

Article

Modelling the Shadow Economy: An Econometric Study of Technology Development and Institutional Quality

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Abstract

This econometric analysis models the conditional expectation of Europe's shadow economy size as a function of technologization and institutional quality indicators, using a balanced panel of 29 countries from 2007 to 2022. Technologization is measured through the four dimensions of Desai's Technological Achievement Index, and institutional quality via core World Government Indicators variables. Rigorous diagnostics select a random-effects model with year dummies and Driscoll-Kraay standard errors, explaining 61% of the variance in informality. Development of Human Skills delivers the largest individual reduction (−7.2 pp), strongly supporting the core hypothesis. Control of Corruption is also highly significant (−2.8 pp). While New Technology Creation showed a negative association, its statistical significance proved unstable across model specifications. Technology diffusion becomes insignificant when common global time shocks are absorbed, implying that mere adoption has limited independent effect. Furthermore, the impact of human skills intensifies significantly in countries with high New Technology Diffusion (−12,489), revealing a potent synergy between human capital and technological advancement. Policy priorities therefore include anti-corruption enforcement, Research and Development incentives, and sustained investment in skills, especially where technology diffusion is high, to draw hidden activity into the formal sector.

Keywords: shadow economy; technology development; institutional quality; panel data; governance; human capital; Europe; Technological Achievement Index

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1. Introduction

The shadow economy lacks a single definition [1], but is understood as a set of economic activities intentionally hidden from fiscal, regulatory and statistical authorities. It frequently includes undeclared work and trade, allowing the avoidance of taxes, labour standards and other legal obligations. The phenomenon is constantly fuelled by corruption, weak institutions, low levels of economic development and lack of trust in authorities. With a significant share in the global economy, shadow economy influences national development trajectories, reduces the financial capacity of the state and accentuates social inequalities [2–9]. It also undermines financial and macroeconomic stability, amplifying long-term economic vulnerabilities [10]. Recent studies also emphasize that weak institutional quality and corruption generate not only informal labour but also economic fraud

and high-risk practices that erode market transparency [11]. Corruption and shadow economy are closely linked, affecting governance and development. Whether their relationship is one of substitution or complementarity depends on the context of each state [12–14]. Identifying and combating these forces is thus the basis for policies aimed at strengthening the formal economy. In contexts of political uncertainty and volatility, institutional instability tends to amplify informal practices and discourage compliance [15].

The link between the shadow economy and technological progress has become increasingly relevant, as nations seek to participate and compete in the technology-driven global marketplace. A groundbreaking contribution to quantifying a nation's technology level was Desai's [16] Technological Achievement Index (TAI). The TAI is a composite indicator designed to assess a country's technological capabilities and performance, reflecting the degree to which it has adopted technological innovations and creating a country ranking. Its composition, widely adopted by the scientific community [17–24], encompasses four key dimensions. These are the creation of new technologies, the diffusion of new technologies, the diffusion of old technologies, and the development of human skills [16]. This comprehensive structure, notably including both new and old technologies, ensures its relevance across a wide range of states at varying stages of technological development. TAI is particularly important to the scientific community, as it allows statistical analyses to be developed, with a time frame that extends beyond just a couple of years. Also, it offers interesting dimensions that can help create a more organic view of the technological state of a country.

Each TAI dimension captures distinct sides of a country's technological standing. The creation of new technologies reflects a nation's innovation capacity and its ability to generate novel technological advancements. The diffusion of new technologies represents a country's success in adopting and integrating modern technological innovations into its economy and benefiting from new opportunities. Conversely, the diffusion of old technologies highlights the foundational spread of basic, widely used technologies, for broader technological progress and for being the enabler in the use of newer innovations. Finally, the development of human skills signifies the mass of skilled individuals necessary for both creating and effectively utilizing new technologies, underpinning overall technological dynamism and progress. Empirical analyses highlight that technological advancement must be paired with adequate institutional and educational adaptation to generate systemic efficiency [25], while crises such as the COVID-19 pandemic have demonstrated the capacity of digitalization to accelerate institutional transformation [26].

Regarding the shadow economy, the role of technology is controversial. Digital governance and ICT have the capacity to reduce informality by increasing transparency and efficiency. Recent empirical evidence confirms that digital finance can reduce the shadow economy, although it may simultaneously increase financial instability [27]. On the other hand, the effectiveness of these tools depends largely on institutional conditions [28–30]. In contrast, the shadow digital economy is also stimulated by technology [31]. It is necessary to strengthen the capacity of institutions to effectively enforce the law and monitor economic activities [32]. Strong institutions stimulate economic growth and attract investment and innovation [33–36]. The degree of trust in artificial intelligence and digital systems strongly influences behavioural compliance and the willingness to engage in transparent economic exchanges [37].

Econometrics combines economic theory, mathematics, and statistics to quantify relationships and turn models into tools for public policy. Panel Data Analysis, widely applied in economics and finance, tracks variables over time and across units. Arellano and Bond [38] emphasized serial autocorrelation tests in validating dynamic GMM models to handle endogeneity, while Supianti [39] showed the flexibility of fixed and random

effects models in studying regional growth. Post-estimation tests like the Hausman guide model choice, and Driscoll and Kraay standard errors correct for heteroskedasticity, autocorrelation, and cross-sectional dependence, ensuring sturdy inference [40]. Panel data is especially apt for examining the shadow economy, as it jointly analyses time and country effects, isolates persistent traits from policy impacts, traces how past values shape future paths, and, by pooling data, improves estimation efficiency and statistical power.

The program R (version 4.5.1) is a powerful statistical programming environment, widely used for data analysis, modelling, and visualization [41]. It provides a flexible platform for conducting structural equation modelling (SEM), especially through packages like SEMinR, which allow researchers to specify and estimate PLS path models efficiently. RStudio (version 2025.09.2-418) serves as an integrated development environment (IDE) for R (version 4.5.1). It offers a user-friendly interface that makes coding, executing scripts, and managing outputs more accessible. Together, R and RStudio support reproducible research, reliable statistical analysis, and the transparent reporting of results. Hence, making them valuable tools in advanced business and social science studies.

The shadow economy, institutional quality, and technology have distinct but increasingly interconnected dimensions. Although necessary, research on how technological and institutional factors together influence the dynamics of the shadow economy is still in its infancy. The increasing relevance of the subject is due to the growing asymmetry between fast-moving digitalisation and the slower institutional capacity to adapt. The resulting imbalance threatens fiscal sustainability and societal well-being, highlighting the need to study this triad to guide effective policy and secure long-term prosperity. This econometric analysis aims to bridge this gap by exploring these complex interactions and providing a basis for more integrated and effective public policies.

