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UNPACKING GLOBAL CRYPTOCURRENCY ADOPTION

A Variance-Decomposition Analysis Using Relative Importance Metrics

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ABSTRACT

Cryptocurrencies, blockchain-based digital assets, are rapidly shifting from niche instruments to globally significant financial tools. However, understanding the diverse factors behind their adoption remains challenging. This study explores global cryptocurrency adoption between 2020 and 2024 across 144 countries, analyzing macroeconomic, socio-cultural, infrastructural, financial, institutional, and risk-related determinants. Employing variance-decomposition metrics (LMG and PMVD) to a cross-sectional, linear model's estimates, it quantifies each factor's relative contribution to adoption, also introducing a custom Monte-Carlo method for computational efficiency. Results highlight financial determinants, especially bank concentration, as major drivers, while traditional factors like GDP per capita and education show minimal influence. Attained findings underscore cryptocurrency adoption as complex and context-dependent, shaped by relationships rather than isolated factors, thus providing nuanced insights for any stakeholder within this context.

1 - INTRODUCTION

Cryptocurrencies, digital assets based on blockchain technology (Garavaglia, 2018), are transitioning from niche financial instruments to globally recognized investment vehicles and payment alternatives (Chainalysis, 2024). Since Bitcoin's inception in 2008 (Nakamoto, 2008), cryptocurrencies have attracted significant attention from investors, policymakers, and researchers due to their disruptive potential and implications for financial systems worldwide. Despite growing recognition, understanding the diverse factors that drive their adoption across different countries remains complex yet crucial.

This paper hence investigates the determinants behind 2020 to 2024's cryptocurrency adoption on a global scale, specifically examining macroeconomic, socio-cultural, infrastructural, financial, institutional, and risk-related (informality) factors across 144 countries from: Central & Southern Asia and Oceania (CSAO), Sub-Saharan Africa, North America, Eastern Europe, Latin America (LATAM), Middle East & North Africa (MENA), Central, Northern & Western Europe (CNWE) and Eastern Asia.

The primary goal is not to predict, but to understand adoption by quantifying the relative importance of each determinant in influencing it. To achieve this, the study employs renowned econometric techniques of variance-decomposition, specifically the *Lindeman-Merenda-Gold* (LMG) and *Proportional Marginal Variance Decomposition* (PMVD) metrics (from Grömping, 2006). These methods effectively assess the relative contribution of each factor to the overall explanatory power (R^2) of our regression model. Given the computational complexity traditionally associated with these methods, especially when applied to large predictor sets, this work also develops and introduces a custom Monte-Carlo-based approach to variance decomposition. This approach *immensely* accelerates computations and represents an important methodological innovation within that research field.

Several closely related studies provide foundational insights for this paper. For instance, Alnasaa et al. (2022) and Saiedi et al. (2020) have shown strong links between macroeconomic stability, financial inclusion, and cryptocurrency adoption, whereas socio-cultural dynamics and institutional factors have been highlighted by Bhimani et al. (2022), Nguyen & Nguyen (2024), and Sergio & Petti (2024) among others. However, the vast majority of the literature, as of today, typically focuses on narrower country samples, little subsets of predictors and basic explanatory evidence. This work firstly differentiates itself by considering a far broader set of factors, encompassing diverse dimensions comprehensively. Moreover, the use of advanced variance-decomposition routines, particularly the custom proprietary ones, allow a nuanced interpretation of each predictor's contribution to the phenomenon, tracing a strong methodological distinction from previous works.

The empirical analysis reveals insightful patterns: the most influential category revealed to be financial determinants, with bank concentration contributing alone more than one fourth in explaining adoption, while collectivism and political instability followed as the most significant and influential drivers, validating and extending findings from the existing literature. However, other commonly cited determinants like GDP per capita, education and internet penetration exhibit surprisingly limited impact. The reached outcomes underscore how cryptocurrency adoption is heavily context-specific, shaped by complex relationships among various determinants rather than isolated factors.

The paper is structured as follows: Section 2 provides a theoretical background discussing adoption determinants and justifying their inclusion based on previous studies. Section 3 offers a detailed overview of data collection, variable construction, and methodological adjustments, including our custom-developed predictors like the bank distrust index. Section 4 outlines the econometric strategy, clearly defining and discussing LMG and PMVD methods and detailing our Monte-Carlo-based algorithmic improvements. Section 5 presents results, complemented by a thorough discussion linking empirical findings to the theoretical framework. Finally, Section 6 concludes with key insights, methodological reflections, and avenues for future research, clearly acknowledging the study's limitations and potential biases inherent in certain data sources.

Ultimately, this study aims to enrich the dialogue surrounding cryptocurrency adoption, offering practical insights to individuals and entities navigating this rapidly evolving financial, and to a certain extent, *societal*, landscape.

2 - ADOPTION DETERMINANTS: THEORETICAL BACKGROUND

Literature review about which factors could drive cryptocurrency adoption and why, as of today.

Starting from 6 'macro-categories', the related variables chosen are exposed, backed by empirical evidence. Choices are made on an 'hypothetical' basis.

2.1 Macroeconomic Environment

Cryptocurrencies, digital assets built on blockchain since Bitcoin's launch in 2008[1] (Nakamoto, 2008; Antonopoulos, 2017), are true innovations whose spread largely depends on socio-economic environments (Rogers, 2003). Both *favorable* conditions (i.e., higher incomes, stable growth and sound institutions, which provide the resources and infrastructure to experiment with new technologies) and *instability* flags (i.e., high inflation and FX volatility, which drive currency-substitution pressures) can spur crypto adoption (Calvo & Reinhart, 2002). These channels and their expected relevance form the 'baseline rationale' for our focus on a broad set of macroeconomic fundamentals when modeling cryptocurrency adoption.

2.1.1 GDP per capita

According to the *Digital-Divide* framework (van Dijk, 2005) and the World Bank's *Digital Dividends report* (2016), higher per-capita income is a key enabler of access to ICTs and financial-technology services[2]. Higher GDP per capita thus signals greater disposable income and better access to the financial-technology ecosystem, lowering barriers to experimenting with digital assets. Empirically, several studies like an IMF Working Paper (Alnasaa et al., 2022) and Guo et al. (2025) find that, across

[1] Bitcoin was the first crypto to become publicly exchangeable and gain global recognition. However, earlier blockchain-based or cryptographic digital currency prototypes existed (Antonopoulos, 2017; Wikipedia - A, B). The summary line exposed is thus a simplification.

[2] As '*material access*'. See van Dijk (2005).

countries, higher per-capita income is significantly associated with increased on-chain crypto activity. Similarly, Parino et al. (2018) show cross‑country evidence between wealthier populations and blockchain-adoption proxies, validating GDP pc as a core 'demand' driver.

2.1.2 Unemployment

Unemployment may capture two opposing pressures on crypto penetration. On one hand, joblessness, especially where social safety nets are weak, can drive individuals toward speculative assets or freelance work engagements[3] (Thurik et al., 2008), which could be paid out in stablecoins or other cryptocurrencies, to supplement their earnings. Indeed, Soomro et al. (2024) show that higher unemployment rates are positively associated with Bitcoin client downloads and relay-node activity across 62 countries. On the other hand, very high unemployment also erodes disposable income, limiting households' capacity to invest. Related to that, Guo et al. (2025) find a significant negative relationship between unemployment and cryptocurrency activity. This dual influence led us to include unemployment in our model to capture both the alternative-income and income-constraint dynamics.

2.1.3 Inflation rate

Inflation erodes the real value of fiat currency, motivating economic agents to seek alternative stores of value (Calvo & Reinhart, 2002). This can bring attention to cryptocurrencies, Bitcoin first, which are often perceived as inflation hedges (Baur & Dimpfl, 2018, Saiedi et al., 2020). Econometric literature also supports inflation rate as a key determinant, showing how a rise in CPI inflation can be associated with an increase in crypto‑adoption indices across states, while other sources exhibit inflation as a positively significant variable in panel regressions of per‑capita Bitcoin ownership (Nguyen et al., 2023, Rabhi & Soujaa 2024).

2.1.4 FX depreciation vs USD

Local‑currency depreciation against the US dollar, as something that weakens the domestic currency, can raise the relative appeal of assets denominated in (or pegged to) foreign money (see the currency-substitution pressures described in Calvo & Reinhart,

[3] Taken from the *push-pull model of entrepreneurial motivation*, elevated unemployment can act as a 'push' factor that compels individuals into alternative income-generating activities (Thurik et al., 2008).

2002). This can bring dollar‑pegged stablecoins[4] demand and other cryptocurrencies interest as quasi‑reserve assets[5]. However, *extreme* FX losses squeeze disposable income and may reduce public investment (as higher FX obligations absorb a larger share of the budget; Reinhart & Rogoff, 2009), potentially reducing private investments and straining the digital infrastructure required for crypto use (Garavaglia, 2018). Both sides are still being explored. Fahlander (2022), for example, finds a positive relationship between historical exchange-rate *volatility* and crypto-adoption proxies in developing countries. Complementing this, Habib et al. (2023) show that sharper weekly depreciation of domestic currencies is associated with notably higher P2P Bitcoin trading volumes, testifying how the magnitude and frequency of devaluation episodes is something influential.

2.1.5 Government size

As explained by Blanchard et al. (2021), larger public‑spending shares can dampen national savings and push up real interest rates, crowding out private investment and reducing households' risk appetite. At the same time, the manual also exposes how more interventionist states often impose higher taxes and capital controls, which can nudge savers toward offshore or permissionless assets like cryptocurrencies. Support to these hypotheses can be found in the work of Alnasaa et al. (2022) for the 'positive' side, and in Nguyen et al. (2023) for the 'negative' effect claim. In fact, the first documents a positive association between capital‑control intensity (a proxy for state intervention) and crypto‑adoption, while the second finds a significant negative coefficient on government‑expenditure/GDP in their cross‑country regressions of crypto‑adoption indices.

2.1.6 Trade openness

Keller (2004) shows that greater trade openness accelerates the international diffusion of technology, including imports of advanced ICT hardware, pertaining to the semiconductors' category. Semiconductors are obviously at the blockchain's backbone, since its whole infrastructure is made up of them. Hence, adoption can indirectly benefit from that openness due to the favorable context it creates for the underlying technology.

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[4] For a more detailed explanation about stablecoins, see Polizu et. al (2023).

[5] Highly liquid assets.

A recent configurational analysis carried by Nguyen & Nguyen (2024) confirms this idea: their findings exhibit trade-freedom indices and lower tariff rates as consistently linked with elevated levels of cryptocurrency and DeFi adoption. Another positive influence brought by open economies relates to exposing domestic firms and consumers to cross-border financial innovations (Obstfeld & Taylor. 2004), possibly increasing the demand for instant, low-cost payment rails. Nguyen et al. (2023), in addition to their previously seen findings, report that higher trade-to-GDP ratios significantly predict greater on-chain crypto activity across 158 countries.

2.1.7 Policy interest rate

The last spot for this macro-category is given to monetary policy effects. Central-bank policy rates work through the credit channel: lower rates reduce borrowing costs and boost market liquidity, while higher yields on traditional deposits raise the opportunity cost of holding non-yielding assets (Bernanke & Gertler, 1995). In this light, looser monetary policy can redirect capital toward speculative alternatives like cryptocurrencies, whereas tightening cycles tend to dampen crypto engagement. Empirical evidence we dispose exhibits in fact that an increase in the US shadow federal funds rate leads to a drop in a *common crypto-price factor*[6] over two weeks (Che et al. 2023). Similarly, Guo et al. (2025) report a significant negative coefficient on policy interest rates in their panel regressions of cryptocurrency activity.

2.2 Development & Infrastructure

The second category relevant to this analysis is recognized as *development and infrastructure* indicators. Indeed, as we already mentioned, digital assets like cryptocurrencies depend critically on both physical and digital infrastructure.

Recalling the digital-divide literature again, it demonstrates that uneven access to ICTs, rooted in disparities like electricity availability and internet connectivity, limits who can participate in new technologies' discovery[7] (van Dijk, 2005). Pairing that with *Human‑capital* theory further shows how education, access means and digital literacy

[6]Che et al. (2023) extract a crypto market proxy by running PCA on daily returns of top coins (≈75 % of market cap); the first component (≈80 % of explained variance) captures shared price dynamics across major tokens.

[7] As '*usage access*'. See van Dijk (2005).

shape individuals' capabilities (Becker, 1964), something fundamental to the understanding and usage comprehension of complex platforms like blockchain and its tools. At the same time, *agglomeration economies*[8] generated by population growth and urbanization can accelerate cryptocurrencies diffusion, as a novelty, through knowledge spillovers and network effects (Duranton & Puga, 2004). In this light, 5 possible determinants have been chosen to reflect this side of crypto adoption.

