDP per capita	0.720270	1				
GII	0.657929	0.599066	1			
DESI	0.367341	0.402209	0.631123	1		
IEF	0.382521	0.544711	0.543788	0.334859	1	
R&D	0.412856	0.331667	0.650190	0.297066	0.244279	1

Source: own calculations.

A linear relationship is observed between the dependent variable, AF per capita, and the other variables (Column 1). AF per capita, GDP per capita, and the Global Innovation Index are strongly correlated. Strong positive correlations exist between AF and GDP per capita and GII, indicating their significant roles in AF development. Moderate or weak correlations with DESI, IEF, and R&D suggest these factors have an indirect impact. We obtain the following results from the panel regression analysis (Table 5).

Given the limited time dimension ($T = 6$) and to preserve parsimony, we report a baseline model that includes all theoretically motivated predictors (Table 5) and a restricted model that retains only variables that remain robustly associated with AF per capita in the fixed-effects setting (Table 6). Importantly, we do not interpret non-significance as evidence of ‘no effect’. Instead, DESI and R&D may overlap with innovation outcomes or operate with lags, so the restricted model is treated as a robustness check rather than a model-selection rule. In short panels, lagged and interaction specifications are natural sensitivity extensions, but they also

reduce degrees of freedom and statistical power (Wooldridge, 2025). The contrast between a significant GII coefficient and a non-significant R&D share is economically meaningful. R&D expenditure is an innovation input, and its impact on market-relevant outcomes is often delayed, nonlinear, and heterogeneous across countries, which can weaken contemporaneous associations in fixed-effects models (Hall et al., 2010; Hammar, Belarbi, 2021). By contrast, GII proxies broader innovation outcomes and ecosystem maturity, which are more directly linked to the capacity to scale platform-based finance. This interpretation aligns with evidence that FinTech and platform credit expand with enabling ecosystems and market conditions rather than raw spending levels alone (Cornelli et al., 2023; Hoque, 2024; Thakor, 2020).

Table 5. Panel regression results

	Coefficients	Standard Error	t Stat	p-value
Intercept	-2.233290	3.90430	-0.5720	0.56813
GDP per capita	0.000134	1.57E-05	8.5448	1.1E-14
GII	0.349295	0.07014	4.9797	1.6E-06
DESI	-0.047010	0.02853	-1.6470	0.10140
IEF	-0.140000	0.06190	-2.2610	0.02510
R&D	-0.115320	0.43526	-0.2640	0.79140

Source: own calculations.

We received new results. The multiple R of 0.781464 indicates a strong positive linear relationship between the AF and dependent variables. R-squared shows that AF accounts for approximately 61.1% of the variance in the dependent variable, meaning that the model fits well. Adjusted R-Square 0.603295 suggests that most of the predictors included in the model contribute meaningfully to explaining the dependent variable. The Standard Error of the regression, 3.477884, represents the average deviation of the observed values from the regression line. One hundred and sixty-two observations are included in the analysis. The sample size is relatively robust for a regression analysis.

Table 6 summarises the estimated coefficients (with standard errors and p-values) from the regression model where AF per capita is the dependent variable. The intercept term represents the value of the dependent variable AF per capita when all independent variables are zero. GDP per capita has a minimal positive influence on AF per capita. The GII coefficient positively influences AF per capita. The IEF coefficient is negative.

Table 6. Regression coefficients and statistical significance

	Coefficients	Standard error	t Stat	p-value
Intercept	-2.085100	3.89540	-0.535	0.59320
GDP per capita	0.000133	1.5E-05	8.474	1.5E-14
GII	0.291194	0.04771	6.103	7.7E-09
IEF	-0.134730	0.06125	-2.199	0.02929

Source: own calculations.

