What Predicts the Legal Status of Cryptocurrencies?

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Abstract. We investigate which factors predict the legal status of cryptocurrencies in a vast sample of countries by conducting the Bayesian model averaging as an innovative technique for variable selection in multinomial logit models. The national levels of democracy and digital adoption appear the most robust predictors, outperforming other candidate financial, macroeconomic, structural and institutional indicators.

Keywords: cryptocurrency, legal status, Bayesian model averaging, democracy, digital adoption.

JEL codes: C53, G20, O16.

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1 Introduction

Cryptocurrencies constitute a major financial innovation of the recent time. Similar to previous financial innovations, e.g. ATMs, the speed of their adoption differs substantially across countries, so does their legal status. For example, in the US, Canada, Australia, Hong Kong cryptocurrencies are fully legal and extensively used, while in such jurisdictions as Pakistan, the United Arab Emirates or Vietnam they are explicitly banned. In some countries, e.g. China, they are implicitly illegal. Overall, according to the Law Library of Congress Report (2018), there are 25 countries where the use of cryptocurrencies is completely or partly forbidden.

Which factors influence the legal status of cryptocurrencies? This paper attempts to shed light on this new research question by comparing the relative importance of nearly 20 potential predictors of cryptocurrency legality. These variables gauge various financial, macroeconomic, structural and institutional factors which can underlie cryptocurrency legality or ban. To identify the most influential predictors we apply a state-of-the-art method for variable selection, Bayesian model averaging adjusted for logit models by Yeung et al. (2005).

We find that the degree of digital adoption and the national level of democracy have the biggest predictive power for cryptocurrency legal status. Somewhat surprisingly, such factors as income per capita, aggregate level of financial development or money laundering and terrorist financing risk appear statistically insignificant.

The remainder of the paper is as follows. Section 2 develops our hypotheses and describes the corresponding data. Section 3 introduces the methodology. Section 4 presents the results and provides an overview of robustness checks. Section 5 concludes.

2 Hypothesis development and data

Our dependent variable, LEGALSTAT, is based on the data from the Law Library of Congress Report (2018) “Regulation of Cryptocurrencies around the World”. It is a categorical variable taking on the following values: 0 – cryptocurrencies are legal, 1 – they are implicitly banned, 2 – explicitly banned. An implicit ban suggests that countries impose indirect restrictions on financial institutions, thereby impeding their transactions involving cryptocurrencies. In addition, we consider a joint category which covers countries with an explicit and implicit ban, thereby transforming our dependent variable into a binary one (0 – legal, 1 – banned).

We assume that the legal status of cryptocurrencies depends on a number of financial, macroeconomic, structural and institutional factors. As far as we know, there are no specific empirical papers seeking to model cryptocurrency legal status[3]. Against this backdrop, we propose a set of heuristic hypotheses about potential predictors of cryptocurrency legality. To some extent our choice of predictors is also motivated by the burgeoning literature on the drivers of fintech and cryptocurrency adoption at the micro-level, e.g. Saiedi et al. (2019).

H1: *A higher proness to digital innovation is likely to correlate with free cryptocurrency circulation.*

We use the Digital Adoption Index (DAI) from the World Bank for 2016 to proxy a country's proness and capacity to digitalize.

H2: *A higher degree of money laundering and terrorist financing risk for a country is likely to entail a cryptocurrency ban.*

To proxy this risk, we exploit the average value of the Basel Anti-Money Laundering Index (AML) for 2012-2018. The data comes from the Basel Institute of Governance.

H3: *An aggregate level of financial development can be a covariate of cryptocurrency legal status.*

To gauge the level of a country's financial development, we take the Financial Development Index (FD) from the IMF (Svirydzenka et al., 2016) and compute its average value for 2012-2017. It is problematic to determine a priori whether this factor promotes or deters free cryptocurrency circulation. For example, less financially developed countries may consider cryptocurrencies as an alternative way to enhance financial inclusion and, thus, may favor or at least not impede their use, while more financially advanced economies may associate cryptocurrencies with financial fraud and money laundering, opting for their implicit or explicit ban.

