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Research article

Does one size fit all? Comparing the determinants of the FinTech market segments expansion

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A B S T R A C T

The paper aims to indentify and compare the determinants of the overall FinTech market expansion and its major segments – cryptocurrency and peer-to-peer lending markets – in a dataset, which covers 64 countries and 51 potentially relevant factors. To this end, we apply a battery of state-of-the-art variable selection techniques from machine learning, comprising Bayesian model averaging (BMA), least absolute shrinkage and selection operator (LASSO), variable selection using random forests (VSURF) as well as spike-and-slab regression. We document substantial heterogeneity of the pivotal determinants across the FinTech market as a whole and its major segments. Thus, specific rather than general policy measures are needed to foster the development of standalone FinTech market segments. Moreover, our findings suggest that most countries don't need to seek a universal specialization in FinTech activities, concentrating on the segment where they have a competitive edge in terms of the pivotal determinants which drive its expansion.

1. Introduction

FinTech has turned into the new buzzword in the financial literature over the recent years. This is a multi-faceted phenomenon, which revolutionizes the design and functioning of financial systems. Although there is no conventional definition of FinTech, the most authoritative scholarly studies concur that it encompasses innovations in payments (including cryptocurrencies), capital-raising activities (with a particular focus on peer-to-peer lending), investment management services (including robo-investing), and insurance services associated with Blockchain-assisted smart contracts (Goldstein et al., 2019; Thakor, 2020). Most of these FinTech market segments have spread and entrenched worldwide, demonstrating double-digit growth rates in many jurisdictions.

Against this backdrop, FinTech-related research naturally appears one of the fastest emerging research programs in finance. Nonetheless, not all research questions within this program have so far received sufficient attention. For instance, there are relatively few studies seeking to identify the driving forces of FinTech development in a cross-country framework.[1] Haddad and Hornuf (2019), Kowalewski and Pisany (2020) as well as Sahay et al. (2020) investigate economic and technological determinants of FinTech without distinguishing between its segments. Saiedi et al. (2021) focus on the factors of cryptocurrency adoption, while Claessens et al. (2018),

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[1] Frost (2020) surveys the economic factors driving FinTech adoption across countries, but his paper is not confined to the results from the cross-country research, also building on single-country, firm-level and regional studies.

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Bazarbash and Beaton (2020) as well as Oh and Rosenkranz (2020) examine the determinants of peer-to-peer lending expansion. An et al. (2022) investigate the historical determinants of FinTech development, focusing on ICOs.

In this paper, we tackle the determinants of FinTech development in a cross-country framework from a more nuanced angle by investigating whether they differ in case of the key FinTech market segments – cryptocurrencies and peer-to-peer lending – from those found for the FinTech market as a whole.[2] To our knowledge, this is a novel research question in the FinTech literature with a clear-cut policy implication. Based on our findings, we seek to inform policymakers if measures aimed at promoting (or deterring) financial innovation should be segment-specific or the measures relevant for the overall FinTech market equally apply to its two major segments. This policy implication has become particularly relevant in light of the COVID-19 pandemic, which significantly accelerated the FinTech adoption across countries (Fu and Mishra, 2020).

To conduct such research, we consider a sample of 64 countries and adopt three proxies of FinTech development, namely: (i) a country score in the Global FinTech Index released by Findexable, a private analytical platform, and accounting for the overall FinTech market development; (ii) a country score in the ranking provided by Cointobuy.io, a crypto analysis platform, and capturing the degree of crypto-friendliness; (iii) the volume of peer-to-peer lending, borrowed from the Cambridge Centre for Alternative Finance. The proxies of the overall FinTech market development and that of its cryptocurrency segment refer to the year 2019, whereas the volume of peer-to-peer lending is for the year 2018. We compile a dataset comprising 51 potential determinants of the three proxies, based on earlier research findings and our heuristic considerations. They are averaged across the period 2014–2018 and gauge various institutional, social, structural, macroeconomic and financial factors which may underlie the FinTech expansion.

Since our goal is to identify the most salient determinants of each of the FinTech proxies and juxtapose them, we opt for a battery of variable selection algorithms from machine learning (ML): Bayesian model averaging (BMA), least absolute shrinkage and selection operator (LASSO), variable selection using random forests (VSURF) as well as spike-and-slab regression. These are state-of-the-art ML methods for variable selection, which outperform standard cross-country regressions by addressing model uncertainty and multicollinearity issues more efficiently. All the algorithms apply to each proxy of FinTech development.

We document that, regardless of the variable selection methods used, the number of statistically significant determinants is larger for the overall index of FinTech market development compared to the cryptocurrency and peer-to-peer lending segments. Identified by all the methods, the country rank in the Global Innovation Index (GII) appears the first-tier determinant of the overall FinTech market development. Less robust determinants revealed by at least two methods include the number of fixed and mobile phone subscriptions, financial market depth, UK legal origin, and labor force. However, we find limited commonality between statistically significant determinants of the three FinTech development proxies. For instance, among 13 determinants relevant for the overall index of FinTech market development and identified by at least one of the algorithms only 4 variables contribute to the expansion of the cryptocurrency and/or peer-to-peer lending segments. Besides, the determinants of the cryptocurrency segment are almost completely different from those found for the overall FinTech market development and the peer-to-peer lending segment. The only exception is the number of mobile phone subscriptions, which promotes both the overall FinTech market development and the cryptocurrency segment.

Overall, our analysis indicates that the determinants of the FinTech market expansion are quite heterogeneous, conditional on its key segments considered. This result calls for targeted rather than uniform policy measures to support (or to deter) the FinTech market development. Our estimations suggest that, as shown above, a wider range of factors (institutional, structural, macroeconomic and financial) determines the FinTech market development as a whole. Macroeconomic and financial factors drive the expansion of its cryptocurrency segment, while peer-to-peer lending is mainly boosted by macroeconomic and structural variables. In case of the cryptocurrency segment, the most salient variables are the KOF globalization index, capturing trade and financial openness, and the share of adult population with an account at formal financial institutions, capturing financial inclusion. As regards the peer-to-peer lending segment, its expansion is driven by the number of fixed phone subscriptions and labor force.

The diversity of determinants which we document also means that it can be problematic for most countries to excel in all FinTech activities. Thus, they should specialize in a particular segment where they have a competitive edge in terms of the pivotal determinants boosting this segment.

The remainder of the paper is as follows. Section 2 describes the data. Section 3 introduces the variable selection methods. Section 4 presents and discusses the results, while Section 5 concludes.

2. Data

It is not straightforward to measure FinTech market development as a whole and its segments across countries. There is no generally accepted data source, while ad hoc market reports published by leading consulting companies usually focus on a limited number of countries.[3] In this study, we use country scores from the 2020 Global FinTech Index to capture the overall FinTech market development.

[2] Based on https://coinmarketcap.com/, the overall cryptocurrency market capitalization is around 800 bln US dollars, as of December 2022, while the size of global peer-to-peer lending market is estimated at 572 bln US dollars for 2019, according to Cornelli et al. (2020). Both indicators outperform the size of FinTech investment management (350 bln US dollars, according to the Aite Group) and insurance services (6.3 bln US dollars, according to the 2020 Insurtech Global Outlook (https://insurtechnttdata.everis.com/ReportIntroENPage). The cryptocurrency and peer-to-peer lending segments also tend to prevail from the scientometric perspective, e.g. Liu et al. (2020) find them to be the hottest topics within the Fintech research over the past 10 years.