Key findings emerge with clear policy implications. First, stronger anti-corruption measures consistently reduce the size of the informal sector, underscoring the power of transparent governance. Second, new technology creation and human capital development both exhibit significant negative associations with shadow-economy levels, with skill development producing the largest estimated reduction per unit increase. In contrast, the mere diffusion of technology, whether new or old, loses statistical significance once global time trends are accounted for.

2. Materials and Methods

The central objective of this econometric investigation is to explore the dynamic interplay between a nation's shadow economy and its levels of technologization and institutional quality. Specifically, this study aims to answer the following research questions and test the corresponding hypotheses. In this framework, the shadow economy is appropriately designated as the dependent variable, with all other aforementioned factors serving as independent variables.

RQ1: How do various layers of technologization and institutional quality indicators individually influence the size of the shadow economy?

RQ2: Are the effects of institutional quality and technologization on the shadow economy conditional on the interplay between these two factor blocks (Institutional $\times$ Technological), or on the interaction among the specific dimensions within a block?

H1: *Stronger institutional quality, also new technology creation, new technology diffusion and human skills development are hypothesized to be negatively associated with the shadow economy, while old technology diffusion is hypothesized to be positively associated.*

2.1. Data and Preparation

To retain interpretability and avoid information loss, the four TAI dimensions are examined separately rather than collapsed into a single composite score. This choice reflects both the limited long-run data on technology and the still emerging literature linking technological development to economic outcomes. Analysing the dimensions individually allows the identification of which technological channels, whether is innovation, diffusion or human skills, are most strongly associated with shadow economy. To the best of our knowledge, this approach is novel and provides a more nuanced perspective than the traditional use of the aggregate TAI score.

Each of the four dimensions is measured with two targeted sub-indicators. Consistent with the allocation principles outlined in Desai's work [16], each of the 8 sub-indicators was assigned a specific conceptual weight (50% of the dimension), reflecting their assumed similar role in classifying technological achievement. To ensure comparability across variables and follow established methodology for constructing the TAI dimensions, all sub-indicator values were normalized using the min-max method, scaling them to a uniform range, based on their observed minimum and maximum values, using the formula in Equation (1).

$$\text{Normalised Sub-indicators TAI} = \frac{(\text{Current Value} - \text{Minimum Observed Value})}{(\text{Maximum Observed Value} - \text{Minimum Observed Value})} \quad (1)$$

Source: As seen in scientific studies [15–17,20–23].

The dimensions of the TAI show, for each value, a numerical range between 0 and 1. Values closer to 1, rank higher than those closer to 0. In instances of data gaps within the database, missing values were estimated and completed using the linear interpolation method, using the formula in Equation (2). These imputations were limited to non-outcome variables and were insubstantial on the dataset's overall structure. The comprehensive database for these indicators, along with the institutional quality measures, was compiled from reputable sources.

$$\text{Missing Value} = \text{Value From The Previous Year} + \frac{(\text{Value From Last Year} - \text{Value From First Year})}{1 + \text{Number Of Years With Missing Value}} \quad (2)$$

Source: As seen in scientific studies [24,42].

In this study, the four dimensions that constitute the TAI indicator are structured as shown in Table 1, in line with the previous work of the scientific community [17–24], insights from the relevant literature, and the availability of appropriate data.

Table 1. The proposed composition of the econometric analysis.

Dimensions	Sub-Indicators	Source	Description
Creating new technologies (CNT)	Total patent grants	WIPO statistics database https://www3.wipo.int/ipstats/ips-search/patent (accessed on 27 June 2025)	Number of patents officially granted, showing a country's capacity to generate original technological innovations.
	Charges for the use of intellectual property, receipts (BoP, current US\$)	World Bank Data https://data.worldbank.org/indicator/BX.GSR.ROYL.CD?name_desc=true (accessed on 27 June 2025)	Income from foreign entities paying for the use of domestic patents, trademarks, or copyrights, indicating global demand for local innovations.

Table 1. Cont.

Dimensions	Sub-Indicators	Source	Description
Diffusion of new technologies (DNT)	Individuals using the Internet (% of population)	World Bank Data https://data.worldbank.org/indicator/IT.NET.USER.ZS?end=2023&most_recent_year_desc=true&start=1990 (accessed on 27 June 2025)	Shows how widely internet technology is adopted by the population, serving as a proxy for access to digital infrastructure.
	High-technology exports (%)	World Bank Data https://data.worldbank.org/indicator/TX.VAL.TECH.MF.ZS?end=2022&most_recent_year_desc=true&start=2007 (accessed on 27 June 2025)	Share of manufactured exports that are high-tech products, reflecting how successfully a country commercializes advanced technologies.
Diffusion of old technologies (DOT)	Fixed telephone subscriptions (per 100 people) + Mobile cellular subscriptions (per 100 people)	World Bank Data https://data.worldbank.org/indicator/IT.MLT.MAIN.P2?most_recent_year_desc=true (accessed on 27 June 2025) https://data.worldbank.org/indicator/IT.CEL.SETS.P2?most_recent_year_desc=true (accessed on 27 June 2025)	Represents the penetration of older communication technologies, signalling general connectivity and basic technological infrastructure.
	Final consumption—households—energy use—Gigawatt-hour	Eurostat https://doi.org/10.2908/NRG_CB_E (accessed on 27 June 2025)	Measures household energy consumption, a general indicator of technological appliance use and electrification.
Development of human skills (DHS)	Gross enrolment ratio, primary to tertiary, both sexes (%)	UNESCO Institute for Statistics https://databrowser.uis.unesco.org/view#indicatorPaths=&geoMode=countries&geoUnits=&timeMode=range&view=table&chartMode=multiple&chartHighlightSeries=&chartHighlightEnabled=true&indicatorPaths=UIS-EducationOPRI:0:GER.1T8 (accessed on 27 June 2025)	Reflects educational participation across all levels, indicating the potential human capital available to support and adapt to technological progress.
	Scientific and technical journal articles	World Bank Data https://data.worldbank.org/indicator/IP.JRN.ARTC.SC?most_recent_year_desc=true (accessed on 27 June 2025)	Number of peer-reviewed publications, illustrating research output and the creation and dissemination of scientific knowledge.
Control of Corruption (CC)	-	Worldwide Governance Indicators https://www.worldbank.org/en/publication/worldwide-governance-indicators (accessed on 27 June 2025)	Assesses the extent to which public power is exercised for private gain, including both petty and grand forms of corruption.

Table 1. Cont.