H4: *Better institutional quality can promote free cryptocurrency circulation.*

We adopt the following variables to capture the quality of institutions: the average value of the Ease of Doing Business Index (EASEOFBUS) for 2012-2018 and

[3]Nonetheless, there is scarce literature considering theoretical underpinnings of cryptocurrency bans, e.g. Hendrickson et al. (2017).

the national level of democracy measured by a country's score in Polity IV (POLITY) ranking averaged across 2012-2017.

H5: *Limited access to electricity is likely to lead to a cryptocurrency ban.*

We exploit the averages of access to electricity (% of population) (ACCESSTOELEC) and electric power consumption (kWh per capita) (ELPOWCONS) for 2012-2017 from the World Bank. Since cryptocurrency mining is electricity-intensive, their free circulation may involve a significant shrinkage in generating capacity which may hamper the overall economy.

H6: *The intensity of migration and remittance flows matter for cryptocurrency legal status.*

The average value of international migrant stock (MIGRANT_ST) for 2010-2018 and the average share of personal remittances to GDP (REMIT_TO_GDP) for 2012-2017 are used in the analysis. Like in case of FD, we are agnostic whether they promote or deter free cryptocurrency circulation.

In addition to the core hypotheses mentioned above, we test the predictive power of other plausible predictors. Namely, we include the cumulative number of systemic banking crises (CRISIS) for each sample country during 1970-2017, borrowed from the Systemic Banking Crises Database (Laeven and Valencia, 2018). We also test for the predictive power of education and natural resources abundance, using the averages of school tertiary enrollment (TERT_ENROLL) and total natural resources (% of GDP) rent (NATRESRENT) for 2012-2017 from the World Bank. The central bank involvement in supervision index (Romelli and Masciandaro, 2018) along with the central bank independence index (Garriga, 2018) are considered as potential predictors (CBISINDEX and CBINDEP, respectively). Finally, we add to our dataset the following averaged macroeconomic controls for the period 2012-2017: income level and its dynamics (GDP.CAP and GDP.CAP_GR), inflation (CPI) and unemployment rate (UNEMP). The series are the World Bank data.

Overall, due to omissions in the data series, our sample boils down to 72 countries, of which 3 countries completely ban cryptocurrencies and 10 where they are implicitly illegal. The list of sample countries, a detailed description of the predictors, their descriptive statistics as well as cross-correlations are provided in the Appendix (Tables A1-A4).

3 Methodology

We apply the Bayesian model averaging technique (BMA) for logit models proposed by Yeung et al. (2005). Since we have a large number of potential predictors, choosing the best multinomial logit model by stepwise inclusion or deletion of variables is computationally burdensome and creates uncertainty about the best model. The BMA accounts for the model uncertainty by averaging over the best models according to approximate posterior model probability. The general set-up of the BMA is represented in Equation 1:

$$\Pr(Y|D) = \sum_{k \in B} \Pr(Y = 1|D, \quad M_k) * \Pr\,(M_k|D), \qquad (1)$$

where $\Pr(Y|D)$ is a posterior probability of the response variable Y given the training data set D, $\Pr(Y|D, \quad M_k)$ is a posterior probability of Y given the training data set D and model M_k, $\Pr\,(M_k|D)$ is a posterior probability of model M_k given the training data set D. Summing is over a set of models M_k for k in B, where B is a set of indices.

Yeung et al. (2005) modified the conventional BMA by developing an iterative algorithm applicable for binary data[4]. The iterative BMA first ranks variables in line with a univariate variable selection method and then successively applies the traditional BMA algorithm to the ordered variables. In contrast to most feature selection algorithms, in which a prespecified small number of top ranked variables are chosen as relevant, the iterative BMA ensures that all the variables are considered.

In addition, Yeung et al. (2005) extended the iterative BMA to multinomial models, based on the Begg and Grey approach (Begg and Grey, 1984), which approximates logistic regression in which the dependent variable can take more than two values with a combination of individualized binary logistic regressions.