For every one-unit increase in GDP per capita, AF per capita is expected to increase only by approximately 0.00013 units, all else equal. GDP per capita has a minimal positive influence on AF per capita. The t-statistic and the p-value indicate that the coefficient is statistically significant. The GII coefficient suggests that for every one-unit increase in GII, the dependent variable (AF per capita) is expected to increase by approximately 0.29 units, holding other variables constant. This positive relationship suggests that a higher level of innovation within a country is associated with a higher capacity to raise digital capital. The coefficient is statistically significant. The Index of Economic Freedom (IEF) coefficient indicates that AF per capita is predicted to decrease by 1 unit for each 1-unit increase in the IEF. The negative association between economic freedom and AF is counterintuitive, as economic freedom typically promotes entrepreneurship and capital flows. Countries with high economic freedom already have established traditional capital markets. It could reduce the emphasis on AF. One plausible mechanism is the substitution between traditional and alternative external finance. Evidence from European SMEs shows that bank-lending constraints increase firms' demand for non-bank financing alternatives, including trade credit and other external sources (Casey, O'Toole, 2014). Similarly, classic evidence indicates that firms rely more on trade credit when credit from financial institutions is not available (Petersen, Rajan, 1997). In FinTech credit markets, platform lending can substitute for bank lending for specific borrower segments and responds to shocks in bank credit supply (Tang, 2019), which aligns with broader reviews emphasising that FinTech credit often expands access primarily where frictions or constraints limit traditional intermediation (Thakor, 2020).

As a result, the following regression was obtained and approved (2).

$$\text{AF per capita} = -2.0851 + 0.00013 \times (\text{GDP per capita}) + 0.2912 \times (\text{GII}) - 0.13473 \times (\text{IEF}) \quad (2)$$

The positive pairwise correlation between AF per capita and the Index of Economic Freedom (IEF) in Table 4 is not inconsistent with the negative IEF coefficient in the fixed-effects regression (Table 6). The correlation in Table 4 is an unconditional association that pools both between-country and within-country variation. By contrast, the fixed-effects estimator identifies a within-country (over-time) partial effect, net of time-invariant country characteristics and the included covariates. This sign reversal is consistent with partialling-out effects in multivariate settings: once GDP per capita and GII are controlled for, the within-country variation in IEF is associated with lower AF per capita. When between- and within-country relationships differ, a sign reversal between an unconditional correlation and a fixed-effects coefficient can occur, which is a well-known feature of panel-data models and within-between decompositions (Bell, Jones, 2015; Wooldridge, 2025).

The panel regression analysis confirmed only the first two hypotheses: economic development and innovation have a positive effect on AF volume, while digitalisation and regulatory impact showed no significant effect.

Having established that GDP per capita and the Global Innovation Index positively influence AF, we conducted a cluster analysis to examine the interplay among digital investment, economic performance, and innovation capacity across EU countries. The clusters were identified using the K-Means method, utilising averaged data from 2017 to 2022. We obtained 4 clusters (see Table 7 and Figure 1).

Table 7. Cluster descriptions

Cluster	Description	Countries
Cluster 0	Lower AF per capita, GDP per capita, and Global Innovation Index. Economies with moderate innovation capabilities	Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia
Cluster 1	High AF per capita and GDP per capita, moderately high innovation. Distinguished by very high economic indicators and significant digital investment	Ireland
Cluster 2	Moderate to high GDP per capita and innovation index, balanced AF per capita. Economies with solid innovation frameworks	Austria, Belgium, Denmark, Finland, France, Germany, Italy, Malta, the Netherlands, Spain, Sweden
Cluster 3	High GDP per capita and AF per capita, strong innovation index. Represents an economy with a balanced high profile across economic and innovation metrics	Luxembourg

Source: own calculations.

