DOI: https://doi.org/10.53486/cike2023.59

UDC: [336.76:004.738.5]:330.43

ALTERNATIVE FINANCE: A MODERN ECONOMETRIC EXPLORATION INTO GLOBAL TRENDS AND INFLUENCES

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Abstract. In the wake of the 2007-2008 financial crisis, the global landscape experienced the burgeoning growth of the alternative finance sector, a countermeasure to stricter banking regulations. Drawing from 2020 data across 67 countries, this study delivers a meticulous econometric analysis to unravel the intricate determinants of this industry's growth. Utilizing a comprehensive model, the research delineates the associations between alternative financial instruments and critical socio-economic indicators. An ensuing reduced model accentuates these relationships, spotlighting the significant influence of the Financial Development Index and Economic Freedom. A comparison between the two models offers deep insights, emphasizing the industry's resilience and pivotal role in global financial inclusion, particularly evident during adversities like the COVID-19 pandemic. Ultimately, this research underscores the potential of the alternative finance sector while illuminating its interplay with broader economic metrics.

Keywords: alternative finance market, digital finance, econometric analysis

JEL Classification: G23, C51, O16.

Introduction

The seismic aftermath of the 2007-2008 global financial meltdown forever changed the trajectory of the financial world. The resulting credit scarcity and economic slowdown paved the way for introspection and a pursuit for better financial frameworks. Among the significant responses was the Basel Committee's introduction of the Basel III standards in 2009, designed to bolster bank capital adequacy requirements. Such requirements inevitably made loans costlier and less accessible, especially for nascent technology ventures and innovative SMEs, both perceived as risky bets (Schueffel, 2016).

This challenging backdrop gave rise to the alternative finance industry, an unregulated economic sector, attracting initially venture capitalists and evolving to engage a more diverse set of micro-investors. With the world undergoing a digital revolution and a new phase of industrialization, businesses are continuously adapting to maintain a competitive edge. Amid this evolution, alternative finance has grown into an indispensable tool, facilitating funds for consumers and small to medium-sized enterprises, energizing local economies, and backing socially impactful projects (Haddad and Hornuf, 2019).

Enhanced by the ubiquity of the internet, AI and big data analytics, financial inclusion is becoming more of a reality, broadening access to affordable, convenient financial services (Claessens *et al.*, 2018). The alternative finance sector, though still a fraction of the vast lending landscape, is reshaping the capital interaction dynamics on a global scale. It promises numerous benefits like remote transaction capabilities, portfolio diversification, and lower transactional fees due to automation (Boot and Thakor, 2017).

As the global economy has grown more interconnected and digitalized, the market for alternative financing solutions has shown a consistent expansion trajectory. This expansion extends beyond traditional banking, with even established financial institutions tapping into these new avenues. Moreover, the world's current health and economic challenges, as seen during the COVID-19 pandemic, have further underscored the importance of digital financial services. The pandemic's restrictive nature catalysed interest in novel financial areas, particularly in the realms of cryptocurrency and digital assets.

Exploration of the international alternative finance landscape

By 2020, the global alternative finance market achieved a valuation of $114 billion USD (Figure 1). When delineating the global market shares, the United States and Canada were at the forefront with $73.93 billion, trailed by the UK with $12.64 billion, and the rest of Europe (excluding the UK) tallying at $10.12 billion. It's imperative to reflect upon 2017 when the global market scaled to its zenith at $419 billion. China remarkably accounted for 85% of global transactions during this period, relegating Europe to just 2.8%. China's leadership in the global online alternative finance market extended until 2018. However, due to indigenous market realignments and stringent regulatory reforms, its share diminished sharply to 1% by 2020. Notably, China's P2P lending ecosystem burgeoned from 2011 to 2015. Yet, shadows loomed as, in 2016, the China Banking Regulatory Commission unveiled that nearly 40% of these platforms were embroiled in scams. This revelation prompted regulatory rigidity, causing over half of these platforms to cease operations.

The global online alternative finance market, excluding China, displayed a persistent growth over the previous five years, with volumes escalating by 51% from $44 billion in 2015 to $91 billion in 2019. Mirroring this momentum, 2020, despite pandemic-induced headwinds, saw the global volume surging by an additional 24% year-on-year, touching $113 billion.

