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DOES FINANCIAL CRIME UNDERMINE ECONOMIC FREEDOM? GLOBAL EVIDENCE ACROSS AGRICULTURE AND INDUSTRIAL ECONOMIES

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Abstract

This study examines the impact of financial crime on economic freedom using panel data for 46 countries over the period 2015-2024, focusing on key dimensions of financial crime: corruption, money laundering, shadow economy activity, and cybersecurity governance. The empirical results confirm a statistically significant negative effect of corruption, money laundering risk, and shadow economy size on economic freedom, while stronger cybersecurity governance is positively associated with economic freedom. The adverse association is more visible in countries where agriculture plays a larger role in the economic structure. These findings suggest that structural characteristics condition the transmission of institutional weaknesses into broader economic outcomes. This study contributes to the comparative institutional economics literature by providing large-scale cross-country evidence on the systemic channels through which financial crime constrains economic freedom, and by demonstrating that sectoral structure conditions the transmission of institutional weaknesses into market outcomes.

Key words**:** *corruption, cybersecurity, economic freedom, financial crime, shadow economy*

INTRODUCTION

In recent years, economic and financial crime has become an increasingly important concern for both researchers and policymakers. This heightened attention is largely driven by the expansion of international financial flows and the rapid pace of digitalization. Practices such as corruption, money laundering, tax evasion, and the shadow economy not only disrupt market functioning but also erode public trust in institutions and limit the state's ability to provide a stable and predictable business environment (Rider, 2015; Achim & Borlea, 2020) [25, 1].

The effects of financial crime are often more pronounced in economies where agriculture, industry, and services contribute unevenly to GDP and develop at different speeds. In such contexts, institutions face additional challenges in enforcing regulations and controlling illegal activities.

A key concept for understanding this relationship is economic freedom. Economic freedom reflects the extent to which a country's rules and policies allow economic activities to take place freely, protect property rights, and encourage competition. It is most commonly operationalised through the Index of Economic Freedom (IEF), published annually by the Heritage Foundation. A higher composite score indicates that economic activities are subject to fewer governmental constraints and that market mechanisms operate more freely (Heritage Foundation, n.d.) [14]. The IEF thus captures not only narrow market liberalisation but also the quality of the legal environment, the predictability of public policy, and the openness of financial and trade systems, precisely the dimensions most exposed to distortion by financial crime.

Cross-country evidence consistently confirms that countries with higher economic freedom scores exhibit stronger long-run economic growth, greater investment, lower unemployment, and higher income levels (Gwartney & Lawson, 2003; De Haan & Sturm, 2000) [12, 7]. De Haan and Sturm (2000) [7] further demonstrated, using panel data for a large sample of countries, that it is the change in economic freedom, not simply its level, that is most robustly associated with growth performance, implying that the direction of institutional reform matters at least as much as the starting-point. This insight is directly relevant to the present study, which examines cross-country variation in IEF scores over a ten-year panel.

Berggren (2003) [5] provided a comprehensive survey of the empirical literature on the benefits of economic freedom and concluded that economic freedom is not only an outcome of good governance but also a driver of it: economies with more open markets and stronger property rights protection tend to develop more effective anti-corruption systems over time, because competitive markets reduce the rents that motivate corrupt behaviour.

A further strand of the economic freedom literature has examined which specific sub-components are most responsive to institutional change. Heckelman and Stroup (2000) [13] found that property rights, monetary stability, and trade openness are the sub-indices most consistently linked to economic growth, while labour market regulations and government size show weaker and more context-dependent effects. For the purposes of the present study, this granularity matters: corruption, money laundering, and the shadow economy can be expected to affect different sub-components of the IEF through distinct channels.

Thus, research suggests that higher levels of economic freedom tend to coincide with greater institutional capacity to limit informal and illegal economic activity, creating theoretically important feedback between economic freedom and financial crime.

A crucial but underexplored dimension of the financial crime-economic freedom relationship is the structural composition of the economy, specifically, the relative weight of agriculture, industry, and services in national GDP. Economic theory and comparative development evidence consistently show that these three sectors operate under fundamentally different institutional regimes, face different types and intensities of informality, and possess different capacities for regulatory enforcement.

The foundational contribution to understanding structural transformation and its institutional implications is Kuznets (1955) [17], who identified the systematic shift from agriculture-dominant to industry-dominant to service-dominant economic structures as the central feature of modern economic growth. This structural transformation perspective suggests that agricultural dependence may be associated with weaker institutional conditions and lower economic freedom.