[3] For example, the Global FinTech Adoption Index provided by Ernst&Young only covers 27 countries. See https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/banking-and-capital-markets/ey-global-fintech-adoption-index.pdf.

The index (FINDEX) is constructed by an analytical startup Findexable. It is based on proprietary data coming from *Crunchbase* and other data providers partnering with *Findexable*. The FINDEX was constructed to score the overall fintech environment and, thus, it aggregates information on three dimensions of the Fintech industry. First, it considers the size of fintech companies and supporting structures (in the sample observed by FINDEXABLE there are companies of all sizes from small start-ups in African and Asian countries to well-established corporations, like TenX, Stripe or Coinbase). Second, it takes into account performance of the fintech sector, measured by growth rates of the fintech companies, number of investment events, value generation, the scale of the customer-base and web presence. Finally, it considers the overall "friendliness" of the business environment in relation to fintechs, including ease of doing business, regulation and other parameters.[4]

The level of cryptocurrency segment development is assessed on the basis of the country scores from the ranking provided by *Cointobuy.io*, a crypto analysis platform. This ranking (COIN_RANK) is a composite measure of a country's crypto-friendliness, which synthesizes the regulatory stance on Bitcoin (legal, illegal or controversial), the number of conducted and banned initial coin offerings (ICO), the number of cryptocurrency exchanges and public opinion on the crypto environment in the country.[5] To capture the development of peer-to-peer lending segment (P2P), we rely on the market size estimations for the year 2018 by the Cambridge Centre for Alternative Finance (Global Alternative Finance Market Benchmarking Report, 2020). The three proxies of FinTech development are available for a different number of countries, enabling us to compile a common sample of 64 countries, which are enlisted in the Appendix (Table A1). It is noteworthy that the proxies are not tightly correlated, which additionally legitimizes our comparative study of their determinants (Table 1).

The choice of potential determinants rests on two considerations. First, we exploit the statistically significant variables from the cross-country studies on FinTech adoption mentioned in Section 1. For example, we use the number of secure internet servers, the number of mobile phone subscriptions, labor force, GDP per capita, which are found statistically significant by Haddad and Hornuf (2019). Following Kowalewski and Pisany (2020), a number of variables accounting for institutional quality and demography are added. Second, we extend this core list of variables by adding factors which are used in the adjacent literatures on financial and technological innovations.[6] Overall, we obtain 51 potential determinants of the FinTech market development as a whole and its key segments. They are heuristically divided into five categories, comprising institutional, social, structural, macroeconomic and financial variables.

Both the proxies of the FinTech development and their potential determinants are standardized to have the mean equal to zero and the standard deviation set to one. Their detailed data sources, descriptive statistics and cross-correlations are reported in Appendix (Tables A2, A3, Figure A1). Below we provide the list of potential determinants, just giving their official names and acronyms used in the paper to facilitate the discussion of results (Table 2).

3. Methodology

Our dataset encompasses a large number of independent variables. Thus, standard methods for variable selection, e.g. stepwise inclusion or deletion of regressors are not computationally efficient, creating uncertainty about the best model. To address the problem, we adopt a battery of techniques from machine learning (ML): the Bayesian model averaging technique (BMA), least absolute shrinkage and selection operator (LASSO), variable selection using random forests (VSURF) as well as spike- and-slab regression, which are feasible algorithms for variable selection in such data-rich environment. Varian (2014) as well as Athey and Imbens (2019) promote a more extensive use of these methods to ameliorate model uncertainty and multicollinearity issues in economics and finance.[7] All the algorithms apply to each proxy of FinTech development. Based on the coincident results from these techniques, we identify the most robust determinants of the FinTech market segments expansion.

Below we provide a brief and largely non-technical overview of these algorithms.

3.1. BMA

The BMA seeks to resolve the model uncertainty by averaging over the best models in the model class based on approximate posterior model probability. The general set-up of the BMA is given in Equation (1):

[4] See http://www.fintechmundi.com/wp-content/uploads/2019/12/Findexable_Global-Fintech-Rankings-2020.pdf for further details.

[5] See https://cointobuy.io/countries for details.

[6] For example, we add such variables as international migrant stock and the share of urban population, which are found to matter for ICT and financial innovations (Fassio et al., 2019; Krüger and Rhiel, 2016; Shahbaz et al., 2018), but are usually not on the front of these literatures.We also use aggregate indicators of countries' innovation capacity and the level of digitalization – the GII index and the DAI index. By construction, the GII consists of the two sub-indices, the innovation input subindex and the innovation output subindex. The former comprises variables related to institutions' quality, human capital, infrastructure, market and business sophistication. The latter is based on the indices of knowledge creation and diffusion as well as variables related to producing creative goods and services. The DAI measures adoption of digital technologies across three dimensions: country's population, government, and business. The population DAI sub-index focuses on mobile and internet access at home among population, as derived from Gallup World Poll. The business DAI is based on the following variables: the share of firms with websites, the number of secure servers, download speed and 3G coverage. The Government DAI aggregates information on core administrative systems, online public services, and digital identification.

[7] Regarding FinTech-related research, for example, Kowalewski and Pisany (2020) apply ML variable selection methods to identify the potential predictors of FinTech development as a whole, while Stolbov and Shchepeleva (2020) adopt such methods to predict the legal status of cryptocurrencies across countries. Yet, the number of ML methods in both studies is less than in the present research (2 and 3, respectively) and none of them builds on spike-and-slab regression.

Table 1
Correlation matrix for the proxies of the FinTech market segments development.

	FINDEX	COIN_RANK	P2P
FINDEX	1.00		
COIN_RANK	0.47	1.00	
P2P	0.21	0.06	1.00

Table 2
Potential determinants of the proxies of the FinTech market segments development.

Short Name	Full Name
Institutional variables	
POLSTAB	Political Stability and Absence of Violence
REGQ	Regulatory Quality
RULELAW	Rule of Law
GOVEFF	Government Effectiveness
VOICE	Voice and Accountability
CORRUPTION	Control of Corruption
EASEDB	Ease of Doing Business Index
LEGOR_UK	Anglo-Saxon legal origin
LEGOR_FR	French legal origin
LEGOR_GE	German legal origin
MONEY_LAUND	Major Money Laundering Jurisdictions in 2016
EFW_AREA1	Economic Freedom Index Area 1: Size of Government
EFW_AREA2	Economic Freedom Index Area 2: Legal System and Property Rights
EFW_AREA3	Economic Freedom Index Area 3: Sound Money
EFW_AREA4	Economic Freedom Index Area 4: Freedom to Trade Internationally
EFW_AREA5	Economic Freedom Index Area 5: Regulation
Social variables	
URBAN_POP	Urban population, % of total population
MIGRANT_STOCK	International migrant stock, % of population)
YOUNG_MIDDLE AGE	Population ages 15–64, % of total population)
Structural variables	
DAI	Digital Adoption index
GII	Global Innovation Index
ACCESSTOELEC	Access to electricity, % of population
INTERNET_USERS	Individuals using the Internet, % of population
ELECTRPRICE	Price of electricity, US cents per kWh)
FIXEDPHONESUB	Fixed telephone subscriptions, per 100 people)
MOBILE_SUBSCR	Mobile cellular subscriptions
SECURE_INT_SERV	Secure internet servers, per 1 mln people
Macroeconomic variables	
GDPCAP_GR	GDP per capita growth, annual %
GDPCAP	GDP per capita, current US $
CPI	Inflation, consumer prices, annual %
LABOR_FORCE	Labor force, total, mln
UNEMP	Unemployment total, % of total labor force
NATRESRENT	Total natural resources rents, % of GDP
CRISIS	Number of banking crises per country
TRADE_GDP	Trade, % of GDP
KOF	KOF Globalization Index
SHADOW_EC	Size of the shadow economy relevant to official GDP, %
Financial development variables	
FID	Financial Institutions Depth Index
FIA	Financial Instititutions Access Index
FIE	Financial Institutions Efficiency Index
FMD	Financial Markets Depth Index
FMA	Financial Markets Access Index
FME	Financial Markets Efficiency Index
5BANKAS_CONC	5-Bank Asset Concentration
NPL	Bank nonperforming loans to total gross loans, %
ROA	Bank return on assets, % after tax
FINLIT	Financial literacy index
ROE	Return on equity, % after tax
BANKINTMARG	Bank net interest margin, %
ACATFORMALINST	Account at a formal financial institution, %, age 15+
Z-SCORE	Bank Z-score