[4] The BMA algorithm has recently gained momentum in economics and finance. For example, Bencivelli et al. (2017) apply the BMA as an alternative tool to forecast GDP for major EU countries relative to simple bridge and factor models. Arin and Braunfels (2018) investigate the determinants of the resource curse by means of this approach. Hasan et al. (2018) examine the effect of finance on long-term economic growth.

4 Results

We sort the potential predictors based on their posterior inclusion probability (PIP) derived from the BMA for legal status dependent variable accounting for cryptocurrency legality, an explicit or implicit ban. They are ranked in Table 1.

Table 1. Results of BMA for a 3-level LEGALSTAT dependent variable.

	PIP	Post Mean	Post SD
POLITY	100	-0.23	0.08
DAI	62.8	-6.71	6.57
GDP.CAP _GR	20.3	0.08	0.21
EASEOFBUS	15.9	-0.01	0.04
CPI	9.8	-0.03	0.13
CRISIS	7.3	0.09	0.42
UNEMP	6.4	-0.01	0.05
REMIT_TO_GDP	6	-0.01	0.05
AML	5.2	0.02	0.17
GDP.CAP	4.6	0.00	0.00
TERT_ENROLL	3.5	0.00	0.01
FD	3.4	-0.04	0.69
ELPOWCONS	3.2	0.00	0.00
ACCESSTOELEC	2.9	0.00	0.01
MIGRANT_ST	2.7	0.00	0.01
CBINDEP	2.4	-0.01	0.49
NATRESRENT	1.8	0.00	0.01
CBISINDEX	1.7	0.00	0.04

The findings lend support to two of our hypotheses: H1 and H4. There is evidence that the national level of democracy is a robust predictor of cryptocurrency legal status, which is to be included into all the best selected models. It is followed by the level of digitalization, but with a smaller PIP value. For both, POLITY and DAI, the PIP exceeds the 0.5 threshold, which is conventionally used as a benchmark for a variable inclusion into a “true” model. Interestingly, of the institutional variables, the national level of democracy is much more important than the quality of business environment and regulation embedded in the Ease of Doing Business Index. Based on Figure 1, higher levels of POLITY and DAI increase the odds of free cryptocurrency circulation in a given country.

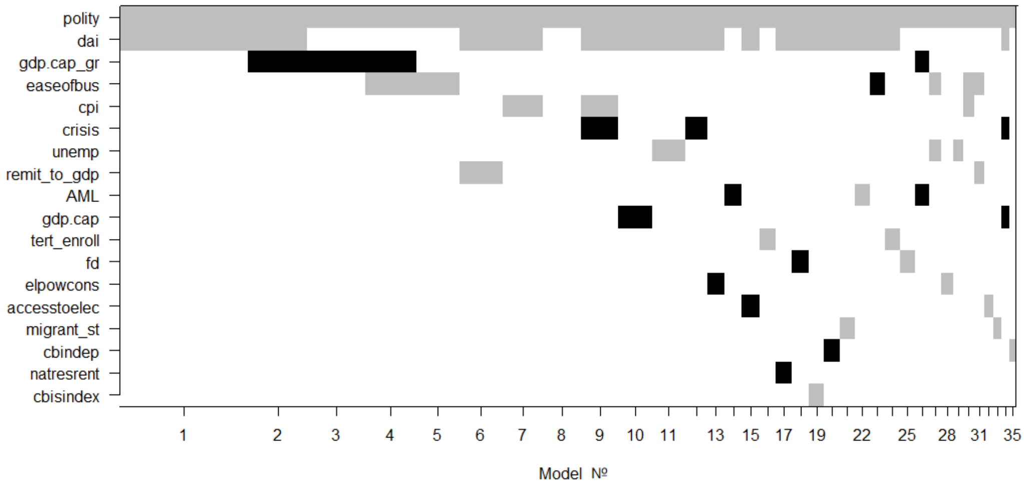

Figure 1. Variable inclusion based on best 35 models for a 3-level LEGALSTAT dependent variable.
Note: Grey color denotes the negative impact of a variable, while black - positive.