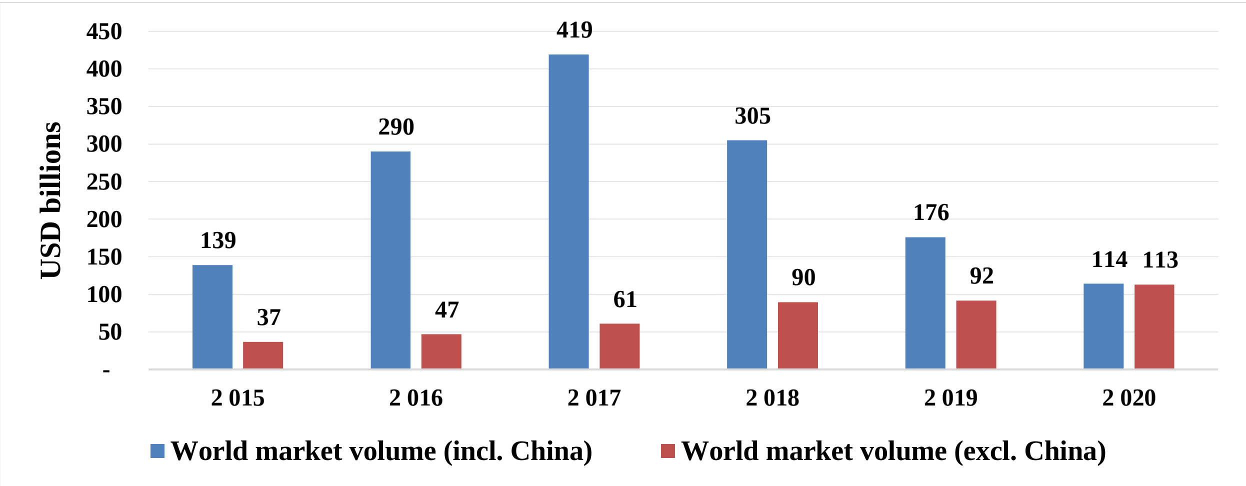

Figure 1 Global alternative finance market volume and growth, 2015-2020
Source: developed by the author based on (Ziegler *et al.*, 2021)

Econometric analysis of the factors driving the development of the market for alternative financial instruments

In this chapter, we endeavor to uncover the intricate interrelationships between the market volume of alternative financial instruments and several pivotal socio-economic variables across a diverse range of nations.

Empirical framework, data, and methodology

The research is anchored in an empirical investigation, with the analysis built on observed and measured phenomena derived from actual data. In this section, we delve deeper into the specifics of the data, highlighting the source, nature, and the methodology employed.

Data description and source.

The dataset is cross-sectional, encapsulating data from 67 diverse countries, offering an encompassing perspective on the global landscape of the alternative financial market for the year 2020 (latest data available). Each observation in the dataset represents a specific country, capturing a snapshot for that year, which allows for drawing meaningful patterns and insights across varying socio-economic frameworks.

-Alternative Financial Market Cap (*AFMcap*)*:* Representing our dependent variable, it quantifies the market volume of alternative financial instruments *per capita* for each nation. This data was primarily extracted from the Global Financial Development Database, a comprehensive source managed by the World Bank.

- Financial Development Index (*FDI*): Capturing the intricacies of the financial ecosystems of nations by depicting the depth, access, and efficiency of financial institutions and markets. This metric was sourced from the International Financial Statistics provided by the International Monetary Fund.

- Global Innovation Index (*GII*): An index highlighting the innovation performance of nations, its data is the culmination of joint efforts by Cornell University, INSEAD, and the World Intellectual Property Organization.

- Economic Freedom Index (*ECF*)*:* Serving as an indicator of the economic liberties exercised in nations, it's based on metrics like business freedom, trade freedom, and fiscal freedom, among others. The dataset for this was curated by the Heritage Foundation.

- Social Capital Index (*Social*): A reflection of the levels of social cohesion and mutual trust among the citizens of a nation. The data for this index was extracted from the World Values Survey.

Methodological approach.

For the sake of ensuring precision and capturing the nuanced relationships between variables, the data was log-transformed with the socep of mitigating potential heteroscedasticity, ensuring that the variance of the residuals remains consistent across levels of the independent variables. Moreover, the log transformation helps address non-linearity and captures exponential relationships more effectively.

The choice of variables wasn't arbitrary. Based on a careful review of existing literature, their presumed significance, and the availability of credible data, these variables were chosen. The intention was to craft a model that provides a panoramic view of the forces and factors shaping the market for alternative financial instruments across the 67 nations.

Econometric tools and software employed

In order to derive meaningful interpretations and insights from the collected data, it was imperative to utilize advanced econometric tools and techniques. This section delves into the specific software packages and functions employed throughout the analysis.