The institutional dimensions of agricultural dominance are further elaborated by La Porta and Shleifer (2014) [18], who documented that informal economic activity, measured both as the share of the shadow economy and as the prevalence of informal firms, is substantially higher in low-income, agriculture-dominant economies than in industrialised or service-oriented ones. Their analysis demonstrated that informal firms in agriculture-dominant economies are not simply small-scale versions of formal firms that will eventually formalise as they grow; rather, they operate under fundamentally different cost structures, governance norms, and regulatory expectations. Informal agricultural activity is characterised by poor land titling, seasonal labour arrangements outside formal employment contracts, and cash-based transactions that are structurally invisible to fiscal authorities. These features simultaneously increase the shadow economy share, weaken the rule-of-law foundations of economic freedom, and reduce the administrative capacity available to enforce AML regulations.

Despite these clear structural differences, comparative studies that explicitly examine the role of economic structure remain limited. Thus, the structural conditioning perspective motivates the extended model specifications in this study, which include the shares of agriculture and industry in GDP as additional explanatory variables alongside the financial crime indicators. Rather than simply controlling for sectoral composition, these variables are theorized as moderating conditions that shape the institutional environment through which financial crime affects economic freedom.

Financial Crime and Its Mechanisms: Channels Linking Crime to Economic Freedom

Many researchers have shown that there is a strong connection between the quality of governance, the level of corruption, and the size of the shadow economy. Countries with weaker institutions and lower governance quality are generally more exposed to informal economic activity and higher corruption (Dreher et al., 2009; Dreher & Schneider, 2010) [8, 9].

Other research has compared the size of the shadow economy across countries at different stages of economic development, examining factors such as fiscal policy, regulatory burdens, and institutional quality (Schneider & Klinglmair, 2004; Williams & Schneider, 2016; Medina & Schneider, 2018) [28, 32, 20].

The factors that drive financial crime are diverse and affect economic freedom in several ways. Institutional factors, such as the quality of legislation, judicial efficiency, governance, and press freedom, are critical not only for preventing and punishing financial crimes but also for maintaining a stable and predictable economic environment, which is essential for the functioning of markets and for attracting investment (Dreher et al., 2009; Kalenborn & Lessmann, 2013) [8, 16]. Technological factors have become increasingly important, with fiscal digitalization, electronic payment systems, anti-fraud mechanisms, and the use of artificial intelligence helping to reduce corruption and fraud while strengthening investor confidence and protecting market integrity (Ryman-Tubb et al., 2018; Achim et al., 2021) [27, 2]. Cultural and social factors, including social norms, tax morale, religion, and business ethics, also play a role by shaping how individuals and firms comply with economic regulations. Taken together, these cultural and social dynamics shape the institutional conditions under which economic freedom may either strengthen or weaken over time (Torgler & Schneider, 2007; McGee et al., 2015) [30, 19].

While these general relationships are well established, a more precise analysis requires differentiating the mechanisms through which each dimension of financial crime affects specific components of the Index of Economic Freedom.

Corruption undermines economic freedom primarily through its corrosive effect on the rule-of-law and property-rights sub-components of the IEF. When public officials exercise power for private gain, whether through petty bribery, regulatory capture, or the diversion of public resources, the predictability of legal and regulatory systems is undermined (Rose-Ackerman, 1999) [26]. Firms facing unpredictable enforcement of contracts or property rights cannot reliably plan long-term investments, reducing both investment rates and the efficiency of capital allocation. Ades and Di Tella (1999) [3] demonstrated that markets with fewer rents, that is, more competitive, open markets, exhibit lower corruption, establishing a direct theoretical link between economic freedom (market openness) and corruption levels. This expected positive relationship between CPI and IEF is formalised as Hypothesis 1 in this study.

Money laundering distorts economic freedom primarily through its effect on financial market integrity and investment freedom. By integrating illicit funds into the formal economy, through real estate, financial instruments, or shell companies, money laundering creates artificial demand, distorts asset prices, and crowds out legitimate economic activity from formal credit markets (Ferwerda, 2009) [10]. A higher AML score is therefore expected to be negatively associated with economic freedom (Hypothesis 2), particularly with the financial freedom and investment freedom sub-components of the IEF. Importantly, the AML channel operates largely through slow-moving structural factors, the quality of financial supervision, anti-corruption legislation, and international cooperation frameworks, that may not be fully captured within a short observation window, a consideration that informs the interpretation of the empirical results.

The shadow economy undermines economic freedom through a fiscal-integrity and regulatory-compliance channel. A larger shadow economy implies a reduced tax base, which constrains the government's capacity to provide the public goods, legal systems, property registries, infrastructure, that underpin economic freedom (Schneider & Enste, 2000) [29]. At the same time, informal sector activity creates a competitive distortion against formal-sector firms that face the full burden of taxation and regulation, weakening business freedom and eroding the rule-of-law norms that economic freedom requires. Williams and Schneider (2016) [32] showed that shadow economy size is systematically inversely related to tax morale and institutional trust. The shadow economy variable (SE), is therefore expected to be negatively associated with economic freedom (Hypothesis 3), primarily affecting the fiscal health, government integrity, and business freedom sub-components of the IEF.