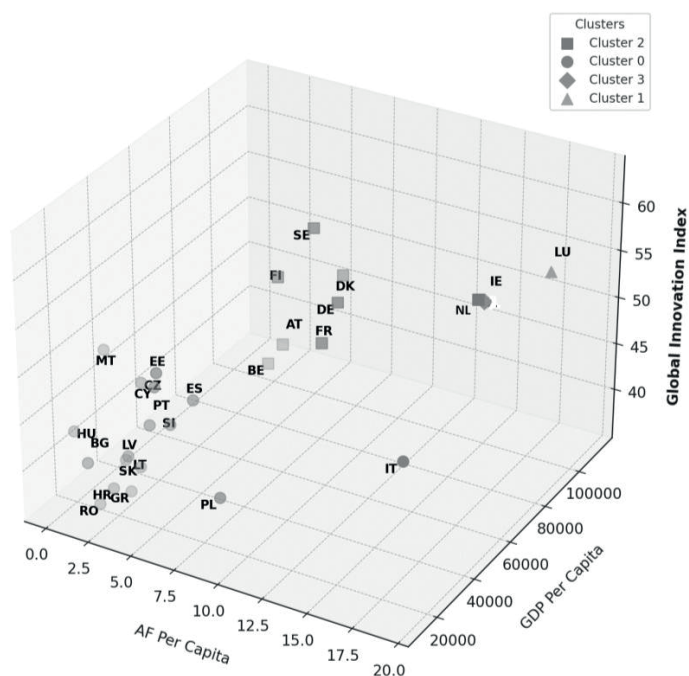


Figure 1. 3D visualisation of clusters

Source: own calculations.

Regarding the analysis of data distribution for each cluster (Figure 2), we observe that cluster 0 exhibits the lowest levels of AF per capita and GDP, with narrow interquartile ranges, indicating limited potential for digital investment and innovation. Cluster 3 is a single-country cluster with the highest GDP and AF per capita, indicating a stable, developed economy; however, its innovation performance was slightly lower than that of Cluster 2. Cluster 2 includes innovation-driven economies with the highest GII values and moderate AF activity. At the same time, Cluster 1 shows above-average AF per capita, reflecting uneven digital progress. These results highlight the need for targeted policies to stimulate digitalisation and innovation in lagging clusters and to facilitate knowledge transfer from leaders.

We analysed year-over-year trends within each cluster to observe significant shifts in average indicator values. AF per capita, GDP per capita, and innovation performance (GII) exhibit persistent cross-cluster differences over 2017–2022. Cluster 0 remains consistently the weakest across all indicators, while Cluster 2 occupies an intermediate position with a visible downturn around 2019–2020 and only partial recovery thereafter. Clusters 1 and 3, each representing a single country, maintain the highest AF per capita and GDP per capita

throughout the period, despite a temporary decline around 2019–2020 and a strong rebound in GDP after 2020. In contrast, GII trends weaken after 2019 in the leading single-country cases, whereas Cluster 2 remains the most innovation-intensive and comparatively stable. Overall, cluster rankings are broadly preserved, indicating structural gaps between lagging and leading cases.