$$\Pr(Y|S) = \sum_{k \in B} \Pr(Y = 1|S, M_k)^* \Pr\ (M_k|S) \tag{1}$$

where $\Pr(Y|S)$ is a posterior probability of the response variable Y given the training data set S, $\Pr(Y|S, M_k)$ is a posterior probability of Y given the training data set S and model M_k, $\Pr\ (M_k|S)$ is a posterior probability of model M_k given the training data set S. Summing is over a set of models M_k for k in B, where B is a set of indices. The output of most BMA procedures involves a ranking of independent variables based on their posterior inclusion probability (PIP) into the "true" model.[8] The variables characterized by the PIP value exceeding 50% (0.5) are to be included into such model. Besides, the BMA output comprises the expected value (EV) of the regression coefficient for each independent variable and its standard deviation (SD).

3.2. LASSO

LASSO is a regression analysis technique, which jointly carries out variable selection and regularization to improve the prediction accuracy of the model it generates. Let us consider a multivariate regression model predicting y_t as a linear function of a constant, b_0, and N regressors. The coefficients for these regressors $(b_1, \ldots, b_N)$ can be chosen by minimizing the sum of squared residuals plus a penalty term in the following form:

$$\gamma \sum_{N=1}^{N} \left[(1-\alpha)|b_N| + \alpha |b_N|^2 \right] \tag{2}$$

If there is no penalty term, i.e. $\gamma = 0$, this is a standard OLS estimator; if $\alpha = 1$, it boils down to a ridge regression. LASSO implies the absence of the quadratic term in expression (2), i.e. $\alpha = 0$. LASSO sets the coefficients of irrelevant independent variables to zero, thereby keeping only significant predictors with non-zero coefficients. However, since LASSO jointly performs a regression estimation and variable selection, it does not enable to compute standard errors for the non-zero coefficients.[9]

3.3. VSURF

VSURF is a three-step variable selection procedure based on random forests. At the first step, it removes irrelevant independent variables. The second step aims to select significant variables for interpretation purposes, while the third one ultimately refines the search for prediction purposes by eliminating redundancy from the set of variables chosen at the previous step[10].

3.4. Spike-and-slab regression

This is a Bayesian variable selection technique, involving Markov chain Monte Carlo (MCMC) algorithm for regression models with a specific prior which places some amount of posterior probability at zero for a subset of the regression coefficients. In this study, we apply a spike-and-slab regression to identify the determinants of the FinTech market segments proxies both in the linear and non-linear settings.[11] The nonlinear setting involves smoothing a non-linear component, using cubic B-slines. Overall, the method selects variables which have the odds of inclusion into the best model over 25%.

4. Results and discussion

We begin by presenting separately the key determinants of the FinTech market as a whole and its key segments.

Tables 3–6 report the findings with respect to FINDEX as a dependent variable. The BMA analysis reveals 10 significant determinants of this variable, based on the PIP exceeding 50%. However, only the first five of them (FIXEDPHONESUB, LABOR_FORCE, MOBILE_SUBSCR, GII and LEGOR_UK) can be taken into account, while in case of the other variables the expected values of regression coefficients are very close to the standard deviation, undermining their statistical reliability and interpretability.

The results from the techniques applied partly overlap. Namely, a country's rank in the Global Innovation Index (GII) identified by all the methods appears to be the first-tier determinant of its FinTech market development. It is followed by the number of fixed phone subscriptions, which is found significant by three out of the four techniques. Two methods corroborate the significance of labor force, the number of mobile phone subscriptions, the UK legal origin and financial markets depth index. Our findings are partly consistent with Haddad and Hornuf (2019) as well as Sahay et al. (2020) who emphasize the relevance of labor force and the number of mobile phone subscriptions as the determinants of FinTech development. We add to the debate by showing that the FinTech market as a whole has more odds to prosper in the jurisdictions with a higher general proness to innovations, well-developed communication infrastructure, deeper financial markets and British law. Although the total number of significant determinants of the overall FinTech development is

[8] We use an R code *BAS* to implement this method in our linear cross-sectional setting. See https://cran.r-project.org/web/packages/BAS/index.html.

[9] LASSO is run on the basis of an R code *HDeconometrics*. See https://github.com/gabrielrvsc/HDeconometrics.

[10] To perform the procedure an R code VSURF is run. See https://cran.r-project.org/web/packages/VSURF/index.html.

[11] Spike-and-slab regression is performed, using an R code *spikeSlabGAM*. See https://cran.r-project.org/web/packages/spikeSlabGAM/index.html.

Table 3
Results of the BMA analysis for the dependent variable FINDEX.

	PIP	EV	SD
FIXEDPHONESUB	1.00	0.62	0.15
LABOR_FORCE	1.00	−2.59	0.60
MOBILE_SUBSCR	1.00	2.29	0.56
GII	0.99	0.64	0.22
LEGOR_UK	0.99	0.68	0.27
FIE	0.81	−0.17	0.12
LEGOR_FR	0.75	0.34	0.28
ELECTRPRICE	0.70	−0.10	0.09
NATRESRENT	0.67	−0.13	0.12
FIA	0.66	−0.14	0.13
REGQ	0.29	0.09	0.20
EFW_AREA1	0.28	0.03	0.07
EFW_AREA4	0.21	−0.04	0.12
SECURE_INT_SERV	0.18	0.02	0.06
KOF	0.17	0.04	0.13
LEGOR_GE	0.15	−0.01	0.15
NPL	0.11	−0.01	0.04
CRISIS	0.11	0.01	0.04
EASEDB	0.10	0.01	0.06
EFW_AREA5	0.09	0.01	0.05
FMD	0.08	0.00	0.05
ACATFORMALINST	0.07	0.00	0.05
DAI	0.07	0.01	0.05
EFW_AREA2	0.06	0.01	0.06
ROA	0.06	0.00	0.02
TRADE_GDP	0.06	0.00	0.03
EFW_AREA3	0.06	0.00	0.03
X5BANKAS_CONC	0.06	0.00	0.03
GDPCAP_GR	0.05	0.00	0.02
INTERNET_USERS	0.05	−0.01	0.05
FMA	0.05	0.00	0.02
FME	0.05	0.00	0.02
GOVEFF	0.05	0.00	0.05
CORRUPTION	0.04	0.00	0.04
UNEMP	0.04	0.00	0.02
VOICE	0.04	0.00	0.03
RULELAW	0.04	0.00	0.04
ROE	0.04	0.00	0.02
YOUNG	0.04	0.00	0.02
FID	0.04	0.00	0.03
GDPCAP	0.04	0.00	0.03
CPI	0.04	0.00	0.02
BANKINTMARG	0.04	0.00	0.03
SHADOW_EC	0.04	0.00	0.02
ACCESSTOELEC	0.04	0.00	0.02
Z-SCORE	0.04	0.00	0.02
URBAN_POP	0.04	0.00	0.02
MONEY_LAUND	0.04	0.00	0.03
FINLIT	0.04	0.00	0.03
MIGRANT_STOCK	0.03	0.00	0.02
POLSTAB	0.03	0.00	0.02

LASSO identifies eight significant determinants, setting other regressors to zero (Table 4).

limited, they represent almost the entire spectrum of factor groups, i.e. institutional, structural, macroeconomic and financial ones. Thus, promoting (deterring) the overall FinTech development involves a multi-faceted policy toolkit.