Cybersecurity governance represents an increasingly critical dimension of the institutional environment for economic freedom in the digital age. Countries with stronger cybersecurity frameworks are better positioned to protect digital financial transactions, reduce exposure to cybercrime-enabled fraud and money laundering, and maintain the integrity of electronic commercial and governmental services (Achim et al., 2021) [2]. Digital infrastructure reliability is a prerequisite for both investment freedom, since foreign investors require assurance that digital assets are protected, and business freedom, since firms increasingly depend on digital platforms for commerce, supply chain management, and regulatory compliance. Higher GCI scores are therefore expected to be positively associated with economic freedom (Hypothesis 4), particularly as financial crime increasingly operates through digital channels.

Research examining the relationship between corruption, the shadow economy, and economic performance helps us understand the complexity of financial crime and highlights the need for studies that combine multiple indicators and data sources. Most existing studies focus either on economic growth or on specific regions, offering fewer insights into economic freedom as a dependent variable or into how sectoral structures influence this freedom at a global level (Borlea et al., 2017; Achim & Borlea, 2020) [6, 1]. In addition, recent evidence points out that financial crime is linked not only to macroeconomic outcomes, but also to corporate outcomes. For example, corruption, money laundering, and the shadow economy are associated with higher risks of business failure and corporate insolvency in European economies (Muntean et al., 2025) [23]. From a corporate-sector stability perspective, weak institutional quality and weak corporate governance, especially when controls are limited, can increase firms' vulnerability and raise insolvency risk, particularly in transition economies (Muntean, 2019) [21]. Finally, cross-country evidence suggests that higher economic freedom is associated with fewer corporate insolvencies across European countries, which supports the idea that a stronger and more predictable institutional environment contributes to firm resilience (Muntean et al., 2021) [22]. Overall, these findings support the motivation of the present study and strengthen the argument that economic freedom should be analysed together with institutional conditions, financial crime, and structural characteristics of the economy.

Research Objective

This study examines the relationship between financial crime and economic freedom using panel data for 46 countries over the period 2015–2024. To capture the complexity of financial crime, four complementary indicators are employed: the Corruption Perceptions Index (CPI), the Basel Anti-Money Laundering Index (AML), estimates of the shadow economy (SE), and the Global Cybersecurity Index (GCI).

The analysis incorporates sectoral composition controls, specifically, the shares of agriculture, industry, and services in GDP, to examine how the structural characteristics of the economy condition the relationship between financial crime and economic freedom.

The novelty of this study lies in its comparative approach. The analysis incorporates sectoral composition variables, specifically the shares of agriculture and industry in GDP, with services as the omitted category, to examine whether economic structure is associated with cross-country differences in economic freedom. This perspective helps to clarify how institutional weaknesses operate alongside structural characteristics and influence market performance and business activity. Moreover, using multiple indicators for financial crime within a panel framework offers new and valuable insights for public policy, particularly when it comes to strengthening institutional capacity and promoting sustainable economic development.

The central question addressed by this research is: *to what extent does financial crime undermine economic freedom, and how does the sectoral structure of the economy shape this effect?* The findings are relevant to both researchers and policymakers, highlighting the need for differentiated strategies to combat corruption and informality, tailored to the specific structural characteristics of each economy.

MATERIALS AND METHODS

Dataset Description and Panel Structure

The analysis draws on an unbalanced panel dataset covering 46 countries over the period 2015–2024, with a theoretical maximum of 460 country-year observations. The sample includes both developed and developing economies: 34 OECD and high-income economies (Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Singapore, Slovakia, South Korea, Spain, Sweden, Switzerland, United Kingdom, and the United States of America) and 12 emerging and transition economies (Brazil, Bulgaria, China, Colombia, India, Moldova, Morocco, Russia, South Africa, Taiwan, Turkey, and Ukraine). This mix of countries allows the results to reflect differences in institutional quality, financial development, and regulatory environments across the world.

Four separate Pooled OLS models are estimated, each featuring one financial crime indicator alongside two sectoral structure controls. The panel is slightly unbalanced: most countries have observations for all ten years (2015–2024), while missing values in specific country-year cells arise from the differential availability of individual indices. The Global Cybersecurity Index (GCI) is unavailable in 2022–2023, while Shadow Economy data are based on Medina and Schneider (2018) [20] up to 2017 and on FinCrime Platform values 2018-2024 (FinCrime Project, n.d.) [11].

Variable Description

Dependent Variable.