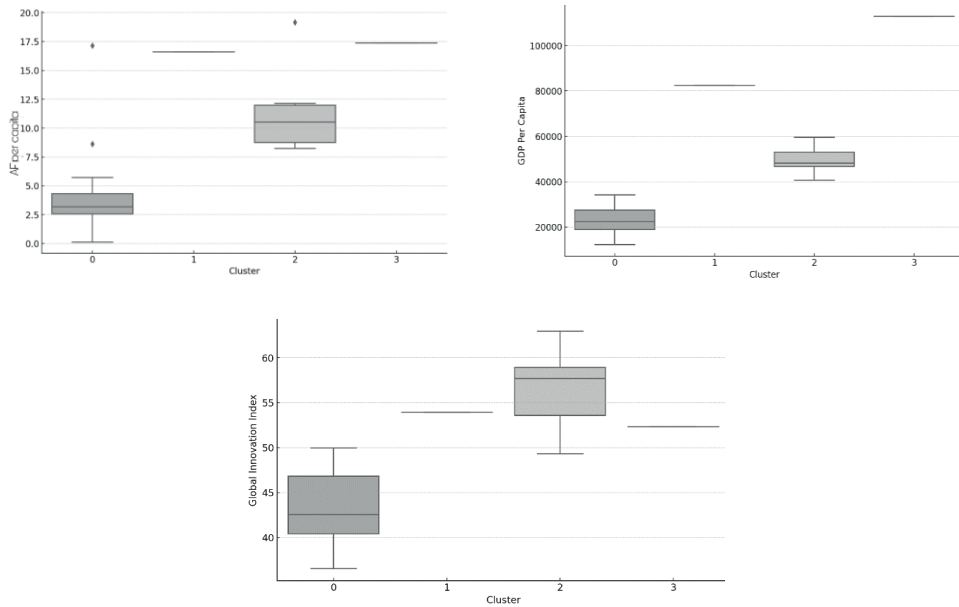


Figure 2. Variations in AF per capita, in GDP per capita and in GII among the clusters

Source: own calculations.

Table 8. Cluster-wise correlation of indicators with AF per capita

Cluster	Indicator	Correlation with AF per capita
Cluster 0	GDP per capita	0.29 (moderate positive)
	Global Innovation Index	0.17 (low positive)
Cluster 1	GDP per capita	−0.31 (moderate negative)
	Global Innovation Index	0.77 (high positive)
Cluster 2	GDP per capita	0.08 (very low positive)
	Global Innovation Index	0.48 (moderate positive)
Cluster 3	GDP per capita	−0.58 (moderate negative)
	Global Innovation Index	0.81 (very strong positive)

Source: own calculations.

We calculated the correlation within each cluster to analyse the interdependence between AF per capita and other indicators. This allows us to determine how strongly these variables are related within each cluster. The results are presented in Table 8.

The correlation between AF per capita and the Global Innovation Index is steadily positive, though its strength varies. Digital investment is essential for innovations, regardless of economic development. In Cluster 0, the correlation between AF per capita and GDP per capita is very low and positive, whereas in Cluster 2 it is moderately negative, and in Clusters 1 and 3 it is moderately negative. Such findings indicate the critical role of innovation in raising AF across diverse economic contexts. The correlation between AF per capita and GDP per capita is positive in Cluster 0 and very low in Cluster 2. In clusters 1 and 3, it is moderately negative. So, these findings show the critical role of innovation in fostering AF across diverse economic contexts.

4. Discussion

The results have allowed us to discuss the implementation of the proposed hypotheses.

Hypothesis 1: The volume of AF is directly influenced by the level of its economic development. This hypothesis needed to be fully substantiated. The regression equation suggests that GDP per capita does not affect AF levels, contradicting earlier research by (Bilan et al., 2019), which identified a strong correlation between GDP and the volume of AF in a country. Additionally, the study by Zhang et al. (2016) argued that AF is a source of economic growth. Although we did not confirm a strong influence of economic development on the state of AF, we can assert a limited positive effect. This can be explained by the fact that, unlike previous studies, our research included only EU countries characterised by high levels of development and convergence (Lyzun et al., 2023). Other scholars analysed countries across different continents and with varying levels of economic growth, sometimes with limited access to banking financing. So, AF had a more substantial impact on the population's well-being in those instances. However, some studies, for example, Bednarz et al. (2017), have demonstrated no discernible correlation between a country's GDP per capita and online AF. A nation's wealth is independent of individuals' inclination to invest funds through online platforms. Instead, countries with average levels of prosperity exhibit a broader adoption of AF.

Hypothesis 2: The volume of AF is directly influenced by the level of a country's innovativeness. We confirmed this hypothesis, which is understandable, as innovative development is the primary cause of emerging technologies utilised in A. Paslari (2023)

obtained similar results and confirmed a positive and statistically significant correlation between the development of information technology and the amount of alternative funding per capita. Bilan et al. (2019) also confirmed that the volume of AF depends directly on a country's level of innovation.