In case of the cryptocurrency segment of the FinTech market, the number of relevant determinants tends to be smaller. Tables 7–10 report the key determinants with respect to the COIN_RANK dependent variable.

The first-tier determinant of the cryptocurrency segment expansion is the level of financial inclusion (ACATFORMALINST), i.e. the share of adult population having an account with a formal financial institution. The variable is selected by all the techniques. The finding is in line with the literature, which argues that higher levels of financial development and inclusion are likely to complement rather than substitute an increased cryptocurrency adoption (Saiedi et al., 2021). Besides, it shows that the relationship between FinTech development and financial inclusion can run from the latter to the former, since economic agents may first need to obtain access to modern financial services to adapt themselves afterwards to riskier and more sophisticated products. Such dimension of the relationship between FinTech and financial inclusion is overlooked in the literature, which mostly discusses how FinTech can facilitate financial

Table 4
Results of the LASSO analysis for the dependent variable FINDEX.

Variable	Coefficient
FIXEDPHONESUB	0.18
SECURE_INT_SERV	0.13
CRISIS	0.05
LEGOR_UK	0.12
FMD	0.18
EASEDB	0.13
EFW_AREA1	0.04
GII	0.21

The VSURF technique reveals five significant determinants (Table 5).

Table 5
Results of the random forest (VSURF) analysis for the dependent variable FINDEX.

Selected predictors for the dependent variable FINDEX
GII
FMD
BANKINTMARG
EFW_AREA2
EFW_AREA3

The spike-and-slab regression yields four significant covariates of the overall FinTech development. It is notable that one of them produces only a linear effect (GII), another (FIXEDPHONESUB) helps predict FINDEX both in the linear and non-linear settings, and the remaining two variables (LABOR_FORCE, MOBILE_SUBSCR) have only a non-linear impact (Table 6).

Table 6
Results of the spike-and-slab analysis for the dependent variable FINDEX.

Variable	Coefficient
lin (FIXEDPHONESUB)	0.551**
sm (FIXEDPHONESUB)	0.591**
sm (LABOR_FORCE)	0.285*
sm (MOBILE_SUBSCR)	0.263*
lin (GII)	0.294*

Note: lin(variable name) means the significance of the variable in a linear specification, sm(variable name) – in a non-linear setting; * - probability of inclusion into the best model equal to 25% or more; * - of inclusion into the best model equal to 50% or more.

inclusion, e.g. Ozili (2018), Philippon (2019), Beck (2020).[12] The KOF globalization index capturing economic and financial openness is the second-tier determinant of the cryptocurrency segment found significant by three out of the four methods. Thus, only financial and macroeconomic factors drive the expansion of the cryptocurrency segment in the FinTech market.

The number of significant determinants of the peer-to-peer lending segment is also rather limited. Tables 11–14 convey the key determinants with respect to the P2P dependent variable.

The number of fixed phone subscriptions is the most salient variable determining the expansion of peer-to-peer lending segment. It is identified by all the methods. Labor force appears the second-tier determinant detected by two out of the four techniques. Similar to the cryptocurrency segment, the determinants belonging in just two factor groups influence the peer-to-peer lending segment expansion, i.e. structural and macroeconomic ones. In contrast to Claessens et al. (2018), Bazarbash and Beaton (2020) as well as Oh and Rosenkranz (2020), our results do not indicate that the level of financial development, its efficiency, concentration in the banking sector or financial literacy are significant determinants of the peer-to-peer lending market expansion in the cross-country framework.

Now we turn to the comparative analysis of the key determinants identified across the whole FinTech market and its segments. They are grouped in Table 15.

There is little commonality between statistically significant determinants of the three FinTech development proxies. For example, the determinants relevant for the overall index of FinTech market development include only four variables (out of 13 identified determinants), also contributing to the expansion of at least one of the FinTech market segments. Besides, the determinants of the cryptocurrency segment are almost completely different from those found for the overall FinTech market development and the

[12] Despite the prevailing evidence that FinTech spurs financial inclusion, such uniddirectional linkage is questioned in some studies. For example, Tok and Heng (2022) find that FinTech has a robust positive correlation only with digital financial inclusion, but not with the traditional measures of financial inclusion. Besides, FinTech does not appear to contribute to closing the gender gap in access to financial services. Using Ghana as a case study, Coffie and Zhao (2023) document that FinTech could not drive financial inclusion in this country without a comprehensive uptake of ICT infrastructure. Thus, the direction of the relationship between FinTech and financial inclusion is to be further investigated as a standalone research question.

Table 7
Results of the BMA analysis for the dependent variable COIN_RANK.

	PIP	EV	SD
KOF	0.99	0.61	0.24
FINLIT	0.99	−0.42	0.17
ACATFORMALINST	0.98	0.47	0.21
SECURE_INT_SERV	0.82	0.22	0.16
EFW_AREA2	0.80	−0.53	0.39
VOICE	0.80	0.33	0.25
MOBILE_SUBSCR	0.65	0.20	0.32
GDPCAP_GR	0.33	−0.05	0.09
CRISIS	0.24	0.03	0.07
LABOR_FORCE	0.24	−0.04	0.30
FMA	0.18	0.02	0.07
RULELAW	0.17	−0.06	0.19
INTERNET_USERS	0.16	0.04	0.13
URBAN_POP	0.16	0.03	0.08
ACCESSTOELEC	0.12	0.02	0.07
MONEY_LAUND	0.09	0.01	0.08
POLSTAB	0.08	−0.01	0.07
ELECTRPRICE	0.08	−0.01	0.04
YOUNG	0.08	0.01	0.05
EASEDB	0.08	−0.01	0.07
GOVEFF	0.08	0.02	0.11
REGQ	0.07	0.01	0.09
GDPCAP	0.07	−0.01	0.06
NATRESRENT	0.07	0.01	0.04
TRADE_GDP	0.07	0.00	0.04
FIXEDPHONESUB	0.06	0.01	0.04
SHADOW_EC	0.06	0.00	0.05
Z-SCORE	0.06	0.00	0.03
CORRUPTION	0.05	−0.01	0.07
FMD	0.05	0.00	0.03
EFW_AREA4	0.05	0.00	0.04
LEGOR_GE	0.05	−0.01	0.06
MIGRANT_STOCK	0.05	0.00	0.03
GII	0.05	−0.01	0.07
LEGOR_FR	0.05	0.01	0.06
FIE	0.04	0.00	0.02
EFW_AREA1	0.04	0.00	0.03
BANKINTMARG	0.04	0.00	0.03
DAI	0.04	0.00	0.05
CPI	0.04	0.00	0.03
FID	0.04	0.00	0.03
FME	0.04	0.00	0.02
EFW_AREA5	0.04	0.00	0.03
NPL	0.04	0.00	0.02
ROA	0.04	0.00	0.02
UNEMP	0.04	0.00	0.02
FIA	0.04	0.00	0.03
ROE	0.04	0.00	0.02
5BANKAS_CONC	0.04	0.00	0.02
EFW_AREA3	0.03	0.00	0.02
LEGOR_UK	0.03	0.00	0.04

Table 8
Results of the LASSO analysis for the dependent variable COIN_RANK.