Software and packages.

The mainstay of our analysis was the R programming environment, a powerful and robust tool for statistical computing and graphics. R's extensive library support and its ability to handle complex data structures make it an ideal choice for econometric research.
Specific R packages that were instrumental in our analysis include:
- *stats*: A core R package, it provided the fundamental functions to run linear regressions and ANOVA tests, vital to our full and reduced models' analyses.
- *lmtest*: This package facilitated various tests on linear regression models, helping in the diagnosis and refinement of our econometric models.
- *car*: Companion to Applied Regression, or `car`, offered additional diagnostic tools. Functions from this package were crucial in testing assumptions and identifying potential issues with the regression models.

Functions and techniques:

1. Linear Regression: At the heart of our analysis was the linear regression function. It allowed us to ascertain relationships between our dependent variable (*AFMcap*) and multiple independent variables, producing both the full and reduced models.
2. ANOVA: The Analysis of Variance technique was employed to compare the variance between our full and reduced models. It provided clarity on the significance of each model and its individual predictors.
3. AIC & BIC functions: The Akaike Information Criterion and the Bayesian Information Criterion functions were utilized to evaluate the relative quality of the models. By penalizing model complexity, they offer a more holistic gauge on the preferred model.
4. Residual Analysis: Residual plots and tests for normality were executed to ensure the assumptions of linear regression were met.

By utilizing a combination of these tools and functions in R, we were able to dissect the data, ensuring rigorous, reliable, and reproducible results. The choice of tools was guided by the specific needs of our research and the nature of the data, ensuring that the techniques employed provided maximum clarity and insight into the relationships between our chosen variables.

Comprehensive analysis of the full model

The full econometric model was conceived to capture the depth and intricacy of the relationship between the volume of the market for alternative financial instruments (*AFMcap*) and the selected socio-economic indicators. This model can be succinctly represented as:

$$\log(AFM_{CAP}) = \alpha + \beta * \log(FDI) + \gamma * \log(GII) + \delta * \log(ECF) + \zeta * \log(SOCIAL) + \varepsilon \quad (1)$$

Where:
- $\boldsymbol{\alpha}$ is the intercept
- $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}$ and $\boldsymbol{\zeta}$ are the coefficients of the respective independent variables
- $\boldsymbol{\varepsilon}$ represents the error term

Given the processed data (Table 1), the estimated equation based on the full model is:

$$AFMcap = -17.4064 + 1.1544(\mathrm{FDI}) + 1.7192(\mathrm{GII}) + 7.2318(\mathrm{ECF}) + 1.0987(\mathrm{Social}) \quad (2)$$

Table 1 Full model analysis

Residuals	Min	1Q	Median	3Q
	-1.19675	-0.50049	-0.00388	0.41218
Coefficients	Estimate	Std. Error	t value	Pr(>t)
Intercept	-17.4064	3.2258	-5.396	1.18e-06***
FDI	1.1544	0.5426	2.128	| 0.037411*
GII	1.7192	1.0962	1.568	0.121975
ECF	7.2318	1.8668	3.874	0.000264***
SOCIAL	1.0987	1.2391	0.887	0.378709
Residual std. error	0.5978 on 61 degrees of freedom			
Multiple R-squared	0.406			
Adjusted R-squared	0.3671			
F-statistic	10.42 on 4 and 61 DF			
p-value	1.685e-06			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Source: calculations made by author using R software

Let's delve deeper into the significance and implications of these coefficients:
- *Intercept* (-17.4064): This value depicts the predicted volume of *AFMcap* when all other predictors are at zero. While this doesn't necessarily hold a contextual meaning due to the improbability of all predictors being zero, it serves as a baseline for our model.
- *FDI* (1.1544): The coefficient suggests that for every one unit increase in the Financial Development Index (FDI), the *AFMcap* is expected to increase by 1.1544 units, holding all else constant. This relationship is statistically significant at the 0.05 level.
- *GII* (1.7192): This coefficient indicates a positive relationship between the Global Innovation Index and *AFMcap*. For every unit increase in *GII, AFMcap* increases by about 1.7192 units. However, this association is not statistically significant at conventional levels.
- *ECF* (7.2318): Evidently the most influential predictor among the lot, every unit increase in the Economic Freedom Index (ECF) corresponds to a substantial 7.2318 units increase in *AFMcap*, with this being statistically significant at the 0.001 level.
- *Social* (1.0987): The coefficient indicates that for every unit increase in Social Capital Index, the *AFMcap* increases by 1.0987 units. Nonetheless, this variable's impact is not statistically significant in this full model framework.