2.2.1 Access to electricity

Reliable electricity access supports both energy-intensive consensus algorithms (like the classic '*proof-of-work*', at the base of a lot of blockchains)[9] and the everyday use of internet-connected devices for crypto transactions. As Vranken (2017) demonstrates, mining major cryptocurrencies like Bitcoin and Ethereum[10] requires on average 7 to 17 MJ of electricity per US dollar of digital assets, making abundant, low-cost power a necessary precondition for network operations at scale. Corroborating this, there is evidence about national electrification rates being a significant positive predictor of cryptocurrency activity (Nguyen et al. 2023). These insights advise considering electricity access as a main infrastructural determinant.

2.2.2 Education

Literacy level may be one of the most basic though influential factors to include. According to the *Technology Acceptance Model* provided by Davis (1989), users' skills and knowledge shape their perceptions of ease of use and usefulness, which are critical for adopting new systems. Higher educational attainment therefore can bolster both digital and financial literacy, lowering the cognitive barriers to evaluating, trusting and allocating funds to complex assets like cryptocurrencies. At the individual level, this has been demonstrated by Kumari et al. (2023) showing that, in a sample of 312 respondents, subjective financial literacy and technology awareness significantly

[8] Summarizing, Duranton & Puga (2004) define agglomeration economies as the productivity and innovation benefits that arise when firms and workers cluster geographically.

[9] For a deepening on what a 'consensus algorithm' and 'proof-of-work' are, see the introductive glossary of Antonopoulos (2017), the schemes of Garavaglia (2018) or the technical overview of Lesavre et al. (2021).

[10] Note that, from September 2022, Ethereum switched to a *proof-of-stake* consensus (better explained on their portal; see Ethereum Foundation, A). This means the estimates of Vranken (2017) would differ today. His numbers have been maintained for exemplification purposes.

predicted behavioural intentions to adopt cryptocurrencies. On a country scale, Chainalysis report (2024) notes that the top adopters in its *Global Crypto Adoption Index* share above-average tertiary enrollment rates, suggesting a positive overall link between education and crypto detention.

2.2.3 Population growth

Demographic‑dividend theory by Bloom et al. (2003) suggests that rapid increases in the working‑age share of a population, especially among digitally native youth, can accelerate the spread of innovations, like cryptocurrencies. Conversely, neoclassical growth models (Solow, 1956) predict instead that faster population growth dilutes capital per worker and can distress physical infrastructure. Thus, population growth may boost crypto adoption through a young, tech‑adept collectivity while hampering it via infrastructure and fiscal pressures. As of today, the Pew Research Center testified part of the story, finding that 42 percent of Americans aged 18 to 29 have used cryptocurrency compared to only 17 percent of those over 50 (Faverio et al., 2024). On the flip side, the International Telecommunication Union (2021) reports that countries with annual population growth above 2 percent have internet‑penetration rates about 30 percentage points lower than slower‑growth peers, highlighting how demographic pressure can undercut the digital access necessary for crypto use.

2.2.4 Urbanization

Urban agglomerations are taken into consideration mainly as means of concentration for digital infrastructure, talent and peer networks, already quoted as influential. Hence, urbanizing brings possibilities for lowering transaction costs and speeding the diffusion of technology (Duranton & Puga, 2004), like the one we are considering. In fact, Nguyen & Nguyen (2024) identify high urbanization rates as a consistent element in configurations that yield elevated crypto and DeFi adoption across countries. Yet, densely served cities also feature robust banking systems, tighter regulatory oversight and higher living expenses, which can reduce both the need for and the disposable resources available to engage with cryptocurrencies (Christensen, 1997). Some evidence supports this side too, reporting a modest negative association between urban population share and crypto deployment (Bhimani et al., 2022), indicating that urban saturation or regulatory intensity may temper adoption.

The double influence explored underscores urbanization's ambiguous role in this analysis.

2.2.5 Internet-user share

Internet penetration is at the base of every single digital-related and network-related variable, consistently put at the center of indicators like the *network readiness* ones[11]. In our study, more people having access to the internet directly translates first into more potential cryptocurrency users, and then into lower fixed costs per user sustained by platforms (like exchanges) and in executing transactions. This is quite in line with classical *network-externalities* literature, which claims that the utility of a distributed platform rises as more users connect to it (Katz & Shapiro, 1985), validating widespread internet access as a fundamental enabler of cryptocurrency networks. Consistent with this, Nguyen et al. (2023) find that internet penetration positively correlates with cryptocurrency adoption. Likewise, Chainalysis (2024) reports that nations with internet penetration above 80 percent dominate the *Global Crypto Adoption Index*, highlighting connectivity's central role.

2.3 Financial System & Inclusion

The first[12] Cryptocurrency was created in response to how the current, centralized financial system was working, especially after the flaws emerged in the 2008 crisis. In particular, a clear mistrust in the intermediary-based and centralization dynamics arises from the most famous whitepaper[13] on the net (Nakamoto, 2008, Garavaglia, 2018). However, access, usage and concentration of financial means can still be meaningful promoters. Broad financial inclusion equips individuals with bank accounts and familiarity with electronic payments, lowering the barrier to experimenting with related tools like cryptocurrencies (Demirguc-Kunt et al., 2015). Meanwhile, competitive banking markets characterized by low concentration usually foster innovation by reducing entry costs (Beck et al., 2003). These reasons led to narrowing our focus on

[11] Network readiness commonly stands for "the propensity for countries to exploit the opportunities offered by information and communications technology" (United Nations ESCWA, 2022).

[12] See footnote 1.

[13] A 'whitepaper' is a document indicating everything pertaining to a cryptocurrency (and the underlying blockchain) project (Antonopoulos, 2017).

financial-account ownership, electronic-payment penetration, bank concentration and distrust in banks under this category.

2.3.1 Financial-account ownership

Formal bank accounts are the gateway to digital finance: they lower transaction costs, build usage familiarity, and provide access to payment rails essential for crypto. As suggested by Allen et al. (2016), ownership and use of a formal account in fact significantly reduce frictions in accessing financial services. Moreover, In contexts where many adults remain unbanked, cryptocurrencies can become instead a first-best option for digital payments and savings. Guo et al. (2025) attest the consistency of these claims, finding that higher national financial-account ownership rates are significantly associated with increased on-chain crypto activity.

2.3.2 Bank concentration

Back in the fifties, Bain (1951) theorized how market-structure works and its outcomes. It can be deduced from that, how a higher (banking, in our case) concentration reduces competitive pressures, raising profits (hence, fees), although slowing innovation and excluding underserved segments. In such environments, consumers may turn to decentralized financial means as an alternative. That also correlates to systemic-risk concerns around 'too big to fail' banks, further amplifying demand for self-custodied assets. On the other hand, dominant banks can also easily gatekeep access to crypto, by imposing cryptocurrency-related restrictions to their users[14]. In support to this, Alnasaa et al. (2022) report that countries with more concentrated capital-control regimes (Often coinciding with oligopolistic banking sectors) exhibit higher crypto-adoption scores, suggesting it actually is something that 'pushes' away from centralized finance. Bhimani et al. (2022) also find a significant negative relationship between the Herfindahl-Hirschman Index of bank assets and national crypto-adoption rates across 137 countries, indicating that when banks dominate, the overall domestic crypto market is dampened.

[14] There are a lot of real-world examples that could be reported. just for reference, see The Scottish Sun (2024), Associated Press (2023).

2.3.3 Bank distrust

As already mentioned, the blockchain was born to deal with 'financial trust' among its main reasons[15]. Trust in banks here not only represents a proxy for that, but also signals broad financial participation: when individuals believe in the safety and soundness of intermediaries, they are more likely to hold deposits, apply for credit and rely on conventional payment methods (Ampudia & Palligkinis, 2018). This implies, by contrast, that declines in trust, brought by past crises, fears over asset security or dissatisfaction with bank conduct[16], can drive households toward non-bank channels. Strengthening this behaviour there is also a banks' attitude shown in an interesting work provided by Heyert & Weill (2024), which demonstrates that banks don't rule out riskier activities even when their clients start to trust them less, possibly creating a feedback loop. At the same time, Akanksha et al. (2023) find that higher interpersonal trust significantly increases interest in and adoption of cryptocurrencies, implying that low trust in conventional finance actually creates an incentive toward decentralized alternatives.

2.3.4 Electronic-payment penetration

Familiarity with digital payment systems should lower the hurdle to non-cash transactions. The theoretical background behind this concept is grounded in the already seen[17] 'Technology Acceptance Model' by Davis (1989), which received later extension by Venkatesh & Davis (2000) meaningful for this section, incorporating social influence and contextual factors into the model. As previously noted, successful experience with one technology can enhance perceived ease of use and usefulness of related systems. This applies not only to education[18], but also to electronic-payment usage: populations accustomed to digital wallets and mobile payments may find cryptocurrencies both

[15] Still refers to the bitcoin blockchain, as it remains the most known. Differences may apply across other chains, projects, or early prototypes. See footnote 1, Wikipedia (A, B), and Garavaglia (2018).

[16] Common-knowledge proxies. Not sourced elsewhere, although Heyert & Weill (2024) use related terms for their distrust indicator (and our custom indicator's list is broader but similar; see section 2.2.1).

[17] See section 2.2.2.

[18] See section 2.2.2.

easier to use and more useful, particularly as *social norms*[19] and *job relevance*[20] (emphasized in Venkatesh & Davis additions) further reinforce positive perceptions. Supporting this, Alnasaa et al. (2022) report that higher national shares of electronic payments are significantly associated with increased crypto-adoption scores in their sample.

2.4 Socio-Cultural Factors

Cryptocurrency establishment unfolds within the fabric of societal norms, cohesion and risk attitudes. Lower inequality and safer communities foster trust and reduce transaction frictions, whereas high inequality and crime can erode institutional confidence and spur demand for self-custodied alternatives[21] (Putnam, 2000). Cultural-dimensions research (Hofstede, 2010) further demonstrates that societies' levels of collectivism and uncertainty avoidance shape their openness to disruptive financial innovations. Finally, the inequality-crime connection (Fajnzylber et al. 2002) links resource-distribution gaps and homicide rates to economic precarity and diminished trust in formal institutions, conditions that can both drive and limit crypto adoption. Together, these channels support our inclusion of three (out of many) possible socio-cultural determinants.

2.4.1 Equality & resource distribution

Wilkinson & Pickett (2009) show that higher income inequality correlates strongly with worse social outcomes and erodes trust in institutions, conditions that can drive people toward alternative means of value storage. In highly unequal countries, we can indeed find drivers like greater remittance-cost pressures and wealth-preservation motives, among others, which can thus intensify demand for cryptocurrencies. Recalling Bhimani et al. (2022) study, it finds that the Gini coefficient is among the strongest

[19] When peers or superiors endorse system use, user intention to adopt rises significantly, especially early on. This describes the '*subjective norm*' effect in tech adoption (Venkatesh & Davis, 2000).

[20] '*Job relevance'* boosts adoption when a system aligns with one's work tasks (Venkatesh & Davis, 2000). It's less crucial than the subjective norm here, but still relevant.

[21] That was taken from the core concepts in Putnam's *Social-capital* theory (Putnam, 2000).

positive correlates of crypto‑adoption rates in their 137‑country panel, confirming that higher inequality drives greater adoption.

2.4.2 Collectivism index

Hofstede's individualism-collectivism dimension captures how cultures balance group cohesion against personal autonomy (Hofstede, 2010). In particular, we can infer how collectivist societies, placing high value on social harmony and risk aversion, may tend to adopt speculative financial innovations more slowly, whereas individualistic cultures, with greater tolerance for uncertainty and emphasis on self‑reliance, should more readily embrace new assets (Hofstede, 2010). Present evidence shows that a country's individualism score is positively and significantly correlated with its Bitcoin transaction activity (Foley et al., 2022), highlighting individualistic cultural settings as fertile ground for cryptocurrencies.

2.4.3 Homicide rate

According to North et al. (2009), high homicide rates signal weak state capacity and fragile rule‑of‑law, undermining trust in formal institutions and possibly increasing the perceived risk of holding physical cash. In such environments, self‑custodied digital assets appear safer, bringing interest towards cryptocurrencies. Rabhi & Soujaa (2024) find in fact that a one‑unit rise in national homicide rates per 100 000 inhabitants is associated with an increase in per‑capita Bitcoin ownership, from a study run across 30 countries.

2.5 Institutional and Political Landscape

The relevance of this category is rooted not only in economic theory but also in classical liberal thought. From the Austrian School, Hayek (1979) argued that dispersed decision‑making and rule‑bound law form the foundations of a free political order, which fosters in turn the openness in which innovations thrive. However, freedom is not the only influential factor: cryptocurrency adoption may hinge on institutional strength and clarity too. North (1991) demonstrates that robust rule-of-law, secure property rights and transparent regulatory processes lower transaction costs and reduce uncertainty for innovators, while Rodrik et al. (2004) find that institutional quality outranks geography or trade openness in driving economic performance, underscoring why stable governance encourages the diffusion of new financial technologies. Similarly, Kaufmann et al. (2009) show that higher scores on governance indicators correlate with deeper, more resilient financial sectors, conversely indicating that weak or unstable institutions could encourage decentralized assets as 'defensive' measures against excessive government control.

Six possible proxies have been chosen to reflect and explore what has been articulated.