Variable	Coefficient
ACATFORMALINST	0.19
ACCESSTOELEC	0.18
FIA	0.09
KOF	0.15

Table 9
Results of the random forest (VSURF) analysis for the dependent variable COIN_RANK.

Selected predictors for the dependent variable COIN_RANK
ACATFORMALINST
SECURE_INT_SERV
FIA
GDPCAP

Table 10
Results of the spike-and-slab analysis for the dependent variable COIN_RANK.

Variable	Coefficient
lin (ACATFORMALINST)	0.291*
lin (KOF)	0.281*

Note: lin(variable name) means the significance of the variable in a linear specification; * - probability of inclusion into the best model equal to 25% or more.

Table 11
Results of the BMA analysis for the dependent variable P2P.

	PIP	EV	SD
FIXEDPHONESUB	1.00	0.54	0.07
LABOR_FORCE	1.00	2.66	0.26
MOBILE_SUBSCR	1.00	−2.28	0.24
FME	0.53	−0.05	0.05
ELECTRPRICE	0.30	−0.02	0.03
FIA	0.12	−0.01	0.02
LEGOR_GE	0.10	−0.01	0.04
KOF	0.08	0.01	0.03
INTERNET_USERS	0.08	−0.01	0.03
DAI	0.08	0.00	0.02
SECURE_INT_SERV	0.08	0.00	0.02
SHADOW_EC	0.08	0.00	0.02
BANKINTMARG	0.07	0.00	0.02
ROE	0.07	0.00	0.01
EFW_AREA5	0.07	0.00	0.02
TRADE_GDP	0.07	0.00	0.01
NATRESRENT	0.07	0.00	0.01
VOICE	0.07	0.00	0.02
URBAN_POP	0.06	0.00	0.01
GII	0.06	0.00	0.02
UNEMP	0.06	0.00	0.01
FMD	0.06	0.00	0.01
LEGOR_UK	0.06	0.00	0.02
ROA	0.06	0.00	0.01
GOVEFF	0.05	0.00	0.02
EASEDB	0.05	0.00	0.01
RULELAW	0.05	0.00	0.02
EFW_AREA3	0.05	0.00	0.01
FID	0.05	0.00	0.01
CPI	0.05	0.00	0.01
EFW_AREA2	0.05	0.00	0.01
ACCESSTOELEC	0.05	0.00	0.01
REGQ	0.05	0.00	0.02
ACATFORMALINST	0.05	0.00	0.01
MIGRANT_STOCK	0.05	0.00	0.01
CORRUPTION	0.05	0.00	0.02
YOUNG	0.05	0.00	0.01
EFW_AREA4	0.04	0.00	0.01
FIE	0.04	0.00	0.01
FINLIT	0.04	0.00	0.01
X5BANKAS_CONC	0.04	0.00	0.01
NPL	0.04	0.00	0.01
Z-SCORE	0.04	0.00	0.01
LEGOR_FR	0.04	0.00	0.02
POLSTAB	0.04	0.00	0.01
GDPCAP	0.04	0.00	0.01
FMA	0.04	0.00	0.01
EFW_AREA1	0.04	0.00	0.01
MONEY_LAUND	0.04	0.00	0.02
GDPCAP_GR	0.04	0.00	0.01
CRISIS	0.04	0.00	0.01

peer-to-peer lending segment. To quantify the degree of commonality between significant determinants of the FinTech market as a whole and its key segments, we use a parsimonious heuristic index, measuring the ratio of actual coincident variables both across the different variable selection methods and the proxies of the FinTech development to all possible combinations of the determinants represented in Table 15. Given that the total number of such combinations is 107, while coincident elements are only present in 20 of them, the ratio is 18.7%. In a similar vein, a Herfindahl-type index measuring the concentration of the identified determinants yields

Table 12
Results of the LASSO analysis for the dependent variable P2P.

Variable	Coefficient
FIXEDPHONESUB	0.59
LABOR_FORCE	0.26

Table 13
Results of the random forest (VSURF) analysis for the dependent variable P2P.

Selected predictors for the dependent variable P2P
FIXEDPHONESUB

Table 14
Results of the spike-and-slab analysis for the dependent variable P2P.

Variable	Coefficient
lin (FIXEDPHONESUB)	0.966***
sm (FIXEDPHONESUB)	0.971***

Note: lin(variable name) means the significance of the variable in a linear specification, sm(variable name) – in a non-linear setting; *** - probability of inclusion into the best model equal to 90% or more.

Table 15
Determinants selected by all the methods.

	BMA	LASSO	RANDOM FOREST (VSURF)	SPIKE-AND-SLAB
FINDEX	FIXEDPHONESUB	FIXEDPHONESUB	GII	FIXEDPHONESUB
	LABOR_FORCE	SECURE_INT_SERV	FMD	LABOR_FORCE
	MOBILE_SUBSCR	CRISIS	BANKINTMARG	MOBILE_SUBSCR
	GII	LEGOR_UK	EFW_AREA2	GII
	LEGOR_UK	FMD	EFW_AREA3	
		EASEDB		
		EFW_AREA1		
		GII		
COIN_RANK	KOF	ACATFORMALINST	ACATFORMALINST	ACATFORMALINST
	FINLIT	ACCESSTOELEC	SECURE_INT_SERV	KOF
	ACATFORMALINST	FIA	FIA	
		KOF	GDPCAP	
P2P	FIXEDPHONESUB	FIXEDPHONESUB	FIXEDPHONESUB	FIXEDPHONESUB
	LABOR_FORCE	LABOR_FORCE		
	MOBILE_SUBSCR			

a reasonably low value of 793.7 versus a maximum of 10,000 in case there were a single statistically significant determinant across all the proxies and methods.[13] Thus, both indicators confirm that the determinants of the FinTech market expansion exhibit substantial heterogeneity, leaving the question open whether FinTech constitutes an integral market, comprising interrelated segments, or it so far represents a set of markets which can be driven by largely distinctive factors.

All in all, our findings call for specific policy measures to support (or to deter) the FinTech market segment expansion rather than to elaborate uniform ones for all of them. That is, promoting innovations, increasing labor force and financial depth, improving ICT infrastructure along with the adoption of British legal practices which are crucial for the overall level of FinTech development are not necessarily efficient in case of standalone FinTech market segments. The diversity of determinants implies that countries had better engage in specific FinTech activities rather than seek to build a universal specialization, which is attainable only for the most advanced countries in the field, e.g. the USA, the UK, Singapore, thanks to their strong performance across most of the identified determinants.