Other candidate predictors have by far smaller PIP values than the threshold. Thus, our hypotheses related to the role of money laundering, financial development, access to electricity and migration are not confirmed.

When the dependent variable is transformed into a binary one, the findings remain qualitatively the same. The results are reported in Table 2 and Figure 2.

Table 2. Results of BMA for a 2-level LEGALSTAT dependent variable.

	PIP	Post Mean	Post SD
POLITY	100	-0.23	0.08
DAI	58.7	-6.24	6.65
GDP.CAP_GR	24.6	0.10	0.20
EASEOFBUS	15.8	-0.01	0.04
CPI	9.2	-0.03	0.11
UNEMP	7.1	-0.01	0.04
CRISIS	6.1	0.08	0.39
REMIT_TO_GDP	5.6	-0.01	0.04
TERT_ENROLL	5.6	0.00	0.01
AML	5	0.02	0.16
GDP.CAP	3.6	0.00	0.00
FD	3.3	-0.04	0.65
MIGRANT_ST	3.2	0.00	0.01
ELPOWCONS	3	0.00	0.00
ACCESSTOELEC	2.8	0.00	0.01
NATRESRENT	2.8	0.00	0.01
CBISINDEX	2.6	0.00	0.05
CBINDEP	2.3	-0.01	0.36

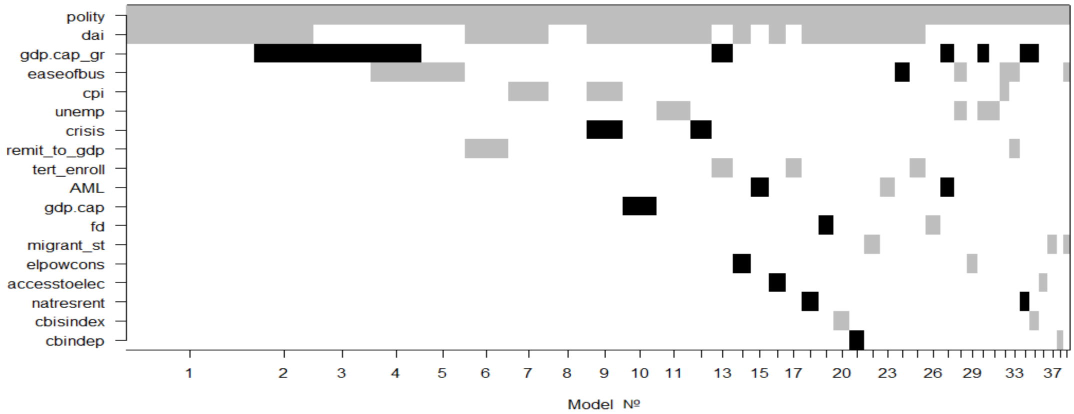

Figure 2. Variable inclusion based on best 35 models for a 2-level LEGALSTAT dependent variable.
Note: Grey color denotes the negative impact of a variable, while black - positive.

We also tried two alternative methodologies, classification and regression trees (CART) and the random forest algorithm, to identify the best splitting factors for our sample. Under these approaches, POLITY is characterized by the maximum predictor importance as well. DAI is also on the list of leading predictors. The details of the CART and random forest analyses are available from the authors upon request.

Overall, our results are consistent with the literature, asserting that democratic political regimes foster innovations (Knutsen, 2015, Zuazu, 2019), and financial development (Huang, 2010, Mandon, 2014, Ghardallou, 2016). Indeed, democracy postulates decentralized economic activity, and free cryptocurrency circulation alongside its auxiliary mechanisms such as distributed ledger technology and initial coin offerings (ICOs) facilitates it in practice. Thus, democratization can contribute to more extensive use of cryptocurrencies by promoting the formalization of their legal status in a greater number of countries.

5 Conclusions

The paper studies the factors which shape the legal status of cryptocurrencies in a vast sample of countries. We apply the Bayesian model averaging for multinomial logit models to a set of 18 potential predictors and find that only two of them, the level of digital adoption and national level of democracy, are to be included into the “true” models, predicting whether free cryptocurrency circulation is legal or banned.