2.5.1 Crypto-specific restrictions

Explicit government bans or tight regulations on cryptocurrency trading, mining and payments directly raise legal risks and compliance costs, suppressing both user demand and infrastructure development. As we said, this found foundation in Kaufmann et al. (2009), who show low regulatory quality (characterized by opaque, restrictive policies) stifles financial innovation and reduces sector depth. Saiedi et al. (2020) actually link that with the cryptocurrency sector, documenting that jurisdictions enforcing outright bans host significantly fewer full nodes[22] and exchange platforms, confirming the dampening effect of prohibitive regulations on crypto adoption.

2.5.2 Social repression

In environments where governments repress dissent, censoring speech, surveilling activists or employing violence, individuals lose faith in formal systems and seek alternatives. *Resource‑mobilization* theory (McCarthy & Zald, 1977) suggests that political repression can encourage social movements to discover new funding mechanisms, and cryptocurrencies offer permissionless, censorship-resistant transactions and protection against asset seizure by nature. Real-world evidence confirms this logic, with the case of the 2019 Hong Kong protests. During those events, Bitcoin trading volumes and peer-to-peer exchange activity spiked (Hamacher, 2019), as protesters and supportive businesses turned to crypto to evade banking controls.

[22] Nodes considered by Saiedi et al. (2020) are the Bitcoin blockchain's ones. As stated before, everything exhibited by Bitcoin is a good proxy for the overall context.

At the same time, severe repression raises legal risks and operational hurdles, something that may deter average users.

2.5.3 Censorship

Deibert et al. (2010) argued that global filtering practices shape technology diffusion and information flows, therefore suggesting that government‑imposed internet filters and content controls can both increase and decrease cryptocurrency use. Strict online censorship surely increases the value of permissionless, censorship-resistant payment networks and distributed ledgers while, on the other hand, blocking of crypto websites, takedown orders and legal penalties raise access costs and heighten user risk. In practice, the positive-effect side exhibits stronger evidence: the Atlantic Council reports that 27 countries impose general bans or partial restrictions, yet peer-to-peer volumes remain strong in many of these regimes (Dale, 2024), testifying users' ability to circumvent these blocks via decentralized channels.

2.5.4 Liberal-democracy 'extent'

Liberal-democratic systems, defined by competitive elections, civil liberties and checks on executive power (Sartori 2012), establish transparent legal frameworks and investor protections (Diamond, 1999), which can ease the entry of regulated crypto products (such as the recent ETFs, custodial services and licensed exchanges) as novel financial means (La Porta et al., 1998). This means that by reducing policy uncertainty and guaranteeing oversight, strong democracies foster the growth of legitimate crypto markets. On the opposite side, in less democratic regimes, necessity and mistrust of institutions can still drive adoption, despite higher legal and technical hurdles. Backing this point, Nguyen & Nguyen (2024) identify high liberal-democracy scores in all countries characterized by elevated cryptocurrency diffusion.

2.5.5 Political instability

Political volatility, characterized by frequent policy reversals, civil unrest or coup threats, is shown to erode confidence in domestic institutions and drive capital toward external or hard assets (Aisen & Veiga, 2013). If we relate that to the cryptocurrency context, such turmoil can boost demand for the borderless value stores of our interest. Severe instability however may disrupt critical infrastructure, or provoke unpredictable regulatory crackdowns, resulting in raised legal and operational barriers to crypto use. Nonetheless, Sergio & Petti (2024) still find that spikes in geopolitical risk lead to significant increases in monthly Bitcoin trading‑volume, underlining how political imbalances can push investors into crypto despite the possible obstacles.

2.5.6 Economic freedom

Economic freedom, characterized by secure property rights, minimal regulatory burdens and open markets[23], creates fertile ground for financial innovations and lowers barriers to entry for new payment systems[24]. In such environments, entrepreneurs and investors hence face fewer hurdles when launching wallets, exchanges or DeFi protocols. Guo et al. (2025) tested these hypotheses, including the Economic Freedom of the World index in their cross-country regressions, and found a positive, statistically significant coefficient, indicating that nations with greater economic freedom exhibit higher per-capita on-chain crypto activity.

2.6 Illicit Economy and Risk Factors

Cryptocurrencies' 'pseudo-anonymity'[25] and borderless design can make them not only new means to explore a trustless resource management, but also attractive vehicles for illicit financial flows, and this rationale stands behind the inclusion of our last category. Weak formal institutions are usually what reflects large informal or 'shadow' economies, and Schneider & Enste (2000) showed how a poor presence of countermeasures conveys funds into those 'parallel' markets, among which crypto ones could find a place. Foleyet al. (2019) estimate that a sizable share of Bitcoin activity actually finances illegal markets, testifying crypto's role in money laundering and illicit trade. At the same time, jurisdictions grappling with high levels of illicit activity are typically advised to impose stricter anti-money-laundering and

[23] Factors involved and characterizing economic freedom are drawn from Gwartney et al. (2021) and the Heritage Foundation's work (Heritage Foundation, A).

[24] Beck et al. (2003) link stronger creditor rights and fewer entry barriers with deeper, more diversified finance. La Porta et al. (1998) similarly show how investor protections fuel equity and bond market growth.

[25] Blockchains are (usually) public ledgers: all transactions are visible (Garavaglia, 2018). Yet linking them to real users is hard without centralized services, or if mixers like Tornado Cash (A) obscure settlement paths.

counter-financing-of-terrorism (AML/CFT) regulations on virtual-asset service providers, raising compliance burdens and deterring mainstream adoption (FATF, 2021).

Three factors have been picked to investigate these possible effects.

2.6.1 Shadow-economy size

Where a large proportion of transactions go unreported or illicit, participants *need* a mode of exchange that eludes formal oversight, and as we said, cryptocurrencies fit this bill well. Schneider & Enste (2000) define the 'shadow economy' as all market activities hidden from official scrutiny[26]. They also provide estimates showing those activities have a meaningful size, suggesting there can be a linked demand for unregulated value-transfer mechanisms. Marmora (2021) tests this directly: using panel data from 28 emerging economies, he shows that countries with larger estimated shadow sectors exhibit significantly higher per-capita Bitcoin trading volumes, consistent with informal actors often opting for crypto instead of cash.

2.6.2 Money-laundering risk

Where anti-money-laundering (AML) controls are weak, the probability of laundering illicit proceeds through cryptocurrencies rises. The Basel AML Index, a composite measure of a country's vulnerability to money-laundering and terrorist-financing, captures this risk (Basel Institute on Governance, 2024). In high-risk jurisdictions, the combination of lax enforcement and crypto's alias-based privacy can make it a convenient medium for moving illicit funds. This finds evidence in Chainalysis data, which show that many of the top peer-to-peer crypto volume per capita markets fall into the bottom quartile of AML/CFT standards, highlighting how elevated laundering risk correlates with higher hidden crypto activity (Chainalysis, 2022, 2023, 2024).

2.6.3 Corruption

The last driver we want to propose relates to corruption and its effects on confidence in public institutions and formal financial channels. Treisman (2000) shows

[26] 'Informal' or 'shadow' economies as terms describing illicit activities' markets are concepts dating far back in time (Schneider & Enste, 2000). To review the grounding literature behind that, see Hart (1973), Feige (1989).

that high perceived corruption correlates in fact with lower institutional trust and greater recourse to informal markets and, as we already showed, these may include blockchain-enabled ones. The assumption is that cryptocurrencies and their intermediary-free transfers, can act as means to bypass corrupt gatekeepers and preserve wealth: Foley et al. (2019) actually estimate not only that roughly one quarter of Bitcoin transaction volume finances illicit markets, but that many operate in jurisdictions with weak anti-corruption frameworks. Since the overall picture described, we consider corruption as highly meaningful in this analysis.

Table 0 - Determinants summary & expectations

Determinant	Expected effect	Determinant	Expected effect
Macroeconomic Environment		***Socio-Cultural Factors***	
[1] GDP per capita	+	*[17] Gini_index*	+
[2] Unemployment rate (%)	?	*[17b] Equality resource distribution*	-
[3] Inflation rate (%)	+	*[18] Collectivism index*	-
[4] Exchange rate depreciation vs USD$	?	*[19] Homicide rates*	+
[5] Government Size	?		
[6] Trade openness (% of GDP)	+		
[7] Interest rates (CB)	-		
Development & Infrastructure		***Institutional and Political Landscape***	
[8] Access to electricity	+	*[20] Crypto-specific restrictions*	-
[9] Education	+	*[21] Social repression*	?
[10] Population growth	?	*[22] Censorship (media/internet)*	?
[11] Urbanization	?	*[23] Liberal-democracy*	+
[12] Internet users (% of pop)	+	*[24] Political instability*	?
		[25] Economic freedom	+
Financial System & Inclusion		***Illicit Economy and Risk Factors***	
[13] Financial account ownership (% of pop)	+	*[26] Shadow-economy size*	+
[14] Bank concentration	?	*[27] Money-laundering risk*	+
[15] Bank distrust Index	+	*[28] Control of Corruption*	-
[16] Electronic Payments (% of pop)	+		

3 - DATA OVERVIEW

Data description and methodological treatment. Variables that underwent any manipulation or require further explanation are presented in their own paragraph.

3.1 Dependent Variable

The dependent variable used is represented by a manipulation of the Chainalysis *Crypto Adoption Index* (Fig. 1). This Index tries to measure adoption based on various sources of cryptocurrency transaction volumes, following a composite, rank-based indicator methodology with a geometric mean aggregation and a min-max normalization (Nardo et al., 2005, Chainalysis, 2020, 2021, 2022, 2024). Specifically, yearly data is gathered to build 3 to 5 sub-indicators for every country showing enough data to permit the process, and results are then weighted by either population size, internet users, purchasing power parity per capita or GDP per capita (PPP adjusted) to form a country weighted rank for each sub-indicator. Finally, all sub-indicators' weighted-ranks are aggregated (per country) by their geometric mean, and the end results normalized on a 0 to 1 scale (Chainalysis, 2020, 2021, 2022, 2023, 2024).

Even if the overall composite indicator approach, aggregation methodology, and data collection tools[27] for the sub-indicators remain consistent across years, nor the weighting factors and the sub-indicators themself remain completely unchanged over time. Below is a breakdown of every component for each year's index:

- 2020 index components:
    - *On-chain cryptocurrency value received, weighted by purchasing power parity (PPP) per capita* : it is described as an estimate of the total

[27] From Chainalysis (2020): "Due to cryptocurrency's decentralized nature, it's impossible to know the precise amount sent and received on-chain by addresses in a specific country. However, we can produce a strong estimate by measuring the cryptocurrency activity occurring on each platform and distributing it by country based on the breakdown of countries accounting for web traffic to each platform's website. We use the web analytics service *SimilarWeb* for those country-based traffic numbers.". This is expressed in every report. Although the *SimilarWeb* service is explicitly indicated in the 2020 and 2022 reports only, the overall recurrent claim has been assumed as enough evidence to presume consistency in data collection across the 5 reports (Chainalysis, 2020, 2021, 2022, 2023, 2024).

cryptocurrency received by a country[28], as a proxy for its total crypto 'activity'. PPP weighting helps to depenalize poorer countries.

- *On-chain retail value transferred, weighted by PPP per capita* : it is a 'retail-segmentation' of the previous data, where only transactions up to 10,000 dollars are accounted for.
- *Number of on-chain cryptocurrency deposits, weighted by number of internet users* : ratio of on-chain cryptocurrency deposits (transactions) to the country's total internet users. It is used to indicate which country's residents are carrying out more crypto transactions (per internet user).
- *Peer-to-peer (P2P) exchange trade volume, weighted by PPP per capita and number of internet users* : This metric represents the user-user cryptocurrency trade volume. It is the only one to be not measurable by on-chain data, therefore *LocalBitcoins* and *Paxful*, the two largest peer-to-peer platforms at the time, were used as data providers for making an approximation of this measure (Chainalysis, 2020).

- 2021 index components:
  - *On-chain cryptocurrency value received, weighted by purchasing power parity (PPP) per capita* : It remains the same metric.
  - *On-chain retail value received[29], weighted by PPP per capita* : It remains the same metric.
  - *Peer-to-peer (P2P) exchange trade volume, weighted by PPP per capita and number of internet users* : It remains the same metric (Chainalysis, 2021).

2021 report split the index into another, measuring DeFi[30] activity only. This has eventually been merged to the overall one from the next year on. Components:

[28] Country-specific collection and estimation methods are reported in footnote 2.

[29] The change in terminology between 2020 and 2021's reports for the retail metrics, passing from '*value transferred*' to '*value received*' reflects a term change only, without any methodology shifts (Chainalysis, 2020, 2021).

[30] *DeFi* stands for 'decentralized finance'. In summary, it indicates the context of financial services delivered on/through public blockchains' various protocols, hence in a peer-to-peer way. It differs from (centralized) 'standard' cryptocurrency exchanges' industry mainly by being almost entirely on-chain (Coinbase, A).