Economic freedom is measured by the Index of Economic Freedom (IEF), published by the Heritage Foundation. The IEF is a score from 0 to 100 built from twelve sub-indices covering rule of law, government size, regulatory efficiency, and market openness. A higher score means greater economic freedom. This index is widely used in cross-country studies as a measure of how freely markets operate (Heritage Foundation, n.d.) [14].

Independent Variables.

<u>Financial Crime Variables</u>. Three direct financial crime indicators and one digital governance indicator are used as main explanatory variables. Corruption levels are measured by the *Corruption Perceptions Index* (CPI), a score published annually by Transparency International on a 0–100 scale, where higher values reflect lower perceived corruption in the public sector (Transparency International, n.d.) [31]. *The Basel Anti-Money Laundering Index* (AML), produced by the Basel Institute on Governance, provides a composite risk score from 0 to 10 that measures a country's exposure to money laundering and terrorist financing risks, with higher scores indicating greater vulnerability (Basel Institute on Governance, n.d.) [4]. *The*

Shadow Economy (SE) is expressed as a share of GDP and reflects informal economic activity, including unreported work and tax evasion, based on data from Medina and Schneider (2018) [20]. It should be noted that the Medina and Schneider (2018) [20] estimates extend through 2015-2017 for most countries; observations beyond this range are not available from this source and therefore the SE variable is based on data up to 2017 from original source, while for 2018-2024 the series were completed with values from the FinCrime Platform comparison module (FinCrime Project, n.d.) [11], these later observations are treated as platform-based estimated values. A larger shadow economy generally means more incentives to avoid formal rules and is linked to financial crime.

Digital Governance Variable. The Global Cybersecurity Index (GCI), published by the International Telecommunication Union (ITU), measures how committed a country is to cybersecurity across five areas: legal measures, technical capacity, organizational structures, capacity development, and international cooperation. The GCI ranges from 0 to 1, where higher values indicate stronger cybersecurity systems (International Telecommunication Union, n.d.) [15]. In this study, cybersecurity capacity is treated as part of financial crime prevention, given the growing link between digital vulnerabilities and financial crime.

Sectoral Structure Variables. Three variables are used to capture the economic structure of each country in the extended model: agriculture value added as a share of GDP (Agr), industry value added as a share of GDP (Ind), and services value added as a share of GDP (Serv), all from the World Bank (World Bank, n.d.) [33]. These variables serve two purposes: they describe the structural environment in which financial crime takes place, and they account for the different institutional pressures found in agrarian, industrial, and service-based economies. Countries with large agricultural sectors tend to have more informality and weaker fiscal capacity. Industrial economies face more complex regulatory environments in manufacturing and trade finance. Service-based economies, especially those with large financial sectors, face more sophisticated financial crime but also tend to have stronger supervisory systems.

Research Hypotheses

H1: *Higher CPI scores (lower perceived corruption) are positively associated with economic freedom across countries.*

H2: *Higher money-laundering risk (higher AML Index) is negatively associated with economic freedom.*

H3: *A larger shadow economy (share of GDP) is negatively associated with economic freedom*.

H4: *Higher Global Cybersecurity Index scores are positively associated with economic freedom*.

Econometric Framework

This study employs a Pooled Ordinary Least Squares (POLS) estimator within a panel data framework. Given the potential for heteroskedasticity across country panels, confirmed by the Breusch-Pagan diagnostic tests reported in Table 4, all regressions use HC1 heteroskedasticity-robust (White-corrected) standard errors. The decision to estimate four separate single-indicator models, rather than a combined specification including all financial crime variables simultaneously, is motivated by the high inter-correlation among the financial crime indicators (notably $r = -0.831$ between Ln(CPI) and Ln(SE)), which would generate severe multicollinearity and make individual coefficient estimates unreliable.

All continuous variables are expressed in natural logarithms (log-log specification), which allows the estimated coefficients to be interpreted directly as elasticities: a 1% change in an independent variable is associated with a β% change in economic freedom, ceteris paribus. The sole exception is the Basel AML Index, which is entered in levels because its bounded 0-10 scale and near-normal distribution do not warrant logarithmic transformation. The resulting coefficient is interpreted as a semi-elasticity: a one-unit increase in the AML score is associated with a $\beta \times 100\%$ change in IEF.

Because sectoral shares (agriculture, industry, and services) sum to 100% of GDP, including all three simultaneously would induce perfect multicollinearity. Accordingly, the services share is excluded from all regressions and serves as the reference category. Coefficients on Ln(Agr) and Ln(Ind) therefore capture structural differences in economic freedom relative to service-dominant economies.