5. Conclusions

The paper empirically investigates if the expansion of the FinTech market as a whole and that of its major segments – the crypto-currency and peer-to-peer lending markets – are driven by the same set of factors. We apply a battery of well-established variable selection techniques - Bayesian model averaging (BMA), least absolute shrinkage and selection operator (LASSO), variable selection using random forests (VSURF) as well as spike-and-slab regression – to detect pivotal determinants out of 51 candidate factors for the sample of 64 countries.

[13] The index is the sum of the squares of the shares which the determinants have relative to their total number in Table 15.

We find that the overall FinTech market development and the expansion of its segments are far from being determined by the same set of factors. Among the 13 determinants relevant for the overall index of FinTech market development only four variables also determine the expansion of at least one of the FinTech market segments. Besides, the determinants of the cryptocurrency segment almost completely differ from those found for the overall FinTech market development and the peer-to-peer lending segment. The findings indicate that specific measures should apply to each of the FinTech market segments to foster their development. Since there is such a substantial diversity of determinants across the overall FinTech market and its major segments, most countries should not seek a universal specialization in FinTech activities, instead centering on the segment where they have a competitive edge in terms of the pivotal determinants spurring this particular segment.

Our study has a natural limitation, as due to the data availability we managed to cover only two key segments of the FinTech market. Once the cross-country sources on the development of FinTech investment management and insurance are available, it will lay foundations to conduct a more comprehensive comparative research on the determinants of FinTech market segments expansion.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1
List of countries.

Argentina, Australia, Austria, Bangladesh, Belarus, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Cyprus, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Ghana, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Korea Rep., Latvia, Lebanon, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russian Federation, Singapore, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Vietnam.

Table A2
List of variables.

Short Name	Full Name	Source		Description
Dependent variables				
FINDEX	The Global Fintech Index 2020	The Findexable Global Fintech Index City Rankings report	https://findexable.com/global-fintech-index-2020-city-rankings-report-registration/	Scores locations of fintech companies combined with metrics on local business infrastructure and fintech ecosystem quality
COIN_RANK	Cointobuy Safety Rank	Cryptocurrency Analysis Tool	https://cointobuy.io/	Features what type of climate crypto-investors can expect for their investments in a particular country
P2P	Peer-to-Peer (P2P) Lending Volume	The Global Alternative Finance Benchmarking Report	https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/publications/the-global-alternative-finance-market-benchmarking-report/	Measures volume of peer-to-peer lending at a country level
Potential determinants				
Institutional				
POLSTAB	Political Stability and Absence of Violence	Worldwide Governance Indicators, World Bank	https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators	Measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism
REGQ	Regulatory Quality	Worldwide Governance Indicators, World Bank	https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators	Reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.
RULELAW	Rule of Law	Worldwide Governance Indicators, World Bank	https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators	Reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.

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Table A2 (*continued*)

Short Name	Full Name	Source		Description
GOVEFF	Government Effectiveness	Worldwide Governance Indicators, World Bank	https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators	Reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies
VOICE	Voice and Accountability	Worldwide Governance Indicators, World Bank	https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators	Reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media
CORRUPTION	Control of Corruption	Worldwide Governance Indicators, World Bank	https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators	Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests
EASEDB	Ease of Doing Business Index	World Bank	https://www.doingbusiness.org/en/rankings	A high ease of doing business ranking means the regulatory environment is more conducive to the starting and operation of a local firm
LEGOR_UK	Anglo-Saxon legal origin	LaPorta, R., F. Lopez-de-Silanes, and A. Shleifer. (2008). The Economic Consequences of Legal Origins. Journal of Economic Literature 46 (2): 285–332.	https://scholar.harvard.edu/shleifer/publications/economic-consequences-legal-origins	Binary variable: 1 - Anglo-Saxon legal origin,0 - other
LEGOR_FR	French legal origin	LaPorta, R., F. Lopez-de-Silanes, and A. Shleifer. (2008). The Economic Consequences of Legal Origins. Journal of Economic Literature 46 (2): 285–332.	https://scholar.harvard.edu/shleifer/publications/economic-consequences-legal-origins	Binary legal origin: 1 - French legal origin, 0 - other
LEGOR_GE	German legal origin	LaPorta, R., F. Lopez-de-Silanes, and A. Shleifer. (2008). The Economic Consequences of Legal Origins. Journal of Economic Literature 46 (2): 285–332.	https://scholar.harvard.edu/shleifer/publications/economic-consequences-legal-origins	Binary legal origin: 1 - German legal origin, 0 - other
MONEY_LAUND	Major Money Laundering Jurisdictions in 2016	Bureau of International Narcotics and Law Enforcement Affairs	https://www.state.gov/bureaus-offices/under-secretary-for-civilian-security-democracy-and-human-rights/bureau-of-international-narcotics-and-law-enforcement-affairs/	Binary variable: 1 - jurisdiction involved in money laundering, 0 - jurisdiction not involved in money laundering
EFW_AREA1	Economic Freedom Index Area 1: Size of Government	Fraser Institute	https://www.fraserinstitute.org/economic-freedom/approach	Indicates the extent to which countries rely on the political process to allocate resources and goods and services
EFW_AREA2	Economic Freedom Index Area 2: Legal System and Property Rights	Fraser Institute	https://www.fraserinstitute.org/economic-freedom/approach	Focuses on protection of persons and their rightfully acquired property. The key ingredients are rule of law, security of property rights, an independent and unbiased judiciary, and impartial and effective enforcement of the law
EFW_AREA3	Economic Freedom Index Area 3: Sound Money	Fraser Institute	https://www.fraserinstitute.org/economic-freedom/approach	In order to earn a high rating in this area, a country must follow policies and adopt institutions that lead to low (and stable) rates of

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Table A2 (*continued*)

Short Name	Full Name	Source		Description
				inflation and avoid regulations that limit the ability to use alternative currencies.
EFW_AREA4	Economic Freedom Index Area 4: Freedom to Trade Internationally	Fraser Institute	https://www.fraserinstitute.org/economic-freedom/approach	In order to get a high rating in this area, a country must have low tariffs, easy clearance and efficient administration of customs, a freely convertible currency, and few controls on the movement of physical and human capital
EFW_AREA5	Economic Freedom Index Area 5: Regulation	Fraser Institute	https://www.fraserinstitute.org/economic-freedom/approach	Identifies the extent to which regulations and bureaucratic procedures restrain entry and reduce competition
Social				
URBAN_POP	Urban population, % of total population	World Bank	https://data.worldbank.org/indicator	Urban population refers to people living in urban areas as defined by national statistical offices
MIGRANT_STOCK	International migrant stock (% of population)	World Bank	https://data.worldbank.org/indicator	The number of people born in a country other than that in which they live. It also includes refugees
YOUNG_MIDDLE AGE	Population ages 15–64 (% of total population)	World Bank	https://data.worldbank.org/indicator	Total population between the ages 15 to 64 as a percentage of the total population.
Structural				
DAI	Digital Adoption index	World Bank	https://data.worldbank.org/indicator	Comprises three sub-indices which measure technologies necessary for the respective agent to promote development in the digital era: increasing productivity and accelerating broad-based growth for business, expanding opportunities and improving welfare for people, and increasing the efficiency and accountability of service delivery for government
GII	Global Innovation Index	World Intellectual Property Organization	https://www.wipo.int/portal/en/	Presents the latest global innovation trends and the annual innovation ranking of 131 economies
ACCESSTOELEC	Access to electricity, % of population	World Bank	https://data.worldbank.org/indicator	The percentage of population with access to electricity
INTERNET_USERS	Individuals using the Internet, % of population	World Bank	https://data.worldbank.org/indicator	Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.
ELECTRPRICE	Price of electricity (US cents per kWh)	World Bank	https://www.doingbusiness.org/en/rankings	A monthly electricity consumption is assumed, for which a monthly bill is then computed for a warehouse based in the largest business city of the economy for the month of January
FIXEDPHONESUB	Fixed telephone subscriptions (per 100 people)	International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database	https://data.worldbank.org/indicator/IT.MONEY_LAUNDT.MAIN.P2?view=chart	Refers to the sum of active number of analogue fixed telephone lines, voice-over-IP (VoIP) subscriptions, fixed wireless local loop (WLL) subscriptions, ISDN voice-channel equivalents and fixed public payphones
MOBILE_SUBSCR	Mobile cellular subscriptions	International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database	https://data.worldbank.org/indicator/IT.CEL.SETS?view=chart	Subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology. The indicator includes the number of postpaid subscriptions, and the number of active prepaid accounts (i.e. that