- *On-chain cryptocurrency value received by DeFi platforms weighted by PPP per capita* : It is the equivalent of the first indicator of the non-DeFi index, accounting for DeFi protocols' data only.
- *Total retail value received by DeFi platforms* : It is the equivalent of the second indicator of the non-DeFi index, accounting for DeFi protocols' data only.
- *Individual deposits to DeFi platforms weighted by PPP per capita* : It is the equivalent of the third indicator of the 2020's index, accounting for DeFi protocols' data only[31] (Chainalysis, 2020, 2021).

- 2022 index components:
  - *On-chain cryptocurrency value received at centralized exchanges, weighted by purchasing power parity (PPP) per capita* : It remains the same, but accounting for centralized services' data only (exchanges mainly). This is due to the fact that the index-split from 2021 had been dropped in favor of an overall unique index, properly accounting for the two adoption sides with well-separated indicators.
  - *On-chain retail value received at centralized exchanges, weighted by PPP per capita* : It remains the same, with the change of focus explained above.
  - *Peer-to-peer (P2P) exchange trade volume, weighted by PPP per capita and number of internet users* : It remains the same metric.
  - *On-chain cryptocurrency value received from DeFi protocols, weighted by PPP per capita* : It remains the same metric as the first component of the 2021's DeFi index.
  - *On-chain retail value received from DeFi protocols, weighted by PPP per capita* : It remains the same metric as the second component of the 2021's DeFi index (Chainalysis, 2021, 2022).

[31] It had been dropped from 2020 overall index and put in the 2021 DeFi one due to DeFi transactions' nature, which 'absorbs' the majority of deposits (exchange trades are indicated in their order books and not on-chain, hence 'lost' for this metric. DeFi platforms trades happen instead on-chain, hence letting every transaction (or the majority of them) being captured here (Chainalysis, 2020, 2021).

- 2023 index components: 2023 version is equal to the previous year's one (Chainalysis, 2022, 2023).
- 2024 index components:
  - *On-chain cryptocurrency value received by centralized services, weighted by GDP per capita on a PPP adjusted basis*[32] : It remains the same metric.
  - *On-chain retail cryptocurrency value received by centralized services, weighted by GDP per capita on a PPP adjusted basis* : It remains the same metric.
  - *On-chain cryptocurrency value received by DeFi protocols, weighted by GDP per capita on a PPP adjusted basis* : It remains the same, with some measurements adjustments: carrying out a transaction on a DeFi protocol involves a series of steps. This year's indicator accounts for data from the first step only instead of the whole process. This results in lower raw estimates along with higher accuracy.
  - *On-chain retail cryptocurrency value received by DeFi protocols, weighted by GDP per capita on a PPP adjusted basis* : It remains the same, along with measurement changes described for the previous DeFi indicator (Chainalysis, 2023, 2024).

  The 2024's index dropped the P2P metric due to one of their major sources being shut down (LocalBitcoins). Since its data heavily relied on that resource, as indicated above, including that component in 2024 would have given biased results (Chainalysis, 2024).

The last relevant change happening between different years' index is the country sample size. Reports from 2020 to 2024 indicate, respectively, a sample size of: 154, 154, 146, 155 and 151 countries. In addition, some countries' data availability seem to

[32] Using GDP per capita (PPP adjusted) as a weighting factor is not indicated in the methodology changes of that year by the company. It is then unclear if it is an actual change or a terminology change, like discussed in footnote 4. This is not the only uncertainty raised by the firm's reports: from the 2023 report, they started including a sort of pre-description for the weighting factors used in the overall methodology description section of the report, quoting that population size has been used too as one of them. However, there is not any clear indication of whether other weighting factors had been used rather than the ones actually stated in the indicator descriptions. This paper then takes the information to be reported from the individual indicator descriptions only (Chainalysis, 2020, 2021, 2022, 2023, 2024).

change over time, leading some to not appear in a report's sample while being there the year before, or to be listed in a new report's sample while not being there in the previous one. This would create serious inconsistencies for any analysis involving the time dimension of the index scores (Chainalysis, 2020, 2021, 2022, 2023, 2024, Wooldridge, 2019).

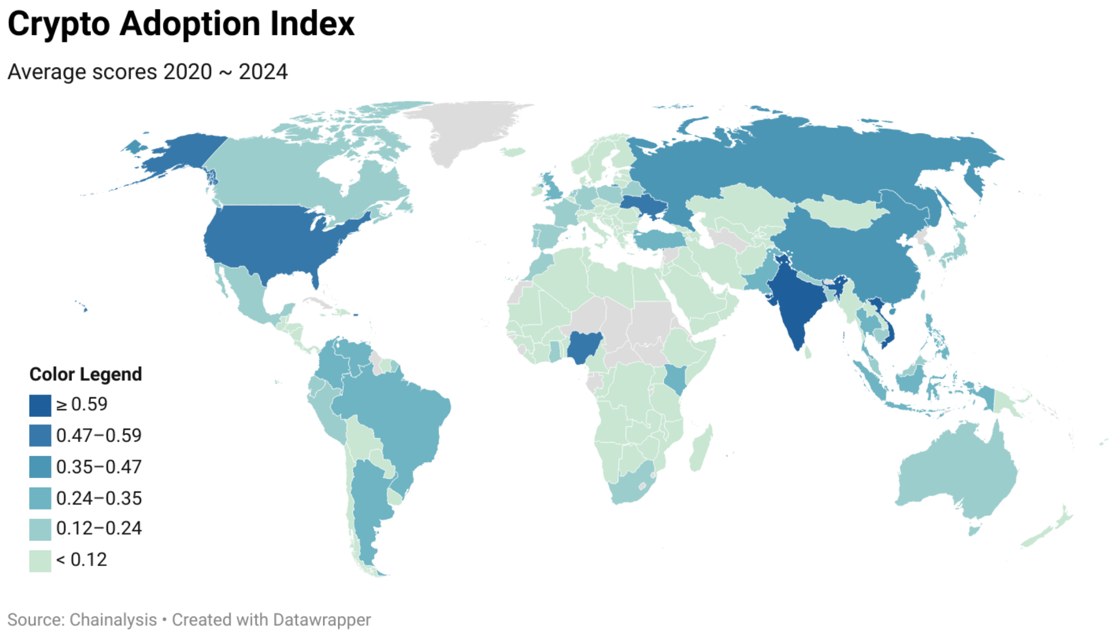

Fig. 1 - Global Crypto Adoption Index Map (yearly measure, averaged over 2020–2024; See paragraph 2.1 for variable description). Top 10 countries are: India, Vietnam, United States, Ukraine, Nigeria, Russia, China, Philippines, Thailand, Pakistan. Bottom 10 countries are: Iceland, Qatar, Fiji, Oman, Andorra, Guinea, Liberia, Papua New Guinea, Mauritania, Aruba.

3.1.1 Dependent variable processing

Since the discussed changes and updates in the variable construction over the five versions available, a panel analysis would be unsuitable, while a cross-sectional one could be possible instead. In order to let the data be manageable for that, the index scores have been hand-collected for every country from both the interactive maps on the reports' web pages and the report documents[33], organized in an excel file and averaged

[33] The 2024 country list has been used as the reference sample for building the database, taking data of its countries from every other year's report/geo map. For the 2021 index, since its 'split' nature,

over the 5 year period for each country. This resulted in a single score per country representing the average crypto adoption score for that particular country over the 2020 to 2024 interval. The overall number of countries we kept for the analysis is 144.

Assumptions in favor of the feasibility of a cross-sectional analysis are summarized by the fact that, for such analysis, measurements must be consistent across observations (units, which are countries), and not necessarily across time (Wooldridge, 2019). In our case, applying a ceteris paribus logic, we can assume that methodological adjustments influence countries' scores consistently within each year, supported also by the fact that the composite indicator, aggregation and normalization approaches remain unchanged, hence ensuring comparability across countries. Therefore, we conclude that averaging the data by country across the period smooths out the outlined differences in the index-building, giving a reasonable cross-sectional proxy for estimating cryptocurrency adoption over that timeframe (Wooldridge, 2019, Nardo et al., 2005).

3.2 Independent Variables

All of our independent variables are drawn averaging from the 2015-2019 period to ensure consistency across data sources and to underline causality other than correlation by picking a prior time span to Y's one. In cases where indicators required tailored construction or faced reporting issues, we extended the reference window either before or after the core period to capture the most complete and comparable measures.

Table 1 - Independent Variables

Variable	Mean	Std	Description	Source
		Macroeconomic Environment		
[1] GDP per capita	25924.38	24783.27	GDP per capita, PPP adjusted	World Bank (D)
[2] Unemployment rate (%)	7.32	5.34	Unemployment, total (% of total labor force) (modeled ILO estimate)	World Bank (E)
[3] Inflation rate (%)	4.32	5.66	Inflation, GDP deflator (annual %)	World Bank (F)
[4] Exchange rate depreciation vs USD$	21.27	50.26	Official exchange rate (LCU per US$, period average)	World Bank (H)
[5] Government Size	29.87	11.84	General government final consumption expenditure (% of GDP)	IMF (A)
[6] Trade openness (% of GDP)	85.74	49.43	Trade (% of GDP)	World Bank (I), Trading Economics (A)
[7] Interest rates (CB)	10.92	63.08	Central bank policy rate (%)	World Bank (J)

we took the average score from the 'overall' index and the DeFi index for each country (Chainalysis, 2021, 2024).

Table 1 - Continued				
Variable	Mean	Std	Description	Source
		Development & Infrastructure		
[8] Access to electricity	85.41	24.99	Access to electricity (% of population).	World Bank (C)
[9] Education	9.10	3.43	Average years of education	World Bank (G), IHME (2025)
[10] Population growth	1.32	1.23	Population growth (annual %)	World Bank (K)
[11] Urbanization	61.73	21.24	Urban population (% of population)	World Bank (L)
[12] Internet users (% of pop)	56.09	27.44	Individuals using the Internet (% of population)	World Bank (B)
		Financial System & Inclusion		
[13] Financial account ownership (% of pop)	56.95	29.54	Financial account ownership (% of pop)	World Bank (M)
[14] Bank concentration	64.14	17.28	Bank concentration	World Bank (O), The Global Economy (A)
[15] Bank distrust Index	9.83	12.64	Distrust sentiment towards banks and the financial system	Custom
[16] Electronic Payments (% of pop)	51.36	28.54	Made or received a digital payment (% age 15+)	World Bank (N)
		Socio-Cultural factors		
[17] Gini_index	45.34	6.55	Gini index	World Bank (P), Solt (A)
[17b] Equality resource distribution	0.61	0.28	Equal distribution of resources index	V-Dem (A)
[18] Collectivism index	0.04	0.79	Collectivism index	Pelham, B. W. et al. (2022b)
[19] Homicide rates	6.63	10.84	Intentional homicides (per 100,000 people)	World Bank (Q), Knoema (A)
		Institutional and Political Landscape		
[20] Crypto-specific restrictions	0.34	0.48	Regulations restricting cryptocurrencies	Custom
[21] Social repression	-1.07	1.23	Civil society and religious organization repression (averaged)	V-Dem (B, C)
[22] Censorship (media/internet)	-0.75	1.27	Government censorship effort of media and internet (averaged)	V-Dem (D, E)
[23] Liberal-democracy	0.44	0.26	Liberal-democracy	V-Dem (F)
[24] Political instability	0.12	0.9	Political Stability and Absence of Violence/Terrorism: Estimate (inverted)	World Bank (R)
[25] Economic freedom	6.95	0.93	Economic Freedom of the World Index (current)	QoG (A)
		Illicit Economy and Risk Factors		
[26] Shadow-economy size	29.86	12	Shadow-economy size	Elgin et al. (2021b)
[27] Money-laundering risk	5.74	1.25	Money Laundering Risk index	Basel Institute on Governance (A)
[28] Control of Corruption	-0.06	0.99	Control of Corruption: Estimate	World Bank (S)

3.2.1 Bank distrust index processing

Due to a lack of proper indicators of mistrust in banks and the financial system online, a custom predictor was developed, following and improving root ideas from Heyert & Weill (2024). They proposed a *Google Trends*-based estimate about people searches on topics that can reflect wavering confidence in financial institutions (i.e., ‘financial crisis’, and so on) as a proxy for a country’s distrust. The main issue comes from Google Trends data being ordinal rather than raw: this makes comparability among countries a difficult feature to reliably achieve, due to different country sample sizes across search topics[34] (Heyert & Weill, 2024).

Maintaining the rationale, our version stands as a trial for a more comprehensive, complete and uniform distrust indicator, with the aim of being tied to raw measurements per capita. In order to pursue the idea, Google Ads' tool '*keyword planner*' has been used instead of Google Trends. The former tool, in fact, allows for the retrieval of the average monthly search volume (on Google and its partners' platforms) for a specified set of keywords[35], in a specified time span[36] (Google, B). We also expanded Heyert & Weill (2024) keywords/topics from 5 to 13, specifically including: *Bailout, Bank failure, Bank insolvency, Bank panic, Bank run, Capital flight, Deposit insurance, Financial crisis, Financial risk, Systemic risk, Economic crisis, Bank collapse, Bank corruption*. Then, even if Google's tool suggests keywords are accounted for in 'all languages', tests we ran showed they are not[37]. Therefore, after collecting the majority of the languages spoken in our country sample using the CIA's *World Factbook* (A) and Ethnologue (A), we translated each of the 13 terms into those languages[38], filtered the duplicates, and gave the final 954 Keywords to the Keyword Planner. Finally, by running single-country queries, we manually collected the aggregate average search volumes for every country in our sample.