The four estimated models are specified as follows:

Model 1 (Corruption):

$$Ln(IEF_{it}) = \beta_0 + \beta_1 \cdot Ln(CPI_{it}) + \beta_2 \cdot Ln(Agr_{it}) + \beta_3 \cdot Ln(Ind_{it}) + \varepsilon_{it} \quad (1)$$

Model 2 (Shadow Economy):

$$Ln(IEF_{it}) = \beta_0 + \beta_1 \cdot Ln(SE_{it}) + \beta_2 \cdot Ln(Agr_{it}) + \beta_3 \cdot Ln(Ind_{it}) + \varepsilon_{it} \quad (2)$$

Model 3 (Money Laundering):

$$Ln(IEF_{it}) = \beta_0 + \beta_1 \cdot AML_{it} + \beta_2 \cdot Ln(Agr_{it}) + \beta_3 \cdot Ln(Ind_{it}) + \varepsilon_{it} \quad (3)$$

Model 4 (Cybersecurity):

$$Ln(IEF_{it}) = \beta_0 + \beta_1 \cdot Ln(GCI_{it}) + \beta_2 \cdot Ln(Agr_{it}) + \beta_3 \cdot Ln(Ind_{it}) + \varepsilon_{it} \quad (4)$$

where i denotes country, t denotes year, and ε_{it} is the idiosyncratic error term. In all specifications, the dependent variable is the natural logarithm of the Index of Economic Freedom. HC1 heteroskedasticity-robust standard errors are used throughout, as confirmed by the Breusch-Pagan diagnostic tests reported in Table 4. Within-country serial correlation is not explicitly corrected under the Pooled OLS specification and represents a limitation of the current design.

It is important to note that the Pooled OLS specification pools all country-year observations without controlling for unobserved time-invariant country characteristics. This implies that the estimated coefficients capture both between-country structural differences and within-country temporal variation. As a consequence, the results should be interpreted as describing cross-country associations rather than strictly causal within-country effects. Endogeneity, arising from potential reverse causality between economic freedom and financial crime indicators, cannot be fully ruled out under this specification and represents a limitation acknowledged in the Limitations section.

Correlation Analysis

Table 1 presents the Pearson correlation matrix computed on log-transformed variables (except AML, which is in levels). The strong negative correlation between Ln(IEF) and Ln(SE) (r = −0.676) and between Ln(IEF) and AML (r = −0.498) confirms the expected inverse relationship between financial crime and economic freedom. The strongest bivariate association is between Ln(IEF) and Ln(CPI) (r =0.823), consistent with corruption being the dominant institutional constraint on economic freedom.

Table 1. Pearson Correlation Matrix (log-transformed variables; AML in levels)

Variable		1	2	3	4	5	6	7
Ln(IEF)	1	1.000						
Ln(CPI)	2	0.823	1.000					
Ln(SE)	3	-0.676	-0.831	1.000				
AML	4	-0.498	-0.525	0.288	1.000			
Ln(GCI)	5	0.243	0.275	-0.262	-0.212	1.000		
Ln(Agr)	6	-0.665	-0.673	0.593	0.162	-0.184	1.000	
Ln(Ind)	7	-0.144	-0.228	0.139	0.070	-0.017	0.389	1.000

Notes: N = 340 complete observations (listwise deletion). All coefficients computed on logarithmic scale except AML. Bold values indicate |r| > 0.5.
Source: Authors' calculations.

The moderately high correlation between Ln(CPI) and Ln(SE) (r = −0.831) confirms that corruption and informality are strongly co-determined, motivating the decision to estimate separate models for each financial crime dimension rather than including all indicators simultaneously.

RESULTS AND DISCUSSIONS

Table 2 presents the Pooled OLS regression results and a side-by-side comparison of the key coefficients and fit statistics across the four models, facilitating direct comparison of the magnitude and significance of each financial crime indicator's effect on economic freedom. Standard errors are HC1 heteroskedasticity-robust (White correction) throughout, addressing the heteroskedasticity detected in the Breusch-Pagan diagnostic tests (Table 4). All models are jointly significant at the 1% level (F-statistic $p < 0.001$).

Table 2. Comparative Summary of Regression Results

	Model 1 CPI	Model 2 SE	Model 3 AML	Model 4 GCI
Dependent variable	Ln(IEF)	Ln(IEF)	Ln(IEF)	Ln(IEF)
Financial crime variable	Ln(CPI)	Ln(SE)	AML (levels)	Ln(GCI)
FC variable - coefficient	0.2920 ***	−0.1141 ***	−0.0653 ***	0.0514 **
FC variable - std. error	(0.0143)	(0.0117)	(0.0053)	(0.0199)
Ln(Agr) coefficient	−0.0271 ***	−0.0496 ***	−0.0724 ***	−0.0793 ***
Ln(Ind) coefficient	0.0455 ***	0.0363 **	0.0639 ***	0.0562 ***
R^2	0.7174	0.5746	0.6164	0.4626
Adjusted R^2	0.7154	0.5717	0.6137	0.4580
F-statistic	378.99 ***	254.88 ***	224.65 ***	97.87 ***
Observations (N)	434	435	425	352

Notes: *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses are HC1 heteroskedasticity-robust. Services share (Ln(Serv)) is excluded as the reference category in all models. AML enters in levels; all other variables are log-transformed. The number of observations varies across models due to missing data in individual indicators.
Source: Authors' processing.