Dimensions	Sub-Indicators	Source	Description
Government Effectiveness (GE)	-	Worldwide Governance Indicators https://www.worldbank.org/en/publication/worldwide-governance-indicators (accessed on 27 June 2025)	The quality of public services, civil service, policy formulation, and implementation, reflects overall institutional performance.
Rule of Law (RL)	-	Worldwide Governance Indicators https://www.worldbank.org/en/publication/worldwide-governance-indicators (accessed on 27 June 2025)	Confidence in and adherence to the legal system, including contract enforcement, property rights, the police, and the courts.
Regulatory Quality (RQ)	-	Worldwide Governance Indicators https://www.worldbank.org/en/publication/worldwide-governance-indicators (accessed on 27 June 2025)	The ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

Source: Own processing based on the literary investigation carried out.

All statistical analyses were conducted using R (version 4.5.1; R Foundation for Statistical Computing, Vienna, Austria) and RStudio (version 2025.09.2-418; Posit Software, PBC, Boston, MA, USA). Panel data estimations relied on the plm package (CRAN, Vienna, Austria), while diagnostic tests were performed using the lmtest and sandwich packages (CRAN, Vienna, Austria).

The initial phase of this study focused on meticulous data preparation, laying a solid technical bedrock for the econometric analysis. The dataset was formatted into a panel data structure using RStudio, explicitly informing the plm package (RStudio version 2025.09.2-418) of the two key identifiers (countries and years) to properly account for both cross-sectional and time-series dimensions. Verification through pdim(pdata) (RStudio version 2025.09.2-418) confirmed a balanced panel consisting of 29 European countries observed over 16 years (2007–2022), yielding 464 total observations. A balanced panel streamlines estimation and avoids complexities of missing data, enhancing the statistical power of the models.

A preliminary step in understanding the joint behaviour of the independent variables was the computation of a correlation matrix covering four technologization indicators and four institutional quality indicators. The heatmap (Figure 1) shows that New Technology Diffusion is the most strongly associated with institutional quality, with correlations ranging from approximately 0.62 to 0.66. This indicates that countries with higher levels of technology diffusion tend to exhibit stronger institutional performance. Development of Human Skills and New Technology Creation display more moderate correlations with the institutional indicators (approximately 0.22 to 0.33), while Old Technology Diffusion shows the weakest links. The heatmap indicates the expected strong negative correlations between the Shadow Economy and all four institutional indicators (approximately -0.73 to -0.79). All correlation coefficients are statistically significant, most at the 0.1% level ($p < 0.001$), confirming that the observed relationships are robust and not driven by random variation. Even the weakest correlation, between New Technology Diffusion and Old Technology Diffusion ($r = 0.10$), has a p -value of 0.0303 (Table A6).

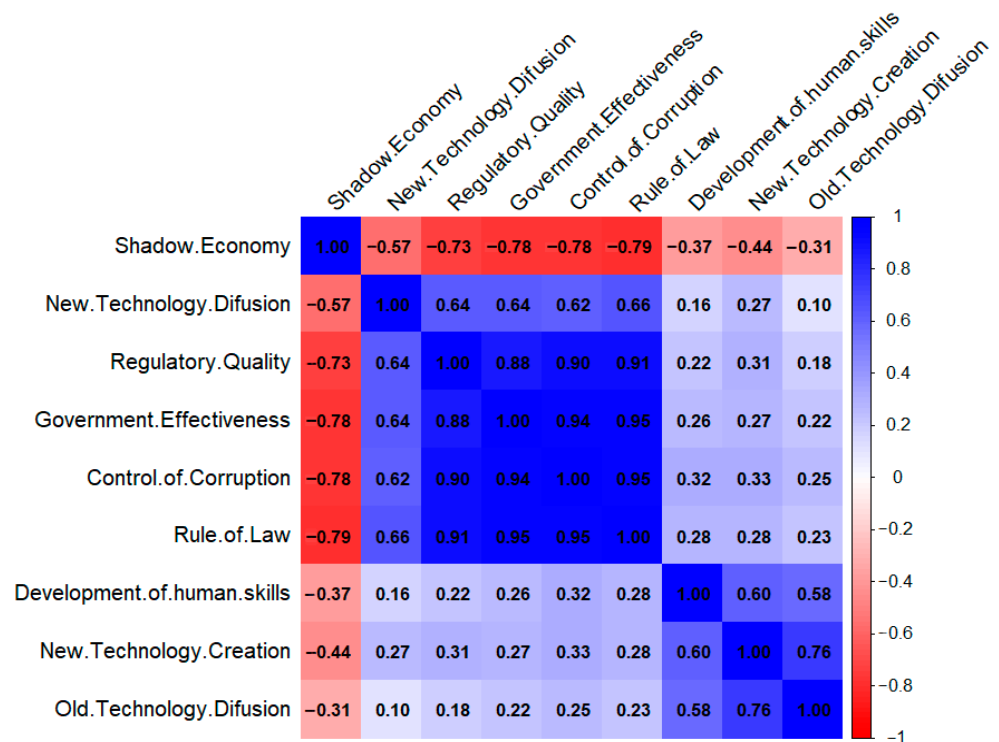


Figure 1. Correlation matrix heatmap. Source: Own calculations via RStudio (version 2025.09.2-418).

Figure 1 also highlights very strong positive intercorrelations among the Institutional Quality variables (approximately 0.88 to 0.95), visually confirming the presence of multicollinearity within this block. To complement the heatmap, a pairwise scatterplot matrix was generated to visually inspect the form, direction, and strength of bivariate relationships among the technologization and institutional quality variables (Figure 2).