The overall model fit, with an R^2 of 0.406, indicates that the full model explains approximately 40.6% of the variance in *AFMcap*. While this is a moderate fit, the implications of each variable and their significance need to be viewed through the broader lens of the research context, as explored in subsequent sections.

Residual Standard Error: This is a measure of the variability of the residuals. It's 0.5978, which means that, on average, the predictions of the model are about 0.5978 units away from the actual values of AFMcap.

F-statistic: It tests the hypothesis that all regression coefficients are equal to zero, meaning no linear relationship exists between predictors and the dependent variable. The F-statistic is 10.42 with a very low p-value (1.685e-06), suggesting that at least one predictor variable is statistically significant.

To sum it up, FDI and ECF have a statistically significant effect on AFMcap at the 0.05 significance level. The variable ECF has the strongest effect. However, GII and Social are not statistically significant in this model.

Introduction of the Reduced Model

In the pursuit of achieving a more parsimonious and possibly more predictive model, we introduced a reduced model that eliminates some of the variables from the full model. This streamlined model focuses on the most significant predictors based on statistical evidence and domain understanding. The reduced model can be expressed as:

$$\log(AFM_{CAP}) = \alpha + \beta * \log(FDI) + \delta * \log(ECF) + \varepsilon \qquad (3)$$

Where:
-**α** is the intercept.
- **β and δ** are the coefficients of the respective independent variables.
- **ε** represents the error term.
Utilizing the gathered data, the equation derived from the reduced model is:

$$AFMcap = -16.0809 + 0.4311(\mathrm{FDI}) + 9.1852(\mathrm{ECF}) \qquad (4)$$

Let's decipher the significance and meaning of these coefficients (Table 2):

Table 2 Full model analysis

Residuals	Min	1Q	Median	3Q
	-1.27254	-0.41597	-0.05811	0.40127
Coefficients	Estimate	Std. Error	t value	Pr(>t)
Intercept	-16.0809	2.9492	-5.453	8.83e-07***
FDI	0.4311	0.3889	1.109	0.272
ECF	9.1852	1.5692	5.854	1.88e-07***
Residual std. error	0.6054 on 63 degrees of freedom			
Multiple R-squared	0.3709			
Adjusted R-squared	0.3509			
F-statistic	18.57 on 2 and 63 DF			
p-value	4.568e-07			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Source: calculations made by author using R software

- *Intercept* (-16.0809): This represents the expected value of *AFMcap* when both *FDI* and *ECF* are zero. As with the full model, this is more of a baseline value and might not have substantial practical implications.
- *FDI* (0.4311): For every one unit rise in the FDI, the *AFMcap* is expected to increase by 0.4311 units, keeping everything else constant. However, it's noteworthy that in this reduced model, the relationship is not statistically significant at traditional significance levels, showing a p-value of 0.272.
- *ECF* (9.1852): The coefficient for the *ECF* suggests a potent relationship. Each unit increase in ECF leads to an increase of 9.1852 units in *AFMcap*. This relationship remains statistically significant at the 0.001 level, just as it was in the full model.

The model's R-squared of 0.3709 suggests that around 37.09% of the variability in the AFMcap can be explained by the model. While this may not seem exceedingly high, it is reasonable for many real-world scenarios and stresses the importance of ECF in explaining AFMcap's variance.

The F-statistic tests the overall significance of the model. A value of 18.57 at a very low p-value (4.568e-07) strongly rejects the null hypothesis that all coefficients (except the intercept) are equal to zero. This implies that the predictors used in the model are statistically relevant in forecasting the response variable, AFMcap.

In summary, the reduced model emphasizes the paramount importance ECF in determining the capitalization of the Alternative Finance Market. While the Financial Development Index is an integral facet of financial progression, in this model, it doesn't have a significant direct correlation with AFMcap.

Comparative Analysis: Full Model vs. Reduced Model

The process of model selection often necessitates a comparison of various models to discern which among them provides the best explanatory power while balancing simplicity. In this section, we shall appose the Full Model against the Reduced Model to discern their relative merits and limitations.

In the Full Model, both *FDI* and *ECF* emerged as statistically significant predictors. *GII* and *Social*, despite being included, didn't manifest significant effects. On the contrary, in the Reduced Model, while *ECF* maintained its statistical importance, *FDI* lost some of its statistical significance, indicating that it might be influenced by the presence of other variables in the Full Model.