Hypothesis 3: The volume of AF is directly influenced by the country's level of digitalisation. Nearly all economic and financial processes depend, directly or indirectly, on various digital technologies. In turn, digital technologies provide enterprises additional opportunities to attract external financing, including through digital lending and platform-based finance (Abbasi et al., 2021; Cornelli et al., 2023). Our study suggests that the marginal effect of digitalisation may be weaker in the EU because baseline levels of digitalisation across European countries are already relatively high, and the scaling gains from digital platforms can exhibit diminishing returns as markets mature (Cornelli et al., 2023; Estrin et al., 2024). The EU's regulatory framework for financial services is characterised by a high degree of harmonisation. At the same time, fragmented national rules have been identified as a barrier for crowdfunding market development and cross-border scaling, motivating harmonisation efforts (Cicchello, 2020). Another reason is market maturity and AF penetration. The relatively early adoption of AF methods, such as crowdfunding and P2P lending, means that the incremental impact of further digitisation might be less noticeable than in emerging markets (Oh, Rosenkranz, 2022).

The non-significance of DESI in the fixed-effects model is a notable and counterintuitive result. A plausible explanation is that DESI overlaps with broader innovation capacity, so its incremental contribution becomes limited once innovation outcomes are controlled for (Duarte, Carvalho, 2024). In addition, saturation effects may operate in digitally mature EU economies. Prior evidence suggests that the effect of digitalisation may be non-linear, with diminishing marginal returns once a certain level of digital maturity is reached (Capelleras et al., 2025). Measurement is also relevant. DESI is a broad composite benchmark of digital readiness rather than a direct proxy for FinTech or platform finance adoption, and its aggregation structure can affect its explanatory power when used as a single regressor (Bruno et al., 2023; Ionaşcu et al., 2023; Olczyk, Kuc-Czarnecka, 2022). While our multicollinearity diagnostics do not indicate severe collinearity, moderate correlation among composite indices can still reduce precision and render incremental effects statistically indistinguishable in finite samples (Dormann et al., 2013). Future work can strengthen identification by using DESI sub-dimensions, lagged digitalisation measures, or FinTech-specific indicators of platform usage.

Hypothesis 4: We found that the size of AF has changed due to the influence of the country's laws and regulatory acts. So, we have received a result confirming a negative relationship between the Index of Economic Freedom (IEF) and AF per capita (AF). However, it is also important to note that the relationship between economic freedom and AF is not linear and can be influenced by factors such as technological infrastructure, cultural attitudes towards entrepreneurship and risk, and overall economic development (Mollick, 2014). A country may have high economic freedom but limited digital capital-raising activity if it needs the necessary technological infrastructure or cultural norms that support entrepreneurial ventures. Financial freedom can enhance a country's integration into global capital markets, providing businesses with broader access to capital, including digital forms.

The negative coefficient on the Index of Economic Freedom (IEF) should be interpreted as capturing a broad, economy-wide institutional environment rather than AF regulation per se. In more economically free settings, conventional finance can be deeper and cheaper, which may reduce the relative demand for alternatives by substituting into bank credit and established capital-market channels (Nguyen et al., 2025). By contrast, the scaling of platform-based finance depends more directly on targeted FinTech and AF-specific rules, including regulatory clarity for platforms, investor protection, disclosure standards, and cross-border operability. Evidence shows that regulatory clarity and the design of specialised rules can materially expand digital financing activity, including crowdfunding markets (Cicchiello, 2020; Kuk, Laidroo, 2020; Ran et al., 2025).

Cluster analysis provides information that can inform development strategies. Each cluster demonstrates unique economic, innovation, and digital growth models, requiring policymakers to develop tailored measures for each.

To make these implications more operational for AF, cluster-level recommendations can be linked to specific AF instruments, particularly crowdfunding (reward, equity, and debt-based models) and P2P/platform lending. These instruments respond to different combinations of digital infrastructure, investor participation, and targeted regulatory design (Cicchiello, 2020; Mollick, 2014; Ran et al., 2025). Table 9 summarises cluster-specific AF policy priorities. Clusters 1 and 3 are single-country clusters and should be interpreted as country-specific policy cases rather than group averages.