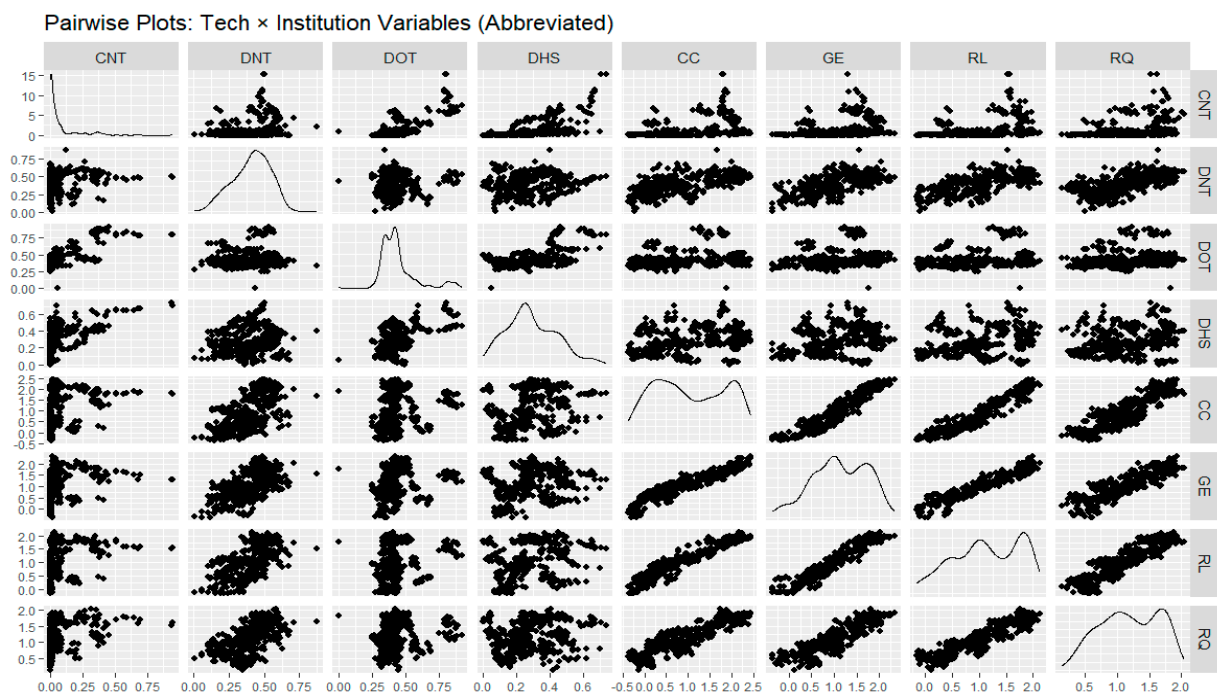


Figure 2. Pairwise scatterplots. Source: Own calculations via RStudio (version 2025.09.2-418).

The scatterplots reveal clear upward-sloping patterns among the four institutional indicators, confirming strong positive linear associations and visually reflecting the mul-

ticollinearity. Positive tendencies are also visible between institutional quality and technologization variables, particularly for New Technology Diffusion, which shows a more concentrated and linear pattern. In contrast, Old Technology Diffusion displays weaker and more dispersed relationships with both institutions and other technology indicators, consistent with its low correlation values. The downward patterns between the Shadow Economy and both institutional and technological variables are also visually noticeable, reinforcing their negative associations. Overall, the figure provides an intuitive visual confirmation of the correlation structure and supports the rationale for model specification and multicollinearity diagnostics.

2.2. Model Selection and Estimation

The analysis began with estimating three core panel data models: Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). Each model captures unobserved country-specific traits differently, allowing for an assessment of the most suitable structure for our data and providing a technical basis for identifying the best-aligned model.

Pooled OLS Model (Appendix A.1, Equation (3)) served as a baseline, treating all 464 observations as one large cross-section. It ignores unobserved, time-invariant country effects and is prone to omitted variable bias if such factors correlate with the regressors.

$$SE_{it} = \beta_0 + \beta_1 CC_{it} + \beta_2 GE_{it} + \beta_3 RL_{it} + \beta_4 RQ_{it} + \beta_5 CNT_{it} + \beta_6 DNT_{it} + \beta_7 DOT_{it} + \beta_8 DHS_{it} + \varepsilon_{it} \quad (3)$$

where

it = country i at time t .

β_k = the estimated change in the dependent variable associated with a one-unit change in predictor k , holding all other predictors constant.

β_0 = the estimated expected value of the dependent variable when all independent variables are equal to zero.

ε_{it} = error term.

FE Model (Appendix A.2, Equation (4)) controlled for unobserved, time-invariant country traits by leveraging only within-country variation over time, effectively removing bias from constant factors.

$$SE_{it} = \mu_{it} + \beta_1 CC_{it} + \beta_2 GE_{it} + \beta_3 RL_{it} + \beta_4 RQ_{it} + \beta_5 CNT_{it} + \beta_6 DNT_{it} + \beta_7 DOT_{it} + \beta_8 DHS_{it} + \varepsilon_{it} \quad (4)$$

where:

μ_{it} = captures time-invariant country-specific effects.

ε_{it} = the error term (or disturbance term).

RE Model (Appendix A.3, Equation (5)) captured unobserved country-specific effects but assumed they are random and uncorrelated with the regressors, offering greater efficiency when this assumption holds.

$$SE_{it} = \beta_0 + \beta_1 CC_{it} + \beta_2 GE_{it} + \beta_3 RL_{it} + \beta_4 RQ_{it} + \beta_5 CNT_{it} + \beta_6 DNT_{it} + \beta_7 DOT_{it} + \beta_8 DHS_{it} + \mu_{it} + \varepsilon_{it} \quad (5)$$

where:

μ_{it} = random individual effect.

ε_{it} = the error term.

The Hausman test was formally employed to compare the FE and RE models. A p -value greater than 0.05 would suggest the consistency and theoretical efficiency of the RE model.

2.3. Diagnostic Testing and Robustness Checks

To secure robust inferences, we ran standard diagnostics on the error structure. Uncorrected violations would distort standard errors and render p -values unreliable. Wooldridge test for autocorrelation (plm package-pbgtest(fe), RStudio version 2025.09.2-418) assessed whether residuals within each country are correlated over time. Breusch-Pagan test (lmtest package-bptest(fe), RStudio version 2025.09.2-418) examined for heteroskedasticity, where the variance of residuals is not constant across observations. Pesaran's CD test (lmtest package-pcdtest(fe, test = "cd"), RStudio version 2025.09.2-418) investigated cross-sectional dependence, where residuals across different countries are correlated at the same point in time due to common shocks.

Given the pervasive and significant violations of all three error structure assumptions identified by these tests, it became imperative to employ hardy standard errors to obtain trustworthy inferences. Driscoll-Kraay standard errors were deemed necessary due to strong evidence of cross-sectional dependence, as they are robust to heteroskedasticity, serial correlation, and cross-sectional dependence. This was implemented using vcovSCC(re, type = "HC1", maxlag = 2, sandwich package, RStudio version 2025.09.2-418).

2.4. Addressing Multicollinearity

Variance Inflation Factor (VIF) was used to detect multicollinearity among independent variables. VIF values typically above 5 or 10 indicate problematic levels of collinearity. Initial diagnostics revealed significant multicollinearity among the included World Governance Indicators (WGI), with several variables exhibiting Variance Inflation Factors (VIFs) exceeding 5. To address this, the WGIs (Government Effectiveness, Regulatory Quality, and Rule of Law) were sequentially removed one by one. The selection criterion prioritized retaining the indicator with the greatest explanatory power and theoretical significance for institutional quality.

2.5. Refining the Model with Time Effects

To capture shared shocks, the RE model includes year dummies. Driscoll-Kraay errors use maxlag = 2, guarding against second-order serial correlation while preserving efficiency for $T = 16$. The refined specification is given in Appendix A.4 and Equation (6).

$$SE_{it} = \beta_0 + \sum_{k=2008}^{2022} \delta_k D_k + \beta_1 CC_{it} + \beta_2 CNT_{it} + \beta_3 DNT_{it} + \beta_4 DOT_{it} + \beta_5 DHS_{it} + \mu_{it} + \varepsilon_{it} \quad (6)$$

where:

D_k = year dummies capturing global shocks or common time effects.