Table 3 Model Fit and Predictive Power

	Full Model	Reduced Model
R^2	0.406	0.3709
Adjusted R^2	0.3671	0.3509

Source: calculations made by author using R software

While the Full Model (Table 3) explains about 40.6% of the variance in *AFMcap*, the Reduced Model accounts for approximately 37.09%. The adjusted R^2 values, which account for the number of predictors, are quite close for both models. This implies that despite the Reduced Model having fewer predictors, its explanatory power isn't vastly diminished compared to the Full Model.

Model Selection Criteria (Table 4). The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are pivotal tools for model comparison. Typically, lower values suggest better-fitting models.

Table 4 Model Selection Criteria

	Full Model	Reduced Model
AIC	126.1857	125.9779
BIC	139.3237	134.7365

Source: calculations made by author using R software

The Reduced Model has slightly lower AIC and BIC values, suggesting it might be a more favorable model when considering model fit relative to complexity.

ANOVA Comparison . Using an ANOVA test, we compared the two models. The test rendered a p-value of 0.1734. This indicates that there isn't a statistically significant difference in the sum of squares between the two models, further underscoring the efficiency of the Reduced Model. The ANOVA test suggests that the reduced model, without the variables GII and Social, fits the data almost as well as the full model. Given this result and considering parsimony (i.e., simpler models are generally preferable when they perform similarly to more complex models), the reduced model seems like a reasonable choice.

Recommendations and forward path

Having rigorously examined the Full Model and Reduced Model, it's evident that our quest to understand the driving forces behind the development of the market for alternative financial instruments is layered with complexity. Herein, we offer recommendations and suggest a potential path forward based on the findings.

1. *Embracing parsimony*:

Given the minimal difference in predictive power between the Full and Reduced Models and the principle of parsimony (Occam's razor) which promotes simplicity, it's advisable to adopt the Reduced Model for subsequent studies or applications. This decision is also bolstered by its more favorable AIC and BIC values.

2. *Re-assessing the role of FDI*:

In the Full Model, FDI was significant; however, its importance diminished in the Reduced Model. This suggests potential multicollinearity or the presence of confounding factors. Further research should be undertaken to delve deeper into this relationship and discern the true impact of FDI on the alternative financial market.

3. *Expanding the dataset*:

While our current study focuses on data from 67 countries for the year 2020, broadening the analyzed period to adopt a panel data approach spanning multiple years could provide a richer understanding and capture dynamic effects.

4. *Exploring other potential variables*

The non-significance of variables like 'GII' and 'Social' in the Full Model suggests that other unexplored variables might hold importance. Continuous exploration and model refinement are essential.

5. *Policy implications*:
For policymakers and stakeholders in the alternative financial market, the prominence of ECF underscores the need to foster an environment conducive to entrepreneurial activities. Policies that ease access to capital for startups, facilitate technological advancements, and ensure a robust regulatory framework can further invigorate the growth of alternative financial instruments.

Our analysis of the determinants of the market for alternative financial instruments has paved the way for intriguing insights and raised new questions. While the Reduced Model emerges as a frontrunner, continuous refinement, and adaptation, rooted in both quantitative and qualitative paradigms, will be the cornerstone of future success in this realm.

Conclusion

The exploration into the realms of alternative financial instruments offers invaluable insights. Both models are instrumental in delineating the underlying relationships, but the reduced model emerges slightly more pragmatic. As we progress, these empirical findings can form the bedrock for future research and policy considerations in the sphere of alternative finance.
The full model of our study in Chapter 2 underscored the interplay of pivotal socio-economic variables, with FDI, GII, ECF, and Social metrics taking center stage. Our findings resonate with the premise that alternative finance is not a standalone construct but one that's deeply intertwined with global economic and social paradigms.

Introduction of the reduced model, with a narrowed focus on FDI and ECF, reiterated that while many variables can influence a market, it is often a select few that drive the lion's share of the impact. While the full model offers breadth, capturing a wide array of influencing factors, the reduced model offers depth, zeroing in on the most potent drivers. This balance between breadth and depth is critical for both academia and industry, ensuring that decisions are both holistic and targeted.

Based on our empirical examination the alternative finance sector's potential is vast, but realizing it necessitates a calibrated approach. Policymakers and industry leaders would benefit from regular econometric analyses, ensuring that decisions are data-driven and cognizant of shifting global dynamics.

As we conclude our exploration, we're left with a profound appreciation of the complexity and promise of alternative finance. It stands as a beacon of modern financial ingenuity, and our study is a humble nod to its vast potential. The journey of understanding this sector is ongoing, and as more data unfolds, the narrative will only get richer.

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