Table 3 reports the Variance Inflation Factors for each model. All VIF values are well below the conventional threshold of 10, and below 5 in all cases, confirming the absence of problematic multicollinearity across all four specifications.

The strategy of estimating separate models for each financial crime variable, rather than a combined specification, was instrumental in achieving these clean diagnostics, given the high inter-correlation between CPI and SE (r = -0.831) observed in the correlation matrix.

Table 3. Variance Inflation Factors (VIF) - Multicollinearity Diagnostics

Variable	Model 1 (CPI)	Model 2 (SE)	Model 3 (AML)	Model 4 (GCI)	Threshold	Assessment
Financial crime variable	1.799	1.558	1.036	1.038	< 10	✓ Acceptable
Ln(Agr)	1.972	1.759	1.176	1.224	< 10	✓ Acceptable
Ln(Ind)	1.152	1.163	1.145	1.184	< 10	✓ Acceptable
Max VIF in model	1.972	1.759	1.176	1.224	< 10	✓ All clear

Notes: $VIF = 1/(1 - R^2_j)$, where R^2_j is the coefficient of determination from regressing predictor j on all other predictors. Values below 5 indicate no meaningful multicollinearity. Values below 2 indicate near-orthogonality.
Source: Authors' processing.

Table 4 reports the Breusch-Pagan (BP) test for heteroskedasticity. The null hypothesis of homoskedastic errors is rejected at the 1% level in all four models (BP $p < 0.001$ for Models 1–3; $p < 0.001$ for Model 4). This finding is consistent with the cross-country nature of the panel, where variance in IEF scores is structurally higher among heterogeneous developing economies than among developed ones. To address this, HC1 heteroskedasticity-robust standard errors are applied throughout, ensuring valid inference on coefficients and test statistics.

Table 4. Breusch-Pagan Heteroskedasticity Test

Model	BP Statistic	Degrees of Freedom	p-Value	Decision ($\alpha = 0.05$)
Model 1: Corruption (CPI)	26.929	3	< 0.001	Reject H_0 - Heteroskedastic
Model 2: Shadow Economy (SE)	37.906	3	< 0.001	Reject H_0 - Heteroskedastic
Model 3: Money Laundering (AML)	46.998	3	< 0.001	Reject H_0 - Heteroskedastic
Model 4: Cybersecurity (GCI)	20.136	3	< 0.001	Reject H_0 - Heteroskedastic

Notes: Breusch-Pagan test: auxiliary OLS regression of squared residuals on the full set of regressors. H_0: homoskedastic errors ($var(\varepsilon_{it}) = \sigma^2$). BP statistic $\sim \chi^2(k)$, where k = number of regressors excluding the constant. Rejection of H_0 confirms the use of HC1 robust standard errors throughout.
Source: Authors' processing.

Model 1 produces the strongest fit of the four specifications ($R^2 = 0.717$, Adj. $R^2 = 0.715$), with 434 observations. The coefficient on Ln(CPI) is +0.2920 and is highly significant ($t = 20.39$, $p < 0.001$), confirming Hypothesis 1. Interpreted as an elasticity, this implies that a 1% improvement in a country's Corruption Perceptions Index score is associated with a 0.292% increase in its Index of Economic Freedom score, ceteris paribus. The magnitude of this effect, nearly three times larger than any other financial crime coefficient in the study, underscores corruption as the dominant institutional mechanism linking financial crime to economic freedom. This finding is consistent with the institutional economics literature: corruption erodes property rights, generates regulatory uncertainty, and undermines the rule-of-law foundations upon which economic freedom depends (Rose-Ackerman, 1999; North, 1990) [26, 24]. The high explanatory power of this model reflects the deep structural co-determination of perceived corruption and economic freedom across the 46-country sample.

In Model 2 ($N = 435$, $R^2 = 0.575$), the shadow economy coefficient is -0.1141 ($t = -9.75$, $p < 0.001$), confirming Hypothesis 3. A 1% increase in the share of the shadow economy as a proportion of GDP is associated with a 0.114% decline in the Index of Economic Freedom. This negative relationship operates primarily through the fiscal-integrity and regulatory-compliance channels: a larger informal sector erodes the government tax base, reducing its capacity to enforce property rights and regulatory standards; simultaneously, shadow economic activity creates competitive advantages for non-compliant firms, weakening the rule-of-law norms that underpin economic freedom (Schneider & Enste, 2000; Williams & Schneider, 2016) [29, 32]. The somewhat lower R^2 compared to Model 1 reflects the fact that shadow economy size, while strongly correlated with economic freedom, captures a distinct and partially independent institutional channel from perceived corruption.