δ_k = time-specific effect, or year dummy coefficient.

μ_{it} = random individual effect.

This approach refined the estimated impacts of the main predictors and improved the overall model fit.

To further assess the robustness and stability of the primary findings, the main econometric analysis was re-conducted using a restricted time period. Specifically, the boundary years of 2007 and 2022 were dropped, limiting the sample to the 2008–2021 period (Tables A7–A9). This exclusion was strategically implemented to mitigate the potential influence of outliers or potential estimation inconsistencies concentrated at the start and end of the original sample window. The results from the restricted 2008–2021 sample were highly consistent with the original findings (2007–2022), particularly in the sign, magnitude, and statistical significance of the key variables. This strong consistency adds to the stability of the model's coefficients and validates that the main conclusions are not driven by idiosyncratic data points from the original boundary years.

Further analytical explorations included examining potential interaction effects and a broader assessment of variable relationships through block correlations. A key interaction effect was explored between Development of human skills and New Technology Diffusion, which was found to be statistically significant.

2.6. Dynamic Panel (GMM) Model Exploration

A Dynamic Panel (Generalized Method of Moments—GMM) model was also estimated to explore the persistence of the shadow economy over time and address potential endogeneity of the lagged dependent variable. However, diagnostic concerns, led to the conclusion that this model was not fully reliable for the primary explanatory goal.

3. Results

Initial estimation techniques compared Pooled OLS, Fixed Effects (FE), and Random Effects (RE) (Table A1). While the Hausman test ($\chi^2 = 14.47$, $p = 0.07$) suggested the consistency of the Random Effects estimator, subsequent diagnostic testing revealed significant violations of standard assumptions. Specifically, the Wooldridge test indicated serial correlation, the Breusch-Pagan test detected heteroskedasticity, and the Pesaran CD test confirmed cross-sectional dependence ($p < 0.001$ for all). To ensure valid inference in the presence of these complex error structures, we employed Driscoll-Kraay robust standard errors, which are consistent under general forms of cross-sectional and temporal dependence.

The model was further refined to enhance specification efficiency and address multicollinearity (Tables A2–A4). First, Government Effectiveness and Rule of Law were excluded due to persistent statistical insignificance across the initial robust specifications. Subsequently, Variance Inflation Factor (VIF) analysis identified high collinearity between Control of Corruption and Regulatory Quality ($VIF > 5$). Consequently, Regulatory Quality was dropped to prioritize Control of Corruption as the theoretically central institutional metric, reducing all remaining VIFs to below 3. Additionally, a dynamic System GMM specification was explored but rejected due to the failure of the AR(2) test ($p < 0.05$), indicating valid instrumentation could not be sustained (Table A5). Therefore, time-specific effects were incorporated into the static model via year dummies to control for common global shocks.

The final preferred explanatory model adopted is the Random Effects specification with country random intercepts and manual year dummies, employing Driscoll-Kraay standard errors (HC1, maxlag = 2, RStudio version 2025.09.2-418) to ensure robustness against heteroskedasticity, serial correlation, and cross-sectional dependence (Table 2). This model achieves an R-squared of approximately 0.606, indicating that it explains a substantial 61% of the variation in the shadow economy across countries and over time.

Table 2. Random Effects (Full Model).

Variable	VIF	Estimate	Std. Error	t Value	Pr (> t)	Significance
(Intercept)		25.415929	1.073930	23.6663	$<2.2 \times 10^{-16}$	***
Control.of.Corruption	1.78	−2.820349	0.533095	−5.2905	1.922×10^{-7}	***
New.Technology.Creation	2.80	−0.960411	0.484250	−1.9833	0.04795	*
New.Technology.Difusion	1.71	−1.255096	1.597236	−0.7858	0.43241	
Old.Technology.Difusion	2.56	−0.371567	1.285490	−0.2890	0.77268	
Development.of.human.skills	1.72	−7.200401	1.612503	−4.4654	1.016×10^{-5}	***
R^2		0.606				

Significance codes: '***' 0.001, '**' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Control of Corruption and Development of Human Skills are highly significant negative predictors of the shadow economy, while New Technology Creation retains significance. A one-unit improvement in corruption control is associated with a 2.8 percentage-point reduction in the shadow economy. Each unit increase in technology creation is associated with an approximate 1.0 percentage-point reduction in the shadow economy. This factor exhibits the largest estimated impact, with a one-unit improvement in human skills associated with a substantial 7.2 percentage-point reduction in the shadow economy. Notably, the diffusion variables (New and Old Technology Diffusion) lose significance when controlling for common time trends, suggesting their effects are largely captured by global temporal shifts.

The least significant predictor, Old Technology Diffusion, was removed (Table 3). This step confirmed the redundancy of the removed variable, as its exclusion resulted in no change to the model's R-squared (remaining at 0.606) and preserved the near-identical magnitude and statistical significance of the remaining core variables: Control of Corruption, New Technology Creation, and Development of Human Skills.

Table 3. Random Effects Model (Intermediate Model).

Variable	VIF	Estimate	Std. Error	t Value	Pr (> t)	Significance
(Intercept)		25.26993	0.674212	37.4807	$<2.2 \times 10^{-16}$	***
Control.of.Corruption	1.78	−2.81483	0.514624	−5.4697	7.54×10^{-8}	***
New.Technology.Creation	2.8	−0.98262	0.478786	−2.0523	0.04073	*
New.Technology.Difusion	1.71	−1.31917	1.699324	−0.7763	0.43799	
Development.of.human.skills	1.72	−7.20776	1.61594	−4.4604	1.04×10^{-5}	***
R^2		0.606				

Significance codes: '***' 0.001, '**' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Following the identification of insignificant predictors in the full model, we estimated a reduced Random Effects specification (Table 4) by excluding both New Technology Diffusion and Old Technology Diffusion. The results confirm the robustness of our core findings. First, the exclusion of these variables resulted in a negligible attenuation of the model's explanatory power, with the R^2 decreasing only marginally from 0.606 to 0.602. This indicates that the diffusion variables added virtually no unique explanatory value beyond what was already captured by the time effects and other covariates. Second, the coefficients for the primary drivers of the shadow economy remained remarkably stable. Control of Corruption (-2.94 , $p < 0.001$) and Development of Human Skills (-7.12 , $p < 0.001$) retained both their magnitude and high statistical significance, reinforcing the validity of the initial estimates. It is noted that New Technology Creation lost its statistical significance ($p = 0.34$) in this reduced specification. However, given the stability of the core institutional and human capital variables, Table 4 represents the most concise estimation of the shadow economy's determinants.