That measurement still needed to be expressed as a yearly per-capita estimate, therefore we collected the total population number and internet penetration (% of population) from the World Bank (A, B), to exhibit the actual number of people having

[34] Even if the authors partially addressed the problem, they still admitted the methodology was not too accurate (Heyert & Weill, 2024).

[35] They were given in the 'broad match' format to account for alternatives and treat them as 'topics' rather than simple keywords. This lets the system be able to consider more than one keyword per given keyword, multiplying the original keyword number by a minimum factor of 2. see Google (B).

[36] The Keyword planner can't provide data older than 5 years (from the present day). The variable's data had been taken during January 2025, therefore using January 2021 -to- January 2022 as the time span for 2021 data (Google, B).

[37] We obtained, using the same time interval, two different results for a single keyword volume when submitting that keyword in English and in the country's native language.

[38] Due to a lot of reasons, mainly pertaining to developmental and cultural factors, some terms don't have direct translations in every language, sometimes being not even recognized as concepts. In those cases, we left the original english terms and filtered them out later. For the general translation and terminology-matching process, tools employed include: PanLex (A), United Nations' *UNTERM* (A), Globse (A), Tatoeba (A), Google translate (A).

access to the internet, and divided our search volume (multiplied by 12) by that number, for every country we are interested in. This hence gives a 'bank distrust *sentiment*[39], per capita, afterwards expressed per 100,000 internet users for ease[40].

3.2.2 Crypto-specific restrictions processing

A dummy variable representing cryptocurrency restrictions imposed by the law is our second custom regressor among the listed independent variables. The idea comes from Saedi et al. (2020), where they built a variable taking a value of '0' for countries not putting in place any form of ban and a value of '1' for countries with rules prohibiting people or institutions from dealing with cryptocurrencies.

We proceeded with the same approach, refining it[41]. In particular: a value of '1' indicates the presence of any enforceable ban in the country, whether targeting institutions or private individuals. A country also gets a value of 1 if it has no enforceable laws but its institutions explicitly said, without contradicting afterwards, cryptocurrencies and related activities are prohibited or deemed illegal. '0' means instead a country has specified it is pro-crypto, has a crypto-friendly legal scenario or it has regulated the cryptocurrency context. A country also gets '0' when it has no rules and has not clearly stated any position, or it has simply disincentivized financial institutions and/or individuals to deal with crypto without enacting any form of enforceable legislation. Absence of data, declarations or any form of information classifies as a '0' too. Assignments are based on information from: Wikipedia (C), Law Library of Congress (2021), Atlantic Council (A).

Our refinements help set a more accurate value for 'limbo' countries reported by those sources, especially for countries classified as having an 'implicit ban' by the Law Library of Congress (2021)[42].

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[39] 'Sentiment' stands for an aggregate measure of mood or confidence.

[40] Even if a lot of efforts were spent for building a comprehensive measure, naturally present biases in search-based data still remain and could skew results to a certain extent, like differences in search behaviour or Google usage across countries or heavy censorships of media, only partially addressed by the employed methodology.

[41] An update to 2021 was also needed to fit our year of focus (Saiedi et al., 2020, used 2018 data).

[42] Coding still relies on publicly available sources and does not weight restriction severity, due to being a boolean (discrete) assignment. Countries with vague or evolving laws may then bring a certain degree of measurement error due to the possibility of misclassification.

4 - ECONOMETRIC STRATEGY

Methodology and analytical tools adopted to quantify and disentangle the relative importance of each determinant.

4.1 LMG & PMVD

After fitting a linear model, described by the formula:

$$y = \beta_0 + \beta_{1:p} X_{1:p} + \varepsilon$$

We adopted a *variance decomposition* approach, employing *LMG* (Lindeman - Merenda - Gold) and *PMVD* (Proportional Marginal Variance Decomposition) methods, to assess the relative importance of each predictor in explaining the R^2 of our model (Grömping, 2006).

Both LMG and PMVD share the same core logic: since the order of predictor inclusion impacts their contribution to the model's explained variance, these methods obtain each predictor's incremental contribution to the full R^2 by averaging those contribution results across all possible predictor orderings. The only difference is that, while the first uses a simple arithmetic average, PMVD computes a weighted average over those orderings, emphasizing more the insightful ones and penalizing the others (Grömping, 2006).

In practice, this translates into sequentially computing each predictor's incremental R^2 contribution across all possible regressors' orderings, by either fitting a new model every time a predictor contribution is seeked for the current permutation or calculating directly the R^2, still one time per predictor 'added'. Then, the marginal effect on the full R^2 is recorded by taking the difference of the 'previous' R^2, (which is the explained variance from the 1st predictor to the 'k-1' predictor) from the actual R^2, (obtained after adding predictor 'k'). As anticipated, LMG then treats all permutations and their obtained computations uniformly, attributing equal importance to each ordering. Conversely, PMVD assigns varying weights to these permutations, accentuating sequences where a predictor's explanatory power emerges more distinctly. Those weights are calculated by computing the inverse of the unexplained variance remaining before each predictor is added in a given ordering. In practical terms, permutations placing highly explanatory predictors earlier, thus quickly reducing the residual variance, receive higher weights. Hence, orderings that defer strong explanatory variables toward the end, leaving large amounts of variance unexplained until the final steps, are penalized by receiving smaller weights, as for orderings including predictors that give zero contributions due to near zero coefficients or strong multicollinearity. Therefore, PMVD emphasizes permutations that rapidly clarify the model's explanatory power, effectively rewarding predictors that consistently deliver significant explanatory strength from earlier stages in the sequence (Grömping, 2006).

These two techniques are quite parallel in the approach, yet distant in their results' interpretation: due to the highlighted difference in treating predictors not adding much to the model's explained variance, LMG is best suited as a *causal* investigation, while PMVD as *predictive* investigation (Grömping, 2006). We employed both to give the analysis a more heterogeneous perspective.

Metrics' formulas[43] follow:

$$Given:$$

$$marg.\ R^2_{(j=1):p}\left(\left\{X_{r_j}\right\} \mid S_{r_{j-1}}\right) = R^2\left(S_{r_j}\right) - R^2\left(S_{r_{j-1}}\right)$$

$$where:\ X_{r_j} \rightarrow \boldsymbol{j^{th}}\ predictor\ (\ up\ to\ p\ =\ predictors'\ n^\circ\ )\ in\ \boldsymbol{r}\ (permutation\ index)$$

$$S_{r_j} \rightarrow subset\ of\ predictors\ (\ 1^{st}\ to\ j^{th})\ in\ \boldsymbol{r}$$

$$Then:$$

$$\boldsymbol{LMG} = \frac{1}{p!}\sum_r\left(\ marg.\ R^2_{(j=1):p}\left(\left\{X_{r_j}\right\} \mid r\right)\right)$$

[43] Formulas are taken from Grömping (2006). Notation has been slightly refined and adapted to this paper.

$Given:$

$$seq.\,R^2_{(j=1):p}\left(\{X_{r_j}\} \mid S_{r_{j-1}}\right) = R^2\left(S_{r_{j-1}} \cup \{X_{r_j}\}\right)$$

$$L(r) = \prod_{j=1}^{p-1}\left(\frac{1}{\left(seq.\,R^2\left(S_{r_{(j+1):p}}\right) \mid seq.\,R^2\left(S_{r_{1:j}}\right)\right)}\right)$$

$$w(r) = \frac{L(r)}{\sum_r L(r)}$$

$$where: \; L(r) \rightarrow ordering - specific\ weight$$
$$w(r) \rightarrow normalised\ ordering\ weight$$

$Then:$

$$\boldsymbol{PMVD} = \frac{1}{p!}\sum_r\left(w(r)\cdot marg.\,R^2_{(j=1):p}\left(\{X_{r_j}\} \mid r\right)\right)$$

4.1.1 Implementation

As Grömping (2006, section 3.3) highlights, fast computational methods are needed especially when dealing with a large set of predictors like the one we are tackling. In fact, instead of doing all the operations required to fit tons of models, the paper opts for a covariance matrix-based approach. Summarizing, it derives a R^2 formula using covariance matrices and obtains the sequential (and marginal) R^2 contributions directly through Schur-complement based formula (see Grömping, 2006, formulae *11* to *14*).

The author's approach and the related R-codes implementation, however, don't come without limits. Grömping's "relaimpo" package (2006) surely uses one if not the most mathematically-efficient way of carrying out the decomposition, but it is specifically developed for non-large predictors' number: in fact, its computations are designed to handle a complete decomposition, matrix-based routine, looping over 2^{p-1} predictor subsets for each predictor leading to an operational burden of (approximately): $p * 2^{p-1}$ (Grömping, 2006). In Big-O notation, it means the algorithm scales in a ‘computational’ (complexity) order of *O(p*2^p)* [44], making it nearly impossible or extremely costly, in matters of time, to manage our set of 28 predictors. In other words, we could either change the code, or develop a new version, and we chose the second way.

Our implementation still follows Grömping (2006) fundamentals, but tries both to propose an approximated yet precise decomposition and to detach the computational scaling from the predictors’ number, so that it fits our analysis constraints. The base rationale is to employ a Monte-Carlo sampling over a fixed number of predictor orderings, and a mathematically elegant (and computationally efficient), per-ordering method to compute the contributions[45].

We started from Grömping 12th formula (2006):

$$R^2 = \frac{S_{xy}^T S_{xx}^{-1} S_{xy}}{s_{yy}} \quad \textbf{[1]}$$

Where S_{xy} is the covariance matrix between the dependent variable and the predictors, S_{xx} is the covariance matrix among predictors themselves, and s_{yy} is the dependent variable’s variance. We then looked for and applied major changes to let it be computationally lighter. The major issue is the inversion of the predictors covariance matrix, something too expensive to be calculated for every sampled permutation. Cholesky factorization is a good way to tackle that, since it can help avoid inversion with forward/backward substitution. We can first state, from Grömping (2006):

$$\hat{\beta}_{1:p} = S_{xx}^{-1} S_{xy} \longrightarrow S_{xx}\, z = S_{xy} \quad \textbf{[2]}$$

Where z is a vector containing the estimated coefficients. Then, using Cholesky, we can obtain:

$$S_{xx} = L\, L^T \quad \textbf{[3]}$$

[44] Asymptotic notation leaves constants behind: $2^{p-1} = 2^p/2$, so 1/2 is not accounted for.
[45] Note that we developed the procedure using Matlab rather than R.

With L being the lower triangular Cholesky factor[46]. Substituting in **[2]** what we got in **[3]**, and setting a system, can lead us to get a fundamental term:

$$L\,L^T z = S_{xy} \quad \longrightarrow \quad \begin{cases} L\,u = S_{xy} \\ L^T z = u \end{cases} \quad \longrightarrow \quad u = L^{-1} S_{xy} \qquad \textbf{[4]}$$

The resulting term u can be referred to as the orthogonal-coefficient vector, containing the coefficients in the orthogonalised basis (usually indicated as '*beta-tilde*' instead of beta-hat). At this point, we already solved the problem of inverting the predictors covariance matrix, since now we have a slim *p x 1* column vector that can be easily obtained with forward/backward substitution[47], entailing two lighter terms (L and S_{xy}) compared to the matrix we wanted to avoid.

Moving forward, that term allows for a manipulation of the numerator in **[1]**, in fact:

$$S_{xy}^T\,(L\,L^T)^{-1}\,S_{xy} \quad \longrightarrow \quad \left(L^{-T} S_{xy}^T\right)\left(L^{-1} S_{xy}\right) \quad \longrightarrow \quad u^T u \qquad \textbf{[5]}$$

Now, knowing that the dot product of a vector with itself and the Euclidean 2nd-norm correspond to, respectively:

$$\textit{Dot product of a vector with itself}: \quad u^T u = \sum_{i=1}^{n} u_i^2$$

$$\textit{Euclidean } 2_{nd} - \textit{norm}: \quad \|u\|_2 = \sqrt{\sum_{i=1}^{n} u_i^2}$$

[46] It has no link with the 'L' (individual ordering weight) used in the previous section.

[47] That L^{-1} is never actually inverted: in Matlab, by using the back-slash '\' operator with such terms, we can tell the code to solve the operation with forward/backward substitution, which has a far lower complexity (MathWorks, A).