Model 3 estimates the effect of the Basel AML Index on economic freedom, with the index entering in levels rather than logarithms ($N = 425$, $R^2 = 0.616$). The AML coefficient is -0.0653 ($t = -12.40$, $p < 0.001$), confirming Hypothesis 2. Because AML enters in levels, this coefficient is interpreted as a semi-elasticity: each one-point increase in the Basel AML risk score (on a 0 -10 scale) is associated with a 6.53% decrease in the IEF, holding sectoral composition constant.

Countries with weaker anti-money laundering frameworks face persistent institutional disadvantages in financial market integrity, investment freedom, and rule-of-law enforcement, precisely the dimensions most directly affected by the distortion of capital flows associated with money laundering activity (Ferwerda, 2009) [10]. The agriculture coefficient in this model (-0.0724) is the second largest among all models, suggesting that the AML channel is particularly pronounced in agrarian economies where land-based asset transfers are commonly used as laundering vehicles and where formal financial supervision is weakest.

To contextualise the economic significance: the full range of AML risk scores in the sample (approximately 5.5 units) is associated with an estimated difference of approximately 35.9% in IEF scores, underscoring the substantial practical importance of anti-money laundering capacity.

Model 4 estimates the effect of the Global Cybersecurity Index on economic freedom (N = 352, R^2 = 0.463). The coefficient on Ln(GCI) is +0.0514 (t = 2.59, p = 0.010), confirming Hypothesis 4, though with a substantially smaller elasticity than the other financial crime variables. A 1% improvement in the GCI score is associated with a 0.051% increase in economic freedom. The smaller sample (352 observations) and lower R^2 in this model reflect the more limited temporal coverage of the GCI, available for fewer country-years than the other indicators, and the relatively recent integration of cybersecurity governance into the institutional framework supporting economic freedom. The result nonetheless confirms that digital governance capacity constitutes an emerging institutional determinant of economic freedom, operating through its impact on digital financial crime prevention and the protection of investment and business freedom in digital markets (Achim et al., 2021) [2].

The sectoral composition variables, Ln(Agr) and Ln(Ind), with services as the excluded reference, yield remarkably consistent results across all four models. The agriculture share coefficient is negative and highly significant ($p < 0.001$) in all four specifications, ranging from -0.0271 (Model 1) to -0.0793 (Model 4).

These estimates carry a clear interpretation under the log-log specification: a 1% increase in the agriculture share of GDP is associated with reductions in the IEF ranging from 0.027% to 0.079%, depending on the model specification. The agriculture effect is largest in absolute terms in Models 3 (AML: -0.0724) and 4 (GCI: -0.0793), suggesting that the institutional channels through which money laundering risk and digital vulnerability impair economic freedom are particularly severe in agrarian economies.

This is consistent with structural transformation theory (Kuznets, 1955) [17]: countries with large agricultural sectors retain institutional features, fragmented land tenure, high informality, limited administrative reach, that compound the damage caused by financial crime to economic freedom.

The industry share coefficient is positive and significant in all four models ($p \leq 0.029$), ranging from +0.036 (Model 2) to +0.064 (Model 3).

This confirms that industrial economies exhibit higher economic freedom relative to service-dominant economies, other things equal, a finding that, together with the negative agriculture effect, is consistent with the view that structural advancement along the Kuznets development sequence is associated with institutional improvements captured in the IEF.

The persistence of these sectoral effects across all four models, irrespective of which financial crime variable is included, confirms that economic structure is an independent conditioning factor rather than merely a proxy for the financial crime indicators.

Even after controlling for corruption, shadow economy size, money laundering risk, or cybersecurity capacity, the structural composition of the economy retains statistically significant explanatory power for cross-country differences in economic freedom.

Table 5 provides a summary of the empirical results in relation to each hypothesis.

Table 5. Hypothesis Testing Summary

Hypothesis	Financial Crime Variable	Expected Sign	Estimated Coefficient	Result
H1: CPI → IEF	Ln(CPI): lower corruption = higher IEF	+	+0.2920 ***	✓ Confirmed
H2: AML → IEF	AML: higher ML risk = lower IEF	−	−0.0653 ***	✓ Confirmed
H3: SE → IEF	Ln(SE): larger shadow econ. = lower IEF	−	−0.1141 ***	✓ Confirmed
H4: GCI → IEF	Ln(GCI): stronger cybersec. = higher IEF	+	+0.0514 **	✓ Confirmed
Additional findings				
Agr → IEF	Ln(Agr): higher agr. share = lower IEF	−	−0.027 to −0.079 ***	✓ Confirmed (all 4 models)
Ind → IEF	Ln(Ind): higher ind. share = higher IEF (vs Serv)	+	+0.036 to +0.064 ** to ***	✓ Confirmed (all 4 models)

Notes: **, *** denote significance at the 5% and 1% levels, respectively. 'Confirmed' indicates that the estimated sign matches the theoretical expectation and the coefficient is statistically significant at the 5% level or better.
Source: Authors' processing.