As the legal status variable is for the year 2018 in our study, we are unable to assess the dynamic interdependence of the countries in their legal adoption of cryptocurrencies. Disentangling such peer effects would be a promising avenue for future research.

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Appendix

Table A1. List of used variables

Short Name	Full Name	Source	
LEGALSTAT	Legal Status of Cryptocurrencies	Library of Congress	https://www.loc.gov/law/help/cryptocurrency/world-survey.php
GDP.CAP_GR	GDP per capita growth (annual %)	World Bank	https://data.worldbank.org/indicator
GDP.CAP	GDP per capita(current US $)	World Bank	https://data.worldbank.org/indicator
REMIT_TO_GDP	Personal remittances, received (% of GDP)	World Bank	https://data.worldbank.org/indicator
AML	Basel Anti-Money Laundering Index	Basel Institute on Governance	https://www.baselgovernance.org/asset-recovery/basel-aml-index
TERT_ENROLL	School enrollment, tertiary (% gross)	World Bank	https://data.worldbank.org/indicator
MIGRANT_ST	International migrant stock, total	World Bank	https://data.worldbank.org/indicator
DAI	Digital Adoption index	World Bank	https://data.worldbank.org/indicator
FD	Financial Development Index	IMF	https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B
ACCESSTOELEC	Access to electricity (% of population)	World Bank	https://data.worldbank.org/indicator
ELPOWCONS	Electric power consumption (kWh per capita)	World Bank	https://data.worldbank.org/indicator
EASEOFBUS	Ease of doing business index (1=most business friendly regualtions)	World Bank	https://data.worldbank.org/indicator
CPI	Inflation, consumer prices (annual %)	World Bank	https://data.worldbank.org/indicator
UNEMP	Unemployment total (% of total labor force) (modeled ILO estimate)	World Bank	https://data.worldbank.org/indicator
NATRESRENT	Total natural resources rents (% of GDP)	World Bank	https://data.worldbank.org/indicator
CRISIS	Number of banking crises per country	Systemic banking crises database (Laeven and Valencia, 2018)	https://www.imf.org/en/Publications/WP/Issues/2018/09/14/Systemic-Banking-Crises-Revisited-46232
CBISINDEX	Central Bank Involvement in Supervision Index	Romelli and Masciandaro (2018)	https://davideromelli.com/data/
CBINDEP	Central Bank Independence Index	Garriga (2018)	https://sites.google.com/site/carogarriga/cbi-data-1
POLITY	Country’s score in Polity IV (POLITY) ranking	Center for Systemic Peace	http://www.systemicpeace.org/inscrdata.html

Table A2. List of Countries

Free cryptocurrency circulation	Implicit ban	Explicit ban
Albania	Bangladesh	Algeria
Armenia	China	Morocco
Australia	Colombia	Pakistan
Austria	Dominican Republic	
Azerbaijan	Indonesia	
Belgium	Kuwait	
Bulgaria	Lithuania	
Brazil	Qatar	
Botswana	Saudi Arabia	
Canada	Thailand	
Switzerland		
Chile		
Costa Rica		
Cyprus		
Czech Republic		
Germany		
Denmark		
Ecuador		
Spain		
Estonia		
Finland		
France		
United Kingdom		
Greece		
Guatemala		
Croatia		
Hungary		
India		
Ireland		

Israel		
Italy		
Jamaica		
Jordan		
Kazakhstan		
Kenya		
Lebanon		
Luxembourg		
Latvia		
Moldova		
Mexico		
Mongolia		
Mauritius		
Malaysia		
Netherlands		
Norway		
New Zealand		
Panama		
Peru		
Philippines		
Poland		
Portugal		
Romania		
El Salvador		
Slovenia		
Sweden		
Turkey		
Ukraine		
Uruguay		
South Africa		