We can indicate what we got in **[5]** as:

$$\|u\|_2^2 = \sum_{i=1}^{n} u_i^2 = u^T u \qquad \textbf{[6]}$$

Finally, we can rewrite **[1]** formula in our final format:

$$R^2 = \frac{\|u\|_2^2}{s_{yy}} \qquad \textbf{[7]}$$

Having reached this point, we can now clarify why this slim and elegant formula can also lead to a fair efficiency gain. Indeed, the whole point of expressing the coefficient of determination in that way is not only to avoid inversions, but also to '*vectorize*' the retrieval of the sequential R^2 [48], so that we shave off (partially) the predictors number from the complexity scaling of the process. This is fundamental for our case, since the large number of regressors is the main issue to deal with.

The final sequential, 'incremental' R^2 formula, computed for each predictors' permutation (returning a vector), can hence be expressed and computed in a single take as:

$$seq.\, R^2_{(j=1):p} = \frac{\sum_{i=1}^{j} u_i^2}{s_{yy}} \qquad \textbf{[8]}$$

This overall approach is applied to both LMG and PMVD, which we process together. PMVD's weighting formula has been left as the one exposed by Grömping (2006).

[48] We don't need to carry out a procedure one time per predictor.

4.1.2 Asymptotic-complexity comparison

This sub-section serves as a quantitative deepening on why our approach is, if not mandatory, preferable for a large number of predictors, with focus on our case where p=28 .

As we already underlined, Grömping (2006) method scales with p and the subset operations, leading to a complexity scale of approximately: $O(p*2^p)$. Our process, on the other hand, computes a Cholesky factorization on every permuted set of predictors, costing $O(p^3)$ (MathWorks, A), up to a cap of N permutations, which we can manually choose. Getting rid of constant factors, but still considering N as a scaling factor, we can establish the asymptotic complexity of our routine as approximately: $O(N*p^3)$, with Cholesky factorization dominating the growth rate.

Therefore, the root question is: *when is our method the best choice, compared to Grömping's one*?

Considering N in the complexity scale makes us be able to answer that question in both N - *permutations* quantity and p - *predictors* number. Taking the two complexity orders, our method 'wins' when it satisfies the inequality:

$$O\left(N\, p^3\right) < O(p\, 2^p) \longrightarrow N\, p^3 < p\, 2^p \longrightarrow N < \frac{2^p}{p^2} \qquad \textbf{[9]}$$

Therefore, solving for N with p=28 yields:

$$N = \frac{2^{28}}{28^2} \approx 342 \cdot 10^3$$

Instead, solving for p by holding N fixed[49], yields the condition:

$$p_{treshold} = min\left\{ p \in \mathbb{N}^+ \ : \ \frac{2^p}{p^2} > N \right\} \qquad \textbf{[10]}$$

[49] We ran some tests, which showed that with 10^4 permutations we can get the same Grömping's results with a precision up to 5 decimals.

Which is the core thing seeked: a threshold indicating for which p is optimal to use our method compared to the other we discussed.

Not surprisingly, solving that by holding N fixed to 10^4 results in:

$$\forall p \in \mathbb{N}^+, \quad \frac{2^p}{p^2} > 10^4 \;\; \Leftrightarrow \;\; p \geq 23$$

Thus, to conclude, we can see that our method is clearly the best option when either N is small or p is large. Taking our specific case (p=28) as an example, it becomes evident that N is not the critical part of the story: calculations holding p fixed and varying N merely serve to show that, using our setting as a benchmark, our method remains vastly superior. In fact, N always remains capped at 10^4 if not manually edited, which is far from the break-even threshold[50] of N ≈ 342,000, also highlighting that N can be increased as the number of predictors grows, while still maintaining an efficiency advantage in cases where very high precision is needed.

The key takeaway, therefore, is that for large predictor sets, specifically when $p \geq 23$, our method is the one to implement in order to avoid prohibitive computation times.

The following graphs (Fig. 2) provide a graphical perspective of this matter[51], labelling '*Asymptotic cost*' as the dependent variable. This cost is expressed in arbitrary units, representing how quickly computational effort, such as actual runtime or total executed operations by the terminal, scales as predictors (or permutations) increase. While abstract, it directly mirrors concrete resource use, indicating algorithmic feasibility limits.

[50] Still referred to our p=28 case.
[51] Scales have been adjusted for visual interpretability ease. See Fig. 2 description.

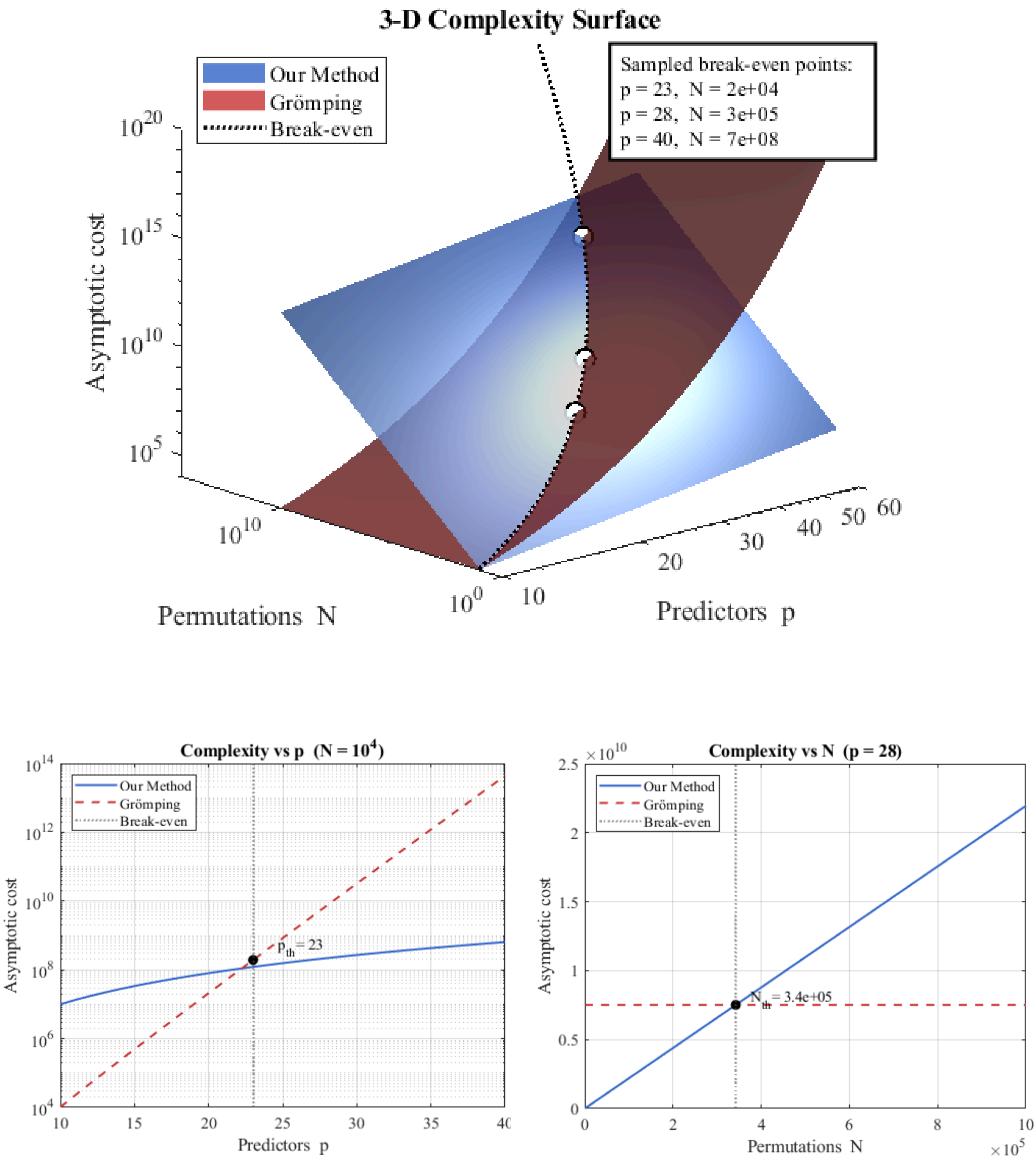

Fig. 2 - Asymptotic Cost insights. Scaling (z, y, x):
1st graph (3D) - log | log | log ; 2nd graph (2D, bottom left) - log | level ; 3rd graph (2D, bottom right) - level | level .
Data spacing: only the 3rd graph is log-spaced.

5 - RESULTS DISCUSSION

Output display and interpretation, from the general model to the chosen decomposition methods, offering insights into predictors' relative importance.

5.1 Decomposition Metrics & Model Results Display

Overall model summary statistics[52]:

Table 2 - Model Insights

item	data	item	data
Dependent variable	C_A_I (2020~2024)	*Mean & std*	0.1134 | 0.1268
N° of parameters	29	*N° of observations*	144
R-squared	0.5032	*Adjusted R-squared*	0.3768
SER	0.1001	*Var(y)*	0.0161
F-statistic	3.9818	*F-test p-value*	0.0000
Cross-validated R-squared	-0.3644	*Cross-validated SER*	0.1481

Complete estimates and decomposition results (following pages):

[52] See Appendix A.1 for a different use of the dependent variable, turned into an independent one.

Table 3 - Results

Variable	β and SE	VIF	LMG (% contr.)	PMVD (% contr.)	LMG Bootstrap CI (95%)	PMVD Bootstrap CI (95%)
			Macroeconomic Environment			
[1] GDP per capita	-0.000001 (0.000001)	6.71	1.00	1.32	[0.705 ~ 4.436]	[0.005 ~ 8.201]
[2] Unemployment rate (%)	-0.004075+ (0.002132)	1.84	3.86	4.79	[0.621 ~ 7.727]	[0.031 ~ 10.356]
[3] Inflation rate (%)	0.00089 (0.002154)	5.19	0.90	0.50	[0.380 ~ 5.881]	[0.005 ~ 6.072]
[4] Exchange rate depreciation vs USD$	-0.000027 (0.000029)	3.77	1.09	2.76	[0.352 ~ 3.464]	[0.009 ~ 4.618]
[5] Government Size	-0.00171 (0.001319)	3.53	1.46	1.98	[0.671 ~ 4.294]	[0.006 ~ 7.895]
[6] Trade openness (% of GDP)	0.000004 (0.00026)	2.36	3.25	2.26	[0.911 ~ 10.742]	[0.015 ~ 15.694]
[7] Interest rates (CB)	0.00004 (0.000142)	1.13	0.15	0.07	[0.101 ~ 2.335]	[0.002 ~ 3.128]
Total contribution (section)	-	-	**11.71**	**13.68**	**[8.457 ~ 21.672]**	**[3.620 ~ 25.671]**
			Development & Infrastructure			
[8] Access to electricity	0.001127++ (0.000779)	5.50	4.55	3.32	[1.236 ~ 9.085]	[0.016 ~ 13.619]
[9] Education	0.000297 (0.005547)	5.15	1.52	0.00	[0.716 ~ 5.237]	[0.003 ~ 7.465]
[10] Population growth	-0.002899 (0.013025)	3.63	4.95	0.12	[1.543 ~ 8.576]	[0.009 ~ 12.896]
[11] Urbanization	0.000162 (0.000767)	3.81	0.44	0.21	[0.470 ~ 3.283]	[0.003 ~ 4.835]
[12] Internet users (% of pop)	-0.001812++ (0.001099)	13.02	2.43	0.72	[1.020 ~ 6.958]	[0.021 ~ 10.711]
Total contribution (section)	-	-	**13.89**	**4.37**	**[7.726 ~ 21.555]**	**[1.790 ~ 25.537]**

Table 3 - continued (a)

Variable	β and SE	VIF	LMG (% contr.)	PMVD (% contr.)	LMG Bootstrap CI (95%)	PMVD Bootstrap CI (95%)
			Financial System & Inclusion			
[13] Financial account ownership (% of pop)	0.000941 (0.000928)	10.75	3.59	4.28	[0.914 ~ 9.911]	[0.016 ~ 18.924]
[14] Bank concentration	-0.002555*** (0.000569)	1.37	26.75	34.00	[12.086 ~ 29.451]	[10.824 ~ 44.320]
[15] Bank distrust Index	-0.001102 (0.000971)	2.14	5.53	5.52	[2.641 ~ 8.819]	[0.007 ~ 14.802]
[16] Electronic Payments (% of pop)	-0.000088 (0.001005)	11.67	1.13	0.05	[0.790 ~ 4.536]	[0.007 ~ 8.150]
Total contribution (section)	-	-	**37.00**	**43.85**	[21.388 ~ 41.534]	[18.236 ~ 54.072]
			Socio-Cultural Factors			
[17] Gini_index	0.001595 (0.001833)	2.05	0.59	0.48	[0.371 ~ 3.330]	[0.006 ~ 4.962]
[17b] Equality resource distribution	-0.052521 (0.065142)	4.85	2.13	1.73	[0.619 ~ 7.229]	[0.009 ~ 11.018]
[18] Collectivism index	-0.121966** (0.036948)	11.97	11.69	12.92	[3.928 ~ 15.921]	[1.590 ~ 29.517]
[19] Homicide rates	0.000936 (0.000984)	1.61	1.43	0.92	[0.279 ~ 6.298]	[0.006 ~ 9.100]
Total contribution (section)	-	-	**15.84**	**16.05**	**[8.711 ~ 21.335]**	**[4.697 ~ 35.864]**