High initial VIF values (exceeding 5 and correlations up to 0.95 among WGI) were observed, a condition known to inflate standard errors and destabilize coefficient estimates. Consequently, Government Effectiveness and Rule of Law were excluded due to persistent statistical insignificance across the initial robust specifications, a result likely exacerbated by this high collinearity. Subsequently, Variance Inflation Factor (VIF) analysis identified high collinearity between Control of Corruption and Regulatory Quality ($VIF > 5$). Regulatory Quality was then dropped to prioritize Control of Corruption as the theoretically central institutional metric, successfully reducing all remaining VIFs to below 3. The marked stability (all values now below 1.75), of the remaining core coefficients (Control of Corruption

and Development of Human Skills) across the subsequent models (Tables 2–4) confirms that the initial collinearity issues were resolved and the final inferences are reliable.

Table 4. Random Effects (Reduced Model).

Variable	VIF	Estimate	Std. Error	t Value	Pr (> t)	Significance
(Intercept)		24.965055	0.791486	31.542	$<2.2 \times 10^{-16}$	***
Control.of.Corruption	1.16	−2.937641	0.476049	−6.1709	1.53×10^{-9}	***
New.Technology.Creation	1.63	−0.717695	0.756844	−0.9483	0.3435	
Development.of.human.skills	1.71	−7.11983	1.694219	−4.2024	3.19×10^{-5}	***
R^2		0.602				

Significance codes: ‘***’ 0.001. Source: Own calculations via RStudio (version 2025.09.2-418).

To visually assess the model’s fit, Residual vs. Fitted Values plot was generated for both models in Tables 2 and 4 (Figure 3a,b). In both panels, the residuals are broadly scattered around the horizontal axis (zero line) without any discernible curvature or funnel shape. This lack of systematic pattern suggests that the assumptions of linearity and homoskedasticity are reasonably satisfied in terms of functional form. The similarity between the two plots further indicates that the exclusion of the two insignificant diffusion variables did not introduce any new bias or misspecification into the reduced model.

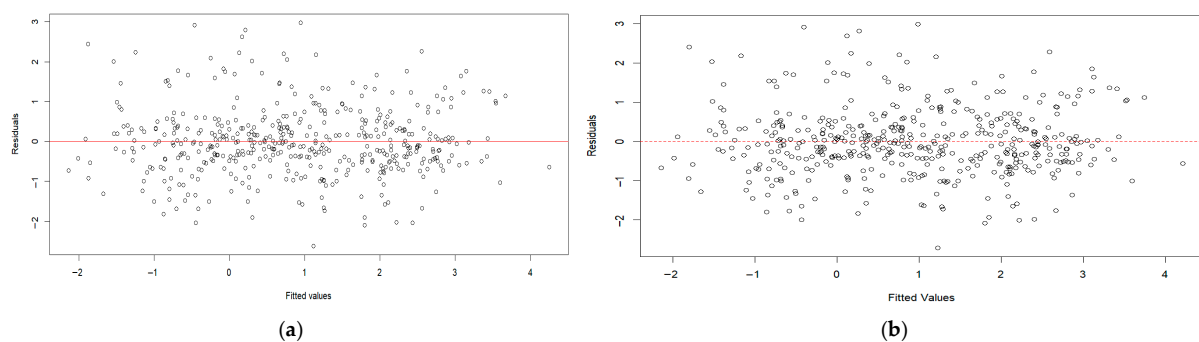


Figure 3. Residual vs. Fitted Values plot (a) Full model (b) Reduced model. Source: Own calculations via RStudio (version 2025.09.2-418).

In both panels (Figure 4), the central bulk of the residuals closely follows the reference line, suggesting that the central tendency is well-behaved and approximately normal. While there are minor deviations confined to the tails, indicating that the residuals are not perfectly normally distributed, these deviations are typical for real-world panel data. The pattern of deviation is highly similar across the two models, confirming that the reduction in the number of predictors did not distort the residual distribution.

Despite the formal rejection of the normality assumption for the idiosyncratic residuals (Jarque–Bera, $\chi^2 = 35.56$, $p < 0.01$ for the full model, Jarque–Bera, $\chi^2 = 32.178$, $p < 0.01$ for the reduced model), the Random Effects (RE) analysis remains statistically robust and valid. The concern over non-normal errors primarily impacts small-sample inference. With a sample size of 464 observations (29 countries over 16 years), the Central Limit Theorem (CLT) ensures that the sampling distribution of the coefficient estimates is asymptotically normal, thereby ensuring the validity of the t tests and p-values [43–46]. Furthermore, the most critical threats to inference in panel data (heteroskedasticity and serial/cross-sectional correlation) are addressed through the use of Driscoll–Kraay standard errors. This robust covariance estimator is asymptotically valid under general forms of dependence and makes the inference immune to the error term’s distributional form, regardless of the non-normality finding [47].

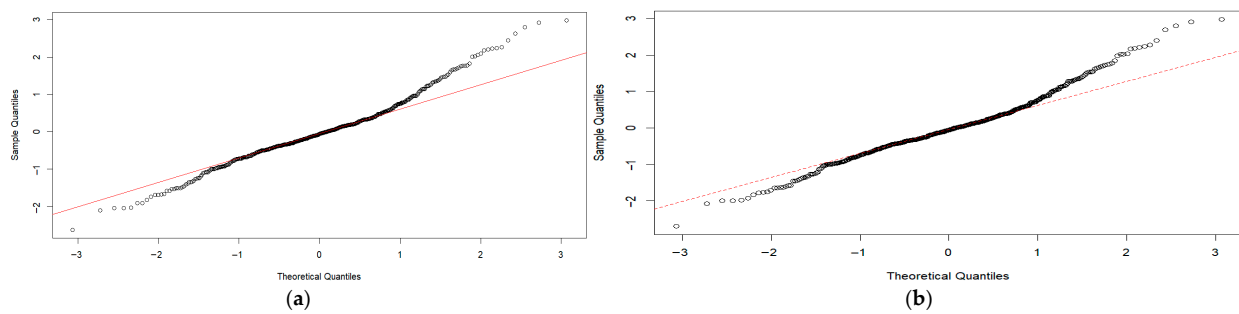


Figure 4. Residual distribution plot (a) Full model (b) Reduced model. Source: Own calculations via RStudio (version 2025.09.2-418).