Table 9. Cluster-specific AF policy priorities and instruments

Cluster	Priority AF instruments	Targeted policy levers
0	Reward and equity crowdfunding	Invest in digital infrastructure; invest in physical infrastructure; expand digital skills programmes. Increase R&D, provide start-up incentives, sustain innovation institutions, and support regional innovation initiatives. Implement proportional crowdfunding rules, standardised disclosure, and baseline investor protection; strengthen digital onboarding and payments
1	P2P lending and debt crowdfunding	Build a clear regulatory framework that enables platform scaling and cross-border reach. Strengthen conduct supervision, risk and default transparency, consumer protection, data governance, and platform resilience
2	Equity and debt crowdfunding; platform lending	Maintain innovation and digital competitiveness; promote cross-industry collaboration to amplify the impact of innovation. Enhance regulatory clarity, harmonised investor protection, and standardised reporting to support platform scaling and cross-border operability
3	Advanced high-volume platform finance	Prioritise workforce education and training to ensure inclusive participation. Strengthen system-level oversight (disclosure, auditing, market integrity, platform-lending risk monitoring) and cross-border safeguards as volumes grow

Source: own elaboration.

Studying AF development in the EU is an important research area; however, as with any scholarly inquiry, it is not without limitations. They are the following:

1. The quality and accessibility of data constitute one of the primary constraints of the conducted panel data analysis. During this study, we used relevant, open, and available public indicators from the official statistical services of the EU, the World Bank, the European Commission, Statista, and other organisations.
2. The country's AF development is featured by only one parameter.
3. While Panel Data Analysis is a powerful tool for studying changes over time, it has limitations - it assumes that the impact of independent variables is constant over time, which may not be the case. Additionally, essential variables may have been omitted in the study.
4. Our AF measure captures formal, platform-mediated AF and excludes informal finance (e.g., family-and-friends funding, informal credit networks, and trade credit).
5. The analysis is conducted at the country level. It therefore cannot account for platform- or firm-level heterogeneity in AF, including platform design, screening, and investor behaviour, which shape crowdfunding and P2P outcomes.
6. Endogeneity between innovation and AF remains a concern. Innovation can foster AF development, while AF can also finance innovative entrepreneurship, creating a reverse-causality loop.

Conclusions

Our investigation aimed to identify the determinants of the EU AF market development. We focused on studying the EU-27 for the years 2017–2022. Our analysis encompassed datasets representing the dependent variable, reflecting AF per capita volumes, and independent variables representing the state of economic development, innovation, digitalisation, and regulatory influence. The findings from the Panel data analysis show that innovations exert the most significant direct impact on the level of AF. Simultaneously, we can observe a positive correlation between economic growth and AF – the cluster analysis segments EU countries based on economic performance, innovation levels, and AF adoption. A complex of factor interactions covering infrastructure, human capital, innovation capacity, and market integration forms economic inequalities among clusters. So, to improve the overall effectiveness of AF and digital transformation across the EU, we suggest encouraging inter-cluster collaboration. This approach would allow high-performing clusters to mentor emerging ones and share expertise in digital transformation and innovation strategies. By launching cooperative initiatives, regions can share knowledge, experience and resources to succeed mutually in growth and innovation. Innovation transfer programs, joint funding and investment initiatives, or talent mobility and exchange programs can be put in place to achieve the result.

Our findings contribute to existing knowledge on the global determinants of AF development. They can inspire future research and have implications for researchers and policymakers, emphasising the importance of digitalisation and a clear regulatory foundation for advancing AF. Moreover, several research challenges in this field must be addressed in future studies. One task involves identifying and classifying risks associated with actively developing AF, such as fraud and cybersecurity threats. Further research is required to identify other EU AF development determinants. Financial inclusion, corruption levels, population structure, and education deserve attention in this exploration. Methodologically, these questions can be strengthened by applying dynamic panel methods (e.g., system GMM) to address persistence and potential endogeneity, and by complementing an EU-wide analysis with focused country case studies, especially for the single-country clusters identified in this study.

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