Table 3 - continued (b)

Variable	β and SE	VIF	LMG (% contr.)	PMVD (% contr.)	LMG Bootstrap CI (95%)	PMVD Bootstrap CI (95%)
			Institutional and Political Landscape			
[20] Crypto-specific restrictions	0.022389 (0.026029)	2.19	3.18	2.97	[0.455 ~ 10.192]	[0.006 ~ 11.521]
[21] Social repression	0.008741 (0.020795)	9.34	1.32	1.37	[0.449 ~ 5.564]	[0.006 ~ 8.025]
[22] Censorship (media/internet)	0.001345 (0.022486)	11.71	0.86	0.01	[0.439 ~ 3.544]	[0.004 ~ 5.958]
[23] Liberal-democracy	-0.015882 (0.120426)	14.17	0.84	0.16	[0.601 ~ 3.069]	[0.008 ~ 7.220]
[24] Political instability	0.057805** (0.018047)	3.91	11.03	14.64	[2.090 ~ 19.633]	[1.325 ~ 29.604]
[25] Economic freedom	-0.005399 (0.020102)	5.05	0.61	0.08	[0.613 ~ 3.165]	[0.004 ~ 6.102]
Total contribution (section)	-	-	**17.84**	**19.23**	**[10.559 ~ 29.789]**	**[5.674 ~ 37.796]**
			Illicit Economy and Risk Factors			
[26] Shadow-economy size	-0.001599++ (0.001094)	2.55	2.57	2.17	[0.435 ~ 11.687]	[0.016 ~ 15.439]
[27] Money-laundering risk	-0.001895 (0.01333)	3.98	0.37	0.02	[0.430 ~ 3.506]	[0.004 ~ 5.489]
[28] Control of Corruption	0.016849 (0.023591)	7.89	0.81	0.63	[0.695 ~ 2.332]	[0.007 ~ 4.776]
Total contribution (section)	-	-	**3.75**	**2.82**	**[2.052 ~ 14.809]**	**[0.444 ~ 18.625]**
Average individual contribution (without '*bank concentration*')	-	-	**2.62**	**2.36**	-	-

Notes:
- Coefficient significance (statistical difference from zero) at the 0.1%, 1%, 5%, 10%, and 15% levels is denoted respectively by the symbols: ***, **, *, +, ++.
- Sectional CIs are obtained by taking the $\alpha/2$ and $(1-\alpha/2)$ percentiles of the bootstrap distribution of summed contributions for all predictors in that section.

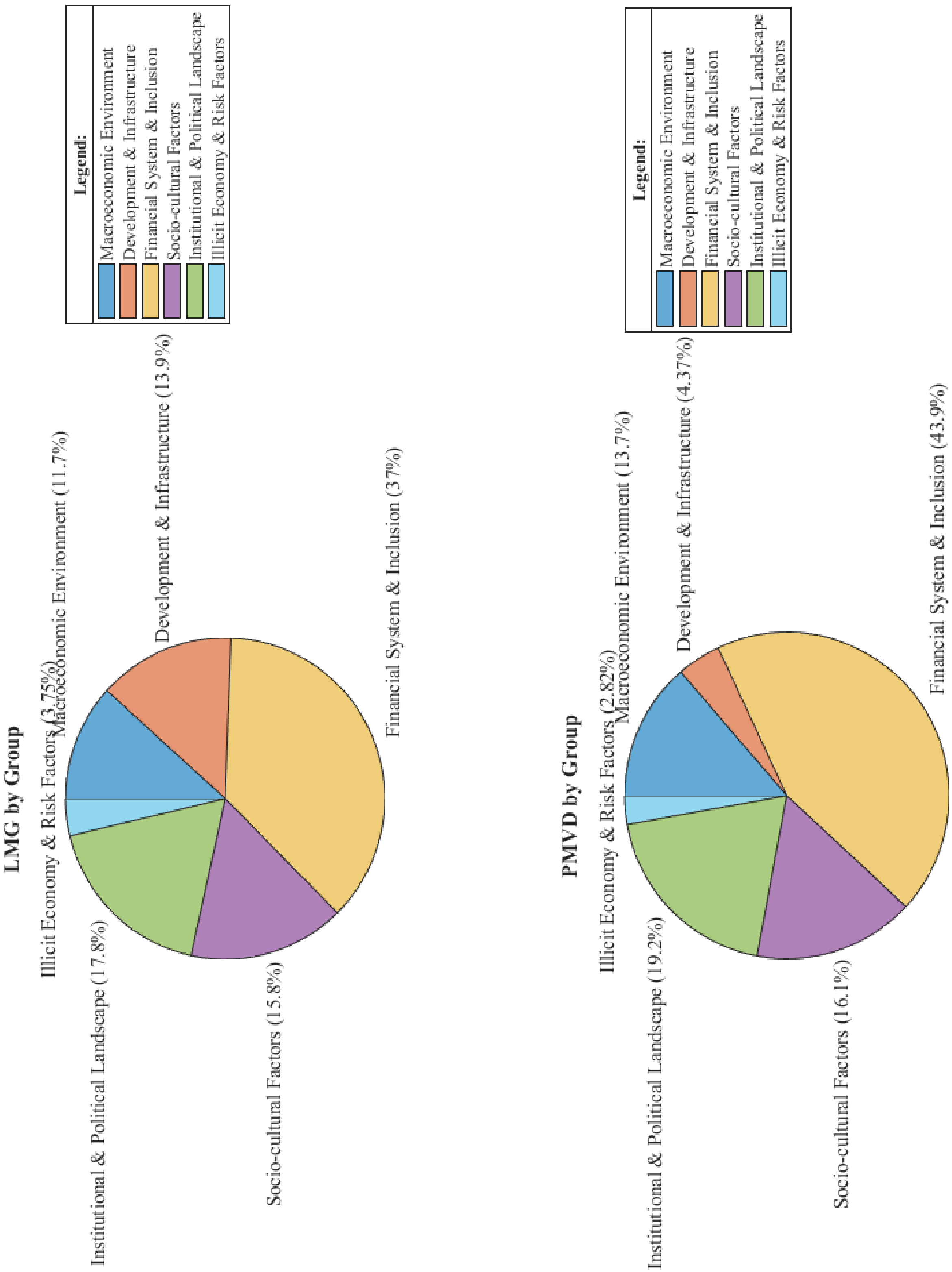

Fig. 3 - Pie charts of sectional results (MATLAB-coded).

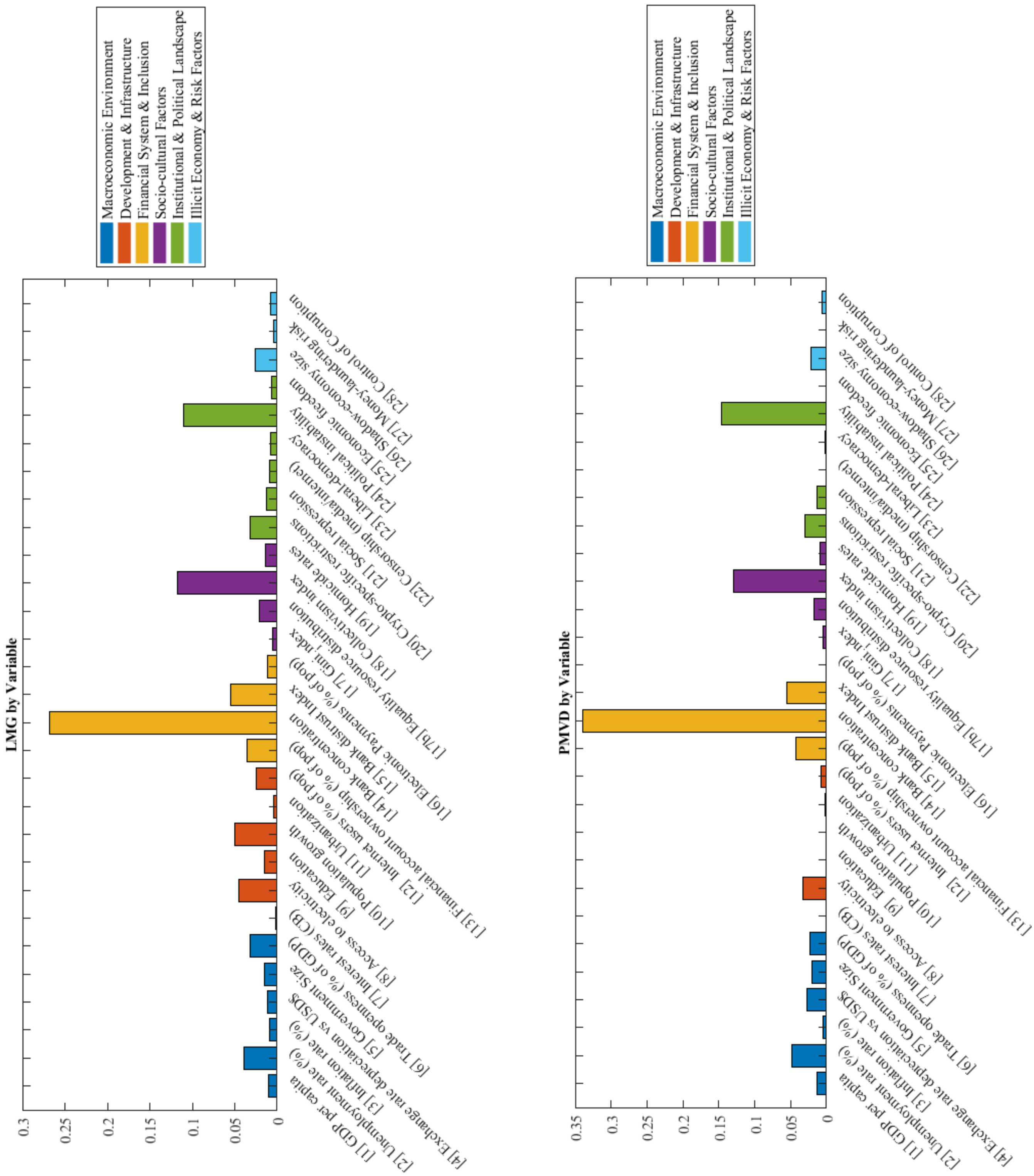

Fig. 4 - Bar charts of individual results (MATLAB-coded).

5.2 Interpretation, Considerations & Opinions

The model demonstrates limited overall performance (Table 2). With such a number of predictors, it would be reasonable to expect a fairly high explanatory power, which instead reaches a medium 50.3%. Adjusting for model complexity, the R^2 drops some percentage points, indicating that 37.7% of Y's variance[53] is being explained. Another marginal issue is shown by the *cross-validation*[54], which reports a negative cross-validated R^2. That suggests the model is not generalizing or, in other words, that it would have a poor performance on unseen data, leading us to conclude that it has a very poor if not absent *predictive power*[55]. This fact has minor relevance though, since the scope of the analysis is *causal*. Since the number of regressors we have, collinearity is also among the most relevant things to account for. Nonetheless, we can see how only 6 of the independent variables suffer from multicollinearity (VIF>10, see Table 3), implying that the majority of them are not heavily collinear and the model is not suffering too much from it. If we combine everything highlighted, we can get a cleaner picture on the overall scenario: the evidence points to moderate *overfitting*, with our equation including variables which may add a little to its coefficient of determination, yet the explanatory inferences remain robust.

In fact, the model as a whole remains insightful, due to a high F-statistic (and related very low F-test p-value) making it jointly significant. This outcome probably derives from a small pool of individual predictors, but it still makes us able to draw conclusions about the relative importance results we obtained.

Not surprisingly, the most influential category corresponds to financial system and inclusion factors, contributing 37% to the model's R^2 and up to 44% if referring to PMVD results. With cryptocurrencies being financial alternatives themself, it is an expected outcome, as pointed out by Saiedi et al. (2020) in their estimates about the magnitude of financial-related variables. The least impactful is the informal economy

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[53] 'Y' refers to the Crypto Adoption Index, our dependent variable.

[54] A 20-fold cross-validation was applied to estimate out-of-sample mean squared prediction error averaged across folds. The c.v. R^2 is computed by dividing this error to the total variance of the dependent variable, then subtracting the result from 1. The c.v. SER is the square root of that mean squared prediction error.

[55] With a negative c.v. R^2 like ours, deriving from a c.v. SER greater than Y's variance, it would be more insightful to simply use Y's mean for predictive purposes rather than the model's estimates.

factors' section, accounting for only 3.8% of the explained variance, and reduced to 2.8% by PMVD routine (see Fig. 3). However, it has to be noted that it only contains three predictors (making it the smallest in variables-size), with one only being over-marginally significant ('*Shadow economy size*', see Table 3). This can still suggest that cryptocurrencies' illicit uses are actually among the least meaningful determinants (confirming Foley et al. claims, 2019), both from a statistical significance and quantitative importance perspective, in enabling adoption.