The analysis further explored whether technological impacts on the shadow economy were conditional on human capital development. Initial tests of other interaction terms generally yielded insignificant results. However, a specific interaction between Development of Human Skills and New Technology Diffusion was found to be statistically significant (coefficient -12.489 , $p = 0.047$). This negative interaction indicates a powerful synergistic effect. Where the New Technology Diffusion is stronger, the beneficial impact of improving human skills on reducing the shadow economy is notably amplified. This means human capital development is more effective in curbing informality in environments with high rates of digital and technological adoption. While the model including this interaction term yields a lower overall R-squared (≈ 0.590 vs. 0.606) and is therefore not selected as the primary specification (Table 2), the statistical significance of the conditional effect is highly relevant for policy insight. This represents a deliberate trade-off between maximizing general explanatory power and capturing a critical, theoretically grounded conditional relationship. Therefore, the simpler RE model remains the main specification, and this significant interaction is presented as a supplemental finding, with its visual illustration provided in a plot (Figure 5) depicting predicted shadow economy based on human skill development, segmented by New Technology Diffusion levels. Figure 5 clearly demonstrates that the line representing High New Technology Diffusion slopes more steeply downward than the line for Low New Technology Diffusion, confirming the negative synergistic effect. This finding suggests that policies aimed at both human capital development and encouraging new technology adoption can have mutually reinforcing benefits in combating the informal sector.

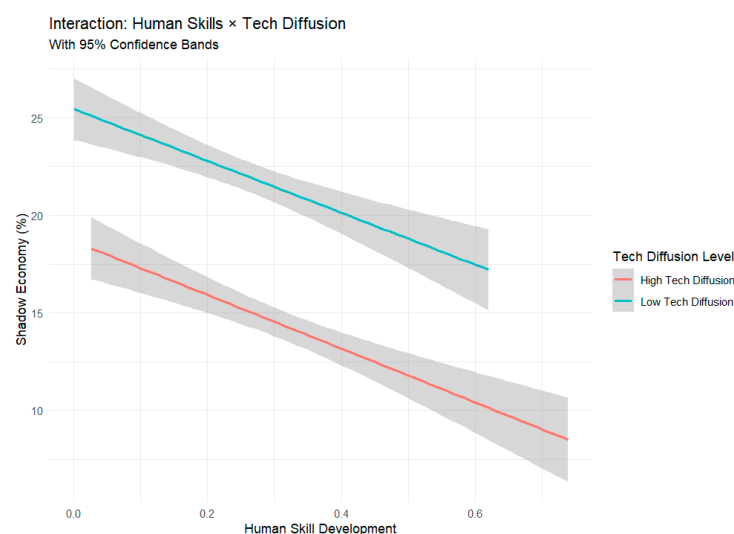


Figure 5. Interaction Plot: Shadow Economy and Human Skill Development. Source: Own calculations via RStudio (version 2025.09.2-418).

4. Discussion

4.1. Structural Drivers: Hierarchy and Conditional Effects

The econometric analysis yields several conclusions regarding the drivers of the shadow economy, highlighting a clear hierarchy of influence and complex conditional effects. The results across the Full (Table 2), Intermediate (Table 3), and Reduced (Table 4) models are highly consistent, with the R-squared remaining stable at approximately 0.606. This stability strongly suggests that the core findings are structural and robust to model streamlined specification, directly addressing RQ1 regarding individual drivers and RQ2 regarding their interaction.

First, Development of Human Skills is identified as the single most robust and impactful variable across all model specifications. Technically, it consistently exhibits the largest coefficient magnitude (ranging from -7.12 to -7.21 across Tables 2–4), an effect size roughly 2.5 times larger than that of institutional factors. This finding strongly supports H1 and underlines that investment in human capital is a fundamental, independent driver of formalization. Even after controlling for complex error structures (via Driscoll-Kraay standard errors) and common global time trends, the effect remains highly significant ($p < 0.001$) and maintains the largest coefficient magnitude. Thus, underscoring its pivotal role in fostering formalization regardless of broader economic or technological shocks.

Second, the study highlights the necessity of careful handling of institutional variables due to pervasive multicollinearity. The high VIFs (above 5) and strong correlations (approaching 0.95) among the WGI confirm they are not independent drivers. This redundancy dictated a targeted approach, prioritizing Control of Corruption, which ultimately demonstrated a strong, significant negative effect (coefficients steadily around -2.8 to -2.9 , $p < 0.001$) across all models (H1). Notably, this effect became even more pronounced and highly significant once common global temporal trends were accounted for. Thus, is indicated that controlling for these shared shocks allows the cross-country differences in anti-corruption efforts to stand out more clearly.

Third, the analysis reveals that technological influence is highly sensitive to model design, refining H1. When controlling for global time trends (year dummies), both New and Old Technology Diffusion consistently fail to reach statistical significance ($p > 0.40$ in Table 2). This implies that the observed effects of technology diffusion are not independent but are instead subsumed by common global time trends (e.g., shared adoption waves or global economic shifts). This implies that the mere adoption or spread of existing technology has a limited independent impact on informality compared to domestic innovation and institutional quality.

Furthermore, the finding that New Technology Creation, which was marginally significant in the fuller models (≈ -0.96 , $p < 0.05$), lost its statistical significance ($p = 0.34$) in the most parsimonious model (Table 4), which had excluded New Technology Diffusion, provides a nuanced answer to RQ1. While H1 proposed a negative association for technology creation, the instability of this variable suggests its effect is conditionally dependent on other technological measures, such as diffusion. This strongly suggests a shared explanatory component between the creation and diffusion of new technologies. In other words, the beneficial effect of technology creation may only fully materialize and be independently measured when the resulting innovation is also being actively diffused or utilized within the economy. More broadly, the persistent non-significance of the technology diffusion variables underscores the conclusion that technology alone does not appear to be a primary, direct driver of shadow economy reduction unless supported and enabled by strong institutions (Control of Corruption) and a highly skilled human capital base.

Moving to RQ2, the analysis revealed a compelling finding. There is a statistically significant negative interaction between Development of Human Skills and New Tech-

nology Diffusion (coefficient -12.489 , $p = 0.047$). This highlights a powerful synergistic effect, indicating that improving human skills' beneficial impact on reducing the shadow economy is substantially amplified in environments with strong technological adoption. Practically, policies for human capital development become significantly more effective when implemented within an environment of robust new technology diffusion, suggesting a complementary approach. Strengthening both human capital and technology adoption yields mutually reinforcing benefits in combating the shadow economy.

4.2. Limitations and Future Directions

The analysis provides a reliable, high-fit explanatory model, but is subject to three key limitations that inform future research. First, while robust standard errors address complex error structures, the current Random Effects specification remains associative. Establishing strict causality requires alternative identification strategies, such as external instrumental variables or quasi-experimental designs, particularly since the dynamic System GMM model was rejected due to the failure of the AR(2) test. Second, the rigorous model refinement process involved a necessary trade-off. Severe multicollinearity (VIF constraints) forced the exclusion of institutional dimensions (GE, RL, RQ) in favour of Control of Corruption. While statistically justified, this limits the ability to isolate specific governance impacts. Future studies might employ Principal Component Analysis (PCA) to create a composite institutional index while maintaining model parsimony. Finally, minor deviations in the residual tails suggest the possibility of non-linearities or threshold effects. Exploring quantile regression techniques would be valuable to assess whether these drivers behave differently in countries with very high versus very low levels of informality.