Table A3. Descriptive statistics

	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
GDP.CAP	2970.78	127817.90	28209.34	22286.52	1.90	8.12
GDP.CAP_GR	-2.84	7.05	1.90	2.04	0.18	3.02
REMIT_TO_GDP	0.01	24.35	3.29	5.12	2.18	7.37
AML	2.87	7.85	5.19	0.97	0.01	2.76
TERT_ENROLL	10.06	118.44	54.65	23.79	0.19	2.80
MIGRANT_ST	0.07	78.99	10.94	14.26	2.66	11.66
DAI	0.37	0.86	0.65	0.12	-0.20	2.31
FD	0.15	0.94	0.47	0.21	0.42	2.12
ACCESSTOELEC	48.46	100.00	96.47	9.45	-3.48	15.30
ELPOWCONS	158.58	23625.94	4919.31	4527.38	1.78	6.47
EASEOFBUS	41.19	87.23	68.58	8.94	-0.35	3.18
CPI	-0.44	14.91	2.90	2.70	1.74	7.04
UNEMP	0.23	25.54	7.98	5.06	1.52	5.65
NATRESRENT	0.00	47.13	4.60	8.59	2.99	12.35
CRISIS	0.00	3.00	0.68	0.65	0.72	3.90
CBISINDEX	1.00	6.00	2.82	1.67	0.67	2.54
CBINDEP	0.22	0.90	0.66	0.20	-0.53	2.03
POLITY	-10.00	10.00	6.74	5.31	-1.97	5.74

Table A4. Correlation matrix

	GDP. CAP	GDP. CAP_GR	REMIT_ TO_GDP	AML	TERT_ ENROLL	MIGRANT _ST	DAI	FD	ACCESS TOELEC	ELPOW CONS	EASEOF BUS	CPI	UNEMP	NATRES RENT	CRISIS	CBIS INDEX	CB INDEP	POLITY
GDP.CAP	1.00																	
GDP.CAP_GR	-0.39	1.00																
REMIT_TO_GDP	-0.43	0.04	1.00															
AML	-0.32	0.08	0.18	1.00														
TERT_ENROLL	0.21	-0.07	-0.34	-0.51	1.00													
MIGRANT_ST	0.77	-0.54	-0.13	-0.06	0.00	1.00												
DAI	0.65	-0.28	-0.43	-0.63	0.57	0.33	1.00											
FD	0.58	-0.24	-0.45	-0.35	0.44	0.30	0.67	1.00										
ACCESSTOELEC	0.33	-0.23	-0.06	-0.43	0.48	0.22	0.55	0.34	1.00									
ELPOWCONS	0.81	-0.41	-0.39	-0.45	0.35	0.61	0.64	0.59	0.32	1.00								
EASEOFBUS	0.46	-0.04	-0.38	-0.68	0.59	0.13	0.77	0.65	0.43	0.53	1.00							
CPI	-0.41	0.09	0.16	0.48	-0.28	-0.24	-0.49	-0.47	-0.37	-0.35	-0.52	1.00						
UNEMP	-0.18	-0.16	0.02	-0.17	0.23	-0.13	0.02	0.05	-0.06	-0.13	0.02	-0.09	1.00					
NATRESRENT	0.26	-0.25	-0.18	0.17	-0.18	0.45	-0.15	-0.18	0.01	0.22	-0.24	0.24	-0.24	1.00				
CRISIS	0.07	-0.07	-0.11	-0.19	0.39	-0.13	0.35	0.19	0.30	0.10	0.24	0.16	0.07	-0.20	1.00			
CBISINDEX	0.15	-0.03	-0.02	-0.14	0.01	0.15	0.11	-0.03	0.02	-0.03	0.00	0.04	0.18	0.10	0.01	1.00		
CBINDEP	0.14	0.08	-0.04	-0.37	0.42	-0.08	0.39	0.09	0.33	0.02	0.35	-0.25	0.20	-0.27	0.30	0.16	1.00	
POLITY	-0.12	0.16	-0.03	-0.32	0.37	-0.42	0.26	0.21	-0.06	-0.03	0.36	-0.19	0.23	-0.65	0.29	-0.15	0.26	1.00