The macroeconomic environment instead shows a lower-than-expected importance. In fact, it is not only the section with the most predictors (7 in total) but also the one with the usually most significant ones (like GDP, or central bank interest rates and their strict link with the analyzed phenomenon). Contrary to the expectations, it exhibits 11.7% of contribution (LMG), making it penultimate in terms of relative importance. The picture shifts a little by using PMVD, which heavily dampened development and infrastructure (14% to 4.4%), making macroeconomic factors rise to the 4th importance position out of all 6 sections in that routine results (Fig. 3, Table 3).

The remaining categories are the institutional-political landscape and socio-cultural factors, respectively accounting for 18% and 16% of the explained variance in Y (both are a bit enhanced when using PMVD). These shares of importance make them the 2nd and 3rd most insightful categories in the analysis, underlying how public institutions, politics, culture and social dynamics are among the main adoption catalysts (as noted in section 2.5 and 2.4).

Regarding individual predictors considerations, we have 3 as higly significant, 1 as marginally significant, and 3 with over-marginal significance. Starting from the most significant one, we can see not only how '*bank concentration*' is strongly significant (0.01% level), but also how it composes 27% of the R^2 alone (34% with PMVD), making it the one bringing the highest explanatory power to the model (Table 3). Its coefficient's sign is negative, confirming financial institution's gatekeeping role towards crypto-assets supported by Bhimani et al. findings (2022) rather than the possible 'incentive to seek alternatives' brought by concentration implications (see section 1.3.2). The other significant (1% level) and again most explaining variables are '*collectivism index*' and '*political instability*', having about 11~12% of relative importance each, although with the first showing a high variance inflation factor (Table 3). Collectivism effect (sing) confirms our expectation drawn in section 1.4.2, underlined by Foley et al. (2022), while political instability turned out to have a positive effect, pushing people into cryptocurrencies when confidence in domestic institutions vacillates, in line with Sergio & Petti (2024). For a more intuitive representation of those effects, see Fig. 4.

Marginally significant variables also play a role. '*Unemployment rate*' is the first to report, showing significance at the 10% level (even if it has to be noted that its p-value is at the low bound of that threshold, being equal to ~0.0585). Its contribution to the model's R^2 is 3.86% (PMVD: 4.79%), which is not among the highest scorers but still above the individual average contribution of all predictors[56] (see the end of Table 3). Its coefficient's sign is negative, which confirms the rationale of it being more a resource limit rather than a risk-taking condition (see section 2.1.2 and Guo et al., 2025). The remaining near-significance regressors are '*shadow-economy size*' and '*internet users (% of pop)*'. However, these two are far more borderline than the previously quoted one, with their marginality going further to the 15% significance level, hence leading to biased or imprecise conclusions if drawn (Table 3). Lowering the model complexity to address its overfitting would most likely let those be among the first to gain statistical significance.

Among the most unexpected effects, we can highlight the coefficients' signs of our custom variables. In fact, both bank distrust and restrictive crypto-regulations uncovered an opposite impact compared to the expected one: negative for '*bank distrust index*', positive for '*crypto-specific restrictions*' (Table 3). Bank distrust sentiment effect could derive from the hypothesis that, with such mistrust in the financial context, that negative feeling may retain people from opening to decentralized finance too. This indicates that the positive link between trust in financial institutions and people's reliance on them seen in Ampudia & Palligkinis (2018) also poses a deterrent to the use of riskier means when that same trust falters. Regulations restricting cryptocurrencies could instead positively influence adoption due to willing users being forced to further

[56] Equal to: 2.62% (LMG) ~ 2.36% (PMVD). The average has been calculated by taking out '*bank concentration*', due to it being a clear outlier for such insight (see Table 3 and its notes).

educate themselves on the topic[57], in order to find ways to circumvent the law to benefit from crypto-assets (taken that '*education*' has a positive effect; see Table 3). Both claims, nonetheless, remain purely hypothetical, and the associated predictors are unfortunately not statistically significant in the reported model.

As we already stated in the econometric strategy chapter, LMG and PMVD carry out slightly different procedures to obtain a result equal in nature yet quantitatively different. We saw how the category that got the highest difference in its relative contribution is the one pertaining to development and infrastructure. In particular, predictors showing the major drops[58] are: '*population growth*', '*education*', '*internet users (% of pop)*' and '*urbanization*'[59]. Nevertheless, we have to remember what we stated about the two methods results' interpretation: LMG provides *causal* conclusions (what we are after), while PMVD better represents *predictive* implications. This also implies that, since the absent generalization ability we experienced when cross-validating (see Table 2), the negligible predictive power of the model makes PMVD outcomes to be poorly meaningful. Therefore, considering both scope focus and statistical perspectives, we strongly advise referring to LMG results as the valid ones for our study.

[57] As noted in section 2.2.2, Chainalysis (2024) report sustains a positive link between adoption and higher education.

[58] Causes are better explained in section 3.1.

[59] Other variables which got a minor but notable decline in their estimated contribution are: '*interest rates (CB)*', '*electronic payments (% of pop)*', '*censorship (media/internet)*', '*liberal-democracy*', '*economic freedom*' and '*money-laundering risk*'. Fig. 4 offers a more direct, visual interpretation of this matter, while Table 3 exposes the precise outcomes.

6 - CONCLUSIONS, CURRENT RESEARCH STATE & FUTURE EFFORTS

This study aimed to uncover the most comprehensive range of determinants shaping cryptocurrency usage across countries, attributing to each of them a quantitative explanatory share by the employment of relative importance metrics. While the overall predictive power of the equation turned out to be limited, suggesting that the true data-generating process is likely to be more complex or context-specific, the model still provides insightful causal signals through the LMG-based decomposition. Our findings confirm how financial system characteristics, cultural traits and political variables remain among the main drivers of adoption, while other categories such as the macroeconomic environment and informal economy dynamics appear to play a more marginal role than typically expected. The importance of individual predictors reveals to be led by bank concentration, bringing the highest contribution in explaining adoption.

However, several limitations emerged throughout the analysis and suggest directions for future work. First, the clear lack of generalization ability flagged by cross-validation opens the door to deeper methodological refinements. A first step could be the introduction of spatial econometric techniques, which would allow the model to account for adoption spillovers and diffusion dynamics across neighbouring or economically tied countries, something currently overlooked in a standard cross-sectional setup. Moreover, the high multicollinearity affecting a subset of regressors (six variables with VIF > 10) suggests that dimensionality reduction strategies, such as principal component analysis or factor models, could help identify latent structures, improve robustness, and reduce noise from over-specification. Another relevant issue concerns endogeneity, which has been partly explored in the appendix by reversing the model and using crypto-adoption as an explanatory variable. The limited statistical support found in that setup hints at possible simultaneity or reverse causality effects. Future research should hence adopt instrumental variable techniques or rely on GMM estimation, especially when further structural modeling is considered.

Beyond econometric refinement, attention must also be paid to how adoption is actually measured. The dependent variable, constructed from five years of Global Crypto Adoption Index data of Chainalysis (see section 3.1), had to be averaged longitudinally due to inconsistencies in sample size, methodology adjustments, and index components across years. This required assuming comparability across countries despite intra-year methodological shifts. While such averaging allowed for a consistent cross-sectional framework, it inevitably flattens dynamic changes and may incorporate residual biases and measurement errors, especially in contexts where sub-index definitions evolved or where the geographic sample varied significantly over time. Moreover, the use of rank-based, normalized index data introduces potential distortions, especially in interpreting coefficient magnitudes and in comparing absolute versus relative adoption levels. Thus, data construction, transparency and general availability remain critical bottlenecks in this field. Improving adoption indices by pushing for standardized methodologies, broader sub-indicator coverage, and clearer treatment of weighting criteria would substantially enhance interpretability and external validity. Similarly, many explanatory variables used in this paper, while comprehensive, still rely on sources with uneven temporal coverage or rely on proxies subject to conceptual ambiguity (i.e., bank distrust sentiment built from search data). These challenges could not be fully eliminated, but they must be made explicit and properly addressed.

Finally, deeper segmentation by region or development level may yield even more interpretable insights. Drivers of adoption are unlikely to be universal across contexts: policy frameworks, financial inclusion levels, and cultural attitudes differ markedly between, say, Sub-Saharan Africa and Western Europe. Exploring regional heterogeneity, by running subsample models or interacting variables with regional dummies, could help reveal conditional effects and improve the model's contextual accuracy. If and when consistent, multi-year country-level adoption data become available, shifting toward panel structures would be the natural evolution, allowing dynamic effects, path dependency, and lag structures to be properly modeled.

In conclusion, despite the limitations faced, the present analysis contributes to the existing literature by proposing a structured, theory-backed categorization of adoption drivers and their relative importance, relying on an empirical strategy aimed at *explaining* rather than *forecasting*. The extremely heterogeneous and 'young' nature of the phenomenon is hence confirmed, hoping to set the basis for more refined and scalable research of cryptocurrency adoption in the years ahead.

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APPENDIX

A.1 - Crypto-adoption as the explanatory variable

An interesting turn-around would be to understand if crypto-adoption could, instead of *being explained*, *explain* some of the predictors and to which extent.

While this is certainly not the right instance for running a deep individual analysis for each predictor we used, it may be captivating to explore at least one major dynamic of this perspective. We then chose to investigate whether cryptocurrencies, together and in interaction with national income, influence economic growth.

We built one simple model by choosing GDP per capita growth (World Bank, T) as the dependent variable, while instead setting the already used adoption index, GDP per capita, and an interaction term between those two as the independent ones. We ran it over the full sample and on the 80 poorer states, to get diverse insights. Results follow:

$$GDP_{pc\ growth} = \beta_0 + \beta_1 C\_A\_I + \beta_2 GDP_{pc} + \beta_3 \left(C\_A\_I \cdot GDP_{pc} \right) + \varepsilon$$

Table 4 - A.1 Model Insights

item	data	item	data
	Complete Sample Model		
Dependent variable	GDP pc growth	*Mean & std*	1.0755 | 2.1651
N° of parameters	3	*N° of observations*	144
R-squared	0.0142	*Adjusted R-squared*	-0.0069
SER	2.1726	*Var(y)*	4.6878
F-statistic	0.6716	*F-test p-value*	0.5708
Cross-validated R-squared	-0.4467	*Cross-validated SER*	2.6042

Table 4 - continued			
item	data	item	data
	Sub-sample Model		
Dependent variable	GDP pc growth (sub)	*Mean & std*	0.8647 | 2.5636
N° of parameters	3	*N° of observations*	80
R-squared	0.0334	*Adjusted R-squared*	-0.0047
SER	2.5697	*Var(y)*	6.5723
F-statistic	0.8764	*F-test p-value*	0.4572
Cross-validated R-squared	-0.4349	*Cross-validated SER*	3.0709

Table 5 - A.1 Results				
Variable	β and SE	VIF	t-statistics	p-value
	Complete Sample Model			
(intercept)	0.698441* (0.346179)	-	2.02	0.0455
[1] C_A_I	2.542393 (2.038766)	2.08	1.25	0.2145
[2] GDP per capita	0.000007 (0.00001)	1.79	0.68	0.4966
*[3] (GDP pc * C_A_I)*	-0.000036 (0.000067)	2.85	-0.53	0.5962
	Sub-sample Model			
(intercept)	-0.057256 (0.668146)	-	-0.09	0.9319
[1] C_A_I	5.992986 (4.4942)	4.77	1.33	0.1864
[2] GDP per capita	0.00007 (0.00006)	2.30	1.17	0.2454
*[3] (GDP pc * C_A_I)*	-0.00037 (0.000376)	6.67	-0.98	0.3290

Notes:
- Coefficient significance (statistical difference from zero) at the 0.1%, 1%, 5%, 10%, and 15% levels is denoted respectively by the symbols: ***, **, *, +, ++.

The model appears completely unreliable, both from an explanatory and predictive perspective (Table 4). The only term showing statistical significance is the intercept of the complete sample version (Table 5). Since every other estimate is off, from the near zero R^2 to the F-statistics, What implications can be deduced?

A hypothetical rationale behind this null pattern is the sheer cross-country heterogeneity that obscures any average signal: structural reforms, shock exposure, and baseline growth paths differ so widely that a common 'crypto-effect' is effectively sunken. Re-estimating the model on a trimmed subset of 80 lower-income economies offers no rescue: slope coefficients remain statistically indistinguishable from zero, with the intercept becoming insignificant too. In short, neither the full sample nor the poorer-country subset shows a robust link between crypto-adoption as an explanatory variable for per-capita growth[60], as of the writing date of this paper.

Last thing to mention is that, like for every regression model, major problems often come down to one or more forms of endogeneity. In our present case, the issue is related to crypto-adoption possibly being endogenous due to reverse causality between it and the dependent variable chosen. While GDP per capita and GDP per capita growth would hardly incur in a reverse causal link due to their 'lagging' relationship, it could be plausible to think that crypto-adoption might respond to economic performance, making Table 5 results in need of further handling like the use of an instrumental variable, not employed for this appendix.

[60] Things of course can drastically change if the explained variable chosen becomes the one among those exhibiting marginal (or strong) significance in the previous section 4, Table 3.