CONCLUSIONS

This research examines the extent to which financial crime undermines economic freedom and how the sectoral structure of the economy shapes this relationship. The study uses panel data for 46 countries over the period 2015-2024 and applies Pooled OLS regression with a log-log specification. Four indicators of financial crime are included: Corruption Perceptions Index, Basel Anti-Money Laundering Index, Shadow Economy, and Global Cybersecurity Index, together with sectoral composition variables for agriculture and industry (with services as the reference category).

The results confirm that financial crime has a negative impact on economic freedom. Corruption emerges as the dominant constraint, with a cross-country elasticity of 0.292: a 1% improvement in a country's CPI score is associated with a 0.292% increase in economic freedom. Shadow economy activity exerts a significant negative effect (elasticity = -0.114), operating through fiscal erosion and institutional non-compliance channels. Money laundering risk is also negatively associated with economic freedom (semi-elasticity = -0.065 per AML unit), with the full range of AML risk in the sample implying an approximate 35.9% difference in IEF scores. Cybersecurity governance contributes positively (elasticity = +0.051), confirming that digital institutional capacity is an emerging determinant of economic freedom.

The sectoral analysis reveals that agricultural dependence is the strongest structural constraint on economic freedom across all four model specifications, consistent with structural transformation theory (Kuznets, 1955) [17] and the informality literature (La Porta & Shleifer, 2014) [18]. Industrial composition, by contrast, is positively associated with economic freedom relative to the service-sector baseline, suggesting that structural advancement along the development sequence brings institutional improvements that expand market freedom.

This study makes three specific contributions to the literature. First, it is to the best of the authors' knowledge, the first study to jointly examine four distinct financial crime dimensions as separate but comparable constraints on economic freedom within a unified panel data framework covering 46 economies over a decade. Second, it introduces sectoral structure as a theoretically motivated conditioning variable, demonstrating that the institutional environment through which financial crime operates differs fundamentally across agricultural, industrial, and service-dominant economies. Third, it provides the most recent and geographically comprehensive cross-country evidence on this research question, covering the period 2015-2024 and encompassing both the COVID-19 institutional shock and the subsequent policy adjustments.

The findings present useful lessons for policymakers. Countries are unlikely to improve economic freedom without addressing the institutional roots of financial crime, especially corruption and informality. Anti-corruption efforts, policies to reduce the shadow economy, and investment in cybersecurity should all be seen as part of a broader strategy to expand economic freedom. These reform priorities should be calibrated to the structural characteristics of the economy. For agrarian economies, where agricultural dependence amplifies the institutional damage of financial crime, reforms targeting land titling, rural fiscal administration, and anti-money laundering capacity in land-based asset markets are most directly relevant. For industrial economies, strengthening trade finance regulation and anti-bribery enforcement in procurement is the priority. For service-dominant economies with large financial sectors, cybersecurity investment and sophisticated AML supervision yield the greatest institutional returns.

This study has several limitations that should be noted. First, the Pooled OLS specification does not control for unobserved time-invariant country heterogeneity, and the results therefore reflect cross-country associations rather than strictly causal within-country effects. Reverse causality, whereby greater economic freedom itself reduces financial crime by strengthening market competition and institutional oversight, cannot be ruled out; future research employing instrumental variable or system-GMM approaches would be valuable in addressing this endogeneity concern. Second, shadow economy data from Medina and Schneider (2018) [20] extend only to 2017 for most countries, while values for 2018-2024 were taken from the FinCrime Platform (FinCrime Project, n.d.) [11], the SE results should therefore be interpreted with this data limitation in mind. Third, the sample is dominated by developed economies (34 of 46 countries), which may limit the generalisability of findings to low-income developing contexts, precisely where the financial crime, agriculture interaction is theoretically most pronounced. Fourth, the slope homogeneity assumption of Pooled OLS, that the effect of each financial crime indicator is identical across all 46 countries, is strong and untested; future research could employ panel threshold models or interaction terms to examine parameter heterogeneity. Fifth, GCI data are missing for 102 country-year observations (22% of the panel), concentrated in 2022-2023, which may introduce selection bias into Model 4 estimates. Future research could analyse sub-groups of countries by development level or dominant sector, extend the panel to more recent years as data become available, and use dynamic panel or fixed-effects specifications to strengthen the identification of causal effects.

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