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Table A2 (*continued*)

Short Name	Full Name	Source		Description
				have been used during the last three months).
SECURE_INT_SERV	Secure internet servers (per 1000 people)	World Bank	https://data.worldbank.org/indicator	The number of distinct, publicly-trusted TLS/SSL certificates found in the Netcraft Secure Server Survey
Macroeconomic				
GDPCAP_GR	GDP per capita growth, annual %	World Bank	https://data.worldbank.org/indicator	Annual percentage growth rate of GDP per capita based on constant local currency. Aggregates are based on constant 2010 U.S. dollars
GDPCAP	GDP per capita, current US $	World Bank	https://data.worldbank.org/indicator	Gross domestic product divided by midyear population
CPI	Inflation, consumer prices, annual %	World Bank	https://data.worldbank.org/indicator	Reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly
LABOR_FORCE	Labor force, total	World Bank	https://data.worldbank.org/indicator/IT.MONEY_LAUNDT.MAIN.P2?view=chart	Comprises people ages 15 and older who supply labor for the production of goods and services during a specified period. It includes people who are currently employed and people who are unemployed but seeking work as well as first-time job-seekers.
UNEMP	Unemployment total, % of total labor force	World Bank	https://data.worldbank.org/indicator	The share of the labor force that is without work but available for and seeking employment
NATRESRENT	Total natural resources rents, % of GDP	World Bank	https://data.worldbank.org/indicator	The sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents
CRISIS	Number of banking crises per country	Laeven, L. and F. Valencia (2018). Systemic Banking Crises Revisited. IMF Working Papers 18/206, International Monetary Fund	https://www.imf.org/en/Publications/WP/Issues/2018/09/14/Systemic-Banking-Crises-Revisited-46232	Categorical variable indicating the number of banking crises experienced by country
TRADE_GDP	Trade, % of GDP	World Bank	https://data.worldbank.org/indicator	The sum of exports and imports of goods and services measured as a share of gross domestic product
KOF	KOF Globalization Index	KOF Swiss Economic Institute	https://kof.ethz.ch/en/	Measures the economic, social and political dimensions of globalization
SHADOW_EC	Size of the shadow economy relevant to official GDP	Medina L., Schneider F. (2019). Shedding light on the shadow economy: a global database and the interaction with the official one. CESifo Working Paper № 7981	https://www.cesifo.org/en/publikationen/2019/working-paper/shedding-light-shadow-economy-global-database-and-interaction	Estimates the size of the shadow economy
Financial Development				
FID	Financial Institutions Depth Index	International Monetary Fund	https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B	Reflects financial institutions' size and liquidity
FIA	Financial Instititutions Access Index	International Monetary Fund	https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B	Reflects ability of individuals and companies to access financial services in financial institutions
FIE	Financial Institutions Efficiency Index	International Monetary Fund	https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B	Reflects financial institutions' ability to provide financial services at low cost and with sustainable revenues
FMD	Financial Markets Depth Index	International Monetary Fund	https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B	Reflects financial markets' size and liquidity
FMA	Financial Markets Access Index	International Monetary Fund	https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B	Reflects ability of individuals and companies to access financial services from financial markets

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Table A2 (*continued*)

Short Name	Full Name	Source		Description
FME	Financial Markets Efficiency Index	International Monetary Fund	https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B	Reflects the level of activity of capital markets
5BANKAS_CONC	5-Bank Asset Concentration	World Bank	https://datacatalog.worldbank.org/5-bank-asset-concentration	Assets of five largest banks as a share of total commercial banking assets
NPL	Bank nonperforming loans to total gross loans (%)	World Bank	https://datacatalog.worldbank.org/5-bank-asset-concentration	Value of nonperforming loans divided by the total value of the loan portfolio
ROA	Bank return on assets (% after tax)	World Bank	https://datacatalog.worldbank.org/bank-return-assets-after-tax	Shows how profitable the company is relative to its assets. ROA is calculated by dividing company's net income by total assets
FINLIT	Financial literacy index	Financial literacy around the world: insights from the Standard and Poor's ratings services global financial literacy survey (S&P Global Finlit Survey)	https://gflec.org/initiatives/sp-global-finlit-survey/	Shows the number of adults who are financially literate (%)
ROE	Return on equity (% after tax)	World Bank	https://datacatalog.worldbank.org/bank-return-assets-after-tax	Measures company's profitability by taking company's annual return (net income) divided by the value of its total shareholders' equity
BANKINTMARG	Bank net interest margin (%)	World Bank	https://datacatalog.worldbank.org/bank-net-interest-margin	Profitability indicator that measures the difference between the interest income generated by banks and the amount of interest paid out to their lenders relative to the amount of their assets
ACATFORMALINST	Account at a formal financial institution (% age 15+)	World Bank	https://datacatalog.worldbank.org/account-formal-financial-institution-age-15	The percentage of respondents with an account (self or together with someone else) at a bank, credit union, another financial institution (e.g., cooperative, microfinance institution), or the post office (if applicable) including respondents who reported having a debit card (% age 15+).
Z-SCORE	Bank z-score	World Bank	https://datacatalog.worldbank.org/bank-z-score	Captures the probability of default of a country's banking system. Z-score compares the buffer of a country's banking system (capitalization and returns) with the volatility of those returns.

Table A3
Descriptive statistics

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Dependent Variables						
FINDEX	0.00	4.91	−1.52	1.00	2.24	11.41
COIN_RANK	0.00	1.29	−3.07	1.00	−1.23	3.76
P2P	0.00	7.57	−0.17	1.00	7.06	53.16
Potential determinants						
5BANKAS_CONC	0.00	1.53	−2.37	1.00	−0.38	2.15
ACATFORMALINST	0.00	1.00	−2.47	1.00	−0.77	2.29
ACCESSTOELEC	0.00	0.34	−5.35	1.00	−3.62	16.72
SHADOW_EC	0.00	2.90	−1.44	1.00	0.61	2.90
BANKINTMARG	0.00	3.49	−1.12	1.00	1.46	4.92
CORRUPTION	0.00	1.28	−1.89	1.00	−0.38	1.87
CPI	0.00	5.42	−0.76	1.00	3.23	15.78
CRISIS	0.00	4.10	−1.60	1.00	0.94	6.06
DAI	0.00	1.38	−2.49	1.00	−0.65	2.57
EASEDB	0.00	1.66	−2.87	1.00	−0.61	2.81
EFW_AREA1	0.00	1.79	−2.60	1.00	−0.16	2.45
EFW_AREA2	0.00	1.56	−2.19	1.00	−0.20	2.06
EFW_AREA3	0.00	0.82	−3.93	1.00	−2.15	7.21
EFW_AREA4	0.00	1.59	−3.06	1.00	−0.95	3.09
EFW_AREA5	0.00	1.70	−3.36	1.00	−1.08	4.65
ELECTRPRICE	0.00	3.05	−1.51	1.00	0.69	2.91
FIA	0.00	1.77	−1.81	1.00	0.04	1.97
FID	0.00	1.84	−1.35	1.00	0.33	1.73
FIE	0.00	1.52	−2.52	1.00	−0.49	2.47
FINLIT	0.00	1.87	−1.68	1.00	0.34	1.97
FIXEDPHONESUB	0.00	6.32	−0.44	1.00	4.71	27.89
FMA	0.00	2.08	−1.55	1.00	0.06	2.25
FMD	0.00	1.70	−1.39	1.00	0.24	1.63
FME	0.00	1.56	−1.22	1.00	0.32	1.64
GDPCAP_GR	0.00	2.93	−2.25	1.00	0.31	3.30
GDPCAP	0.00	3.54	−1.04	1.00	1.19	4.20
GII	0.00	2.02	−1.82	1.00	0.01	1.95
GOVEFF	0.00	1.29	−2.44	1.00	−0.58	2.24
INTERNET_USERS	0.00	1.26	−2.40	1.00	−0.95	2.99
KOF	0.00	1.41	−2.30	1.00	−0.59	2.37
LABOR_FORCE	0.00	6.48	−0.37	1.00	5.25	31.91
LEGOR_FR	0.41	1.00	0.00	0.50	0.38	1.15
LEGOR_GE	0.22	1.00	0.00	0.42	1.36	2.85
LEGOR_UK	0.31	1.00	0.00	0.47	0.81	1.65
MIGRANT_STOCK	0.00	5.45	−0.77	1.00	3.05	15.61
MONEY_LAUND	0.36	1.00	0.00	0.48	0.59	1.34
MOBILE_SUBSCR	0.00	5.85	−0.43	1.00	4.59	24.94
NATRESRENT	0.00	3.55	−0.69	1.00	1.95	6.23
NPL	0.00	4.66	−0.75	1.00	3.00	12.73
POLSTAB	0.00	1.55	−1.76	1.00	−0.25	1.79
REGQ	0.00	1.23	−2.10	1.00	−0.67	2.26
ROA	0.00	1.81	−6.21	1.00	−3.65	24.71
ROE	0.00	2.56	−3.66	1.00	−0.96	6.18
RULELAW	0.00	1.26	−1.97	1.00	−0.42	1.80
SECURE_INT_SERV	0.00	3.49	−0.79	1.00	1.74	5.74
TRADE_GDP	0.00	4.21	−0.99	1.00	2.04	8.03
UNEMP	0.00	4.30	−1.37	1.00	2.33	9.72
URBAN_POP	0.00	1.55	−2.59	1.00	−0.80	2.90
VOICE	0.00	1.26	−2.10	1.00	−0.54	2.07
YOUNG_MIDDLE AGE	0.00	3.92	−3.23	1.00	0.26	7.53
Z-SCORE	0.00	3.60	−1.43	1.00	1.09	4.44

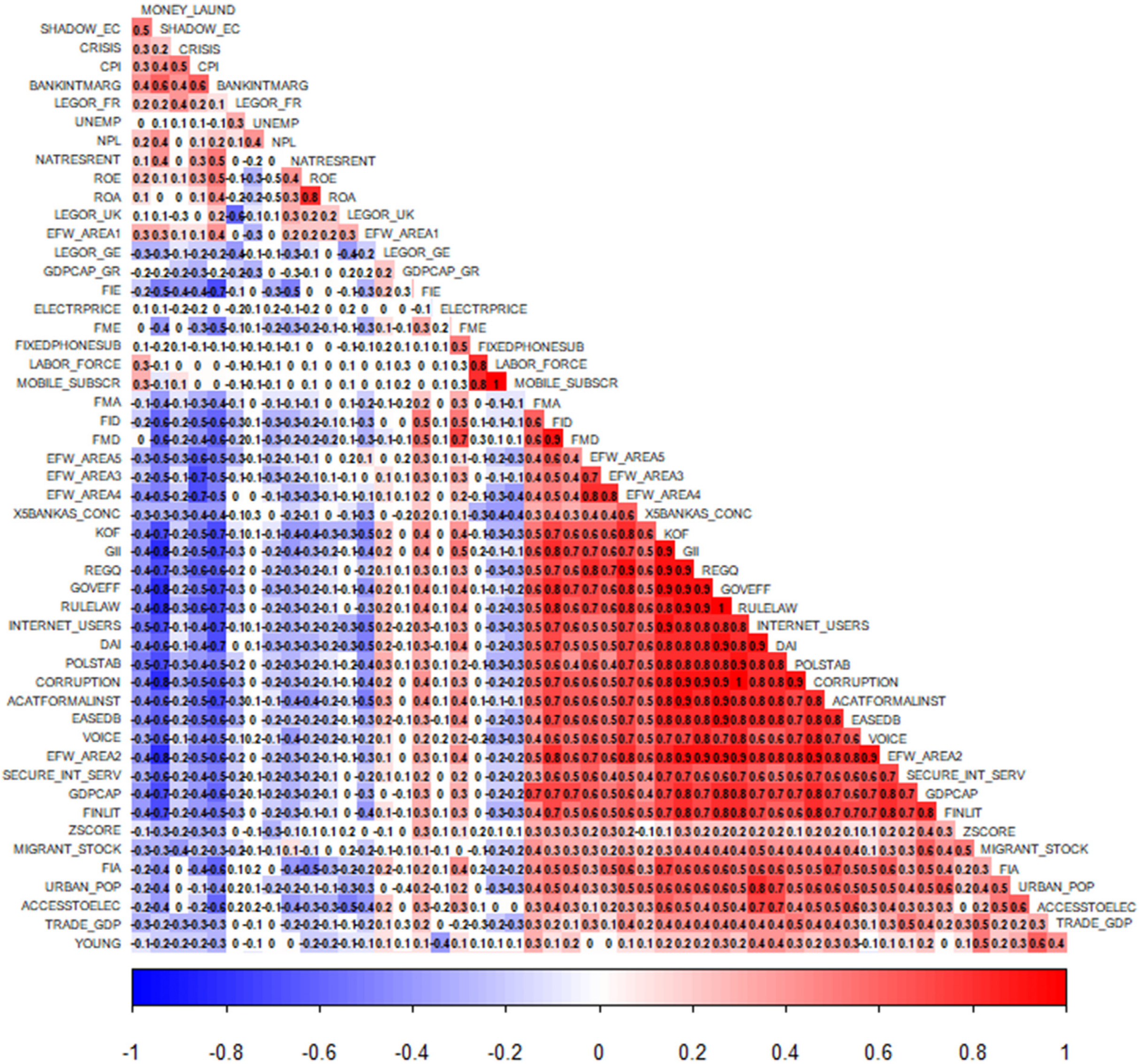

Fig. A1. Correlation matrix for the potential determinants.

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