5. Conclusions

The comprehensive panel data analysis yields highly reliable and actionable conclusions, directly solving RQ1 and RQ2 and providing definitive tests of H1. The final Random Effects model, robustly estimated with Driscoll-Kraay standard errors, demonstrates strong explanatory power, accounting for approximately 61% of the cross-country and time-series variation in shadow economy. The core findings indicate towards the dominance of Development of Human Skills. This surfaced as the most impactful factor, which strongly validates H1 with an estimated reduction of approximately 7.2 percentage points for a one-unit improvement. Similarly, Control of Corruption is substantiated as a significant driver, contributing an approximate 2.8 percentage point reduction. Interestingly, the effects of New and Old Technology Diffusion were found to be statistically insignificant once global time trends were controlled for. Thereby, refining H1 and suggesting that mere technology spread is not an independent domestic lever against shadow economy. Regarding RQ2, a significant negative interaction (-12.489) was identified between Development of Human Skills and New Technology Diffusion, corroborating a powerful synergistic effect where the beneficial impact of human capital is substantially amplified in technologically advanced environments. Based on the quantitative and structural findings, a clear set of policy priorities emerges for governments seeking to reduce the size of the shadow economy.

Strengthening Anti-Corruption Measures: Continued and intensified efforts to improve governance and control corruption are absolutely needed, as they directly contribute to shrinking the shadow economy.

Fostering Innovation and R&D: Investing in the creation of new technologies and promoting a culture of innovation can help formalize economic activities. Although attention must be paid to ensuring those innovations are used domestically.

Investing Heavily in Human Capital Development: Enhancing the skills of the workforce stands out as the single most powerful policy lever identified in this analysis. Pro-

grams focused on education, vocational training, and continuous skill upgrading are likely to yield the largest dividends in reducing informality.

Leveraging Synergies between Skills and Technology: Policies that simultaneously strengthen human capital and encourage thorough new technology diffusion are likely to achieve even greater reductions in the shadow economy due to their highly reinforcing effects.

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Abbreviations

The following abbreviations are used in this manuscript:

TAI	Technological Achievement Index
CNT	Creating New Technologies (TAI dimension)
DNT	Diffusion of New Technologies (TAI dimension)
DOT	Diffusion of Old Technologies (TAI dimension)
DHS	Development of Human Skills (TAI dimension)
CC	Control of Corruption (WGI indicator)
GE	Government Effectiveness (WGI indicator)
RL	Rule of Law (WGI indicator)
RQ	Regulatory Quality (WGI indicator)
OLS	Ordinary Least Squares
FE	Fixed Effects (model)
RE	Random Effects (model)
VIF	Variance Inflation Factor
GMM	Generalized Method of Moments
WGI	Worldwide Governance Indicators
R ²	R-squared (coefficient of determination)

R&D Research and Development
 ICT Information and Communication Technology
 AI Artificial Intelligence

Appendix A

Appendix A.1. RStudio Code Snippet A1

```
R
pooled <- plm(
  Shadow.Economy ~ Control.of.Corruption +
                    Government.Effectiveness +
                    Rule.of.Law +
                    Regulatory.Quality +
                    New.Technology.Creation +
                    New.Technology.Difusion +
                    Old.Technology.Difusion +
                    Development.of.human.skills,
  data = pdata,
  model = "pooling"
)
```

Appendix A.2. RStudio Code Snippet A2

```
R
fe <- plm(
  Shadow.Economy ~ Control.of.Corruption +
                    Government.Effectiveness +
                    Rule.of.Law +
                    Regulatory.Quality +
                    New.Technology.Creation +
                    New.Technology.Difusion +
                    Old.Technology.Difusion +
                    Development.of.human.skills,
  data = pdata,
  model = "within"
)
```

Appendix A.3. RStudio Code Snippet A3

```
R
re <- plm(
  Shadow.Economy ~ Control.of.Corruption +
                    Government.Effectiveness +
                    Rule.of.Law +
                    Regulatory.Quality +
                    New.Technology.Creation +
                    New.Technology.Difusion +
                    Old.Technology.Difusion +
                    Development.of.human.skills,
  data = pdata,
  model = "random"
)
```

Appendix A.4. RStudio Code Snippet A4

```

R
re_time <- plm(
  Shadow.Economy ~ Control.of.Corruption +
                    New.Technology.Creation +
                    New.Technology.Difusion +
                    Old.Technology.Difusion +
                    Development.of.human.skills +
                    factor(year), # adds year dummies
  data = pdata_final,
  model = "random",
  effect = "individual"
)
# Driscoll-Kraay standard errors with lag=2
coeftest(re_time, vcov = vcovSCC(re_time, type = "HC1", maxlag = 2))

```

Appendix B

Table A1. Comparison of Pooled OLS, Fixed Effects, and Random Effects Estimates.

Variable	OLS Estimate (<i>p</i> -Value)	FE Estimate (<i>p</i> -Value)	RE Estimate (<i>p</i> -Value)
(Intercept)	28.366 ($<2.2 \times 10^{-16}$ ***)	N/A	26.631 ($<2.2 \times 10^{-16}$ ***)
Control.of.Corruption	0.058 (0.949)	−1.168 (0.0098 **)	−1.494 (0.0008 ***)
Government.Effectiveness	−3.001 (0.0091 **)	−0.271 (0.561)	−0.508 (0.280)
Rule.of.Law	−5.913 (1.465×10^{-5} ***)	1.116 (0.0627)	0.759 (0.208)
Regulatory.Quality	0.696 (0.526)	−1.649 (0.0007 ***)	−1.584 (0.0013 **)
New.Technology.Creation	−13.288 (9.617×10^{-8} ***)	−2.791 (0.0324 *)	−3.373 (0.0093 **)
New.Technology.Difusion	−2.175 (0.271)	−8.658 ($<2.2 \times 10^{-16}$ ***)	−8.569 ($<2.2 \times 10^{-16}$ ***)
Old.Technology.Difusion	4.278 (0.0652)	5.516 (0.0001 ***)	4.763 (0.0006 ***)
Development.of.human.skills	−3.390 (0.0443 *)	−11.832 ($<2.2 \times 10^{-16}$ ***)	−12.734 ($<2.2 \times 10^{-16}$ ***)
R^2	0.687	0.509	0.505

Significance codes: '***' 0.001, '**' 0.01, '*' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Table A2. Diagnostic Test Results for Fixed Effects Model.

Test Name	Statistic Value	Degrees of Freedom	<i>p</i> -Value	Conclusion
Hausman Test	Chisq = 14.471	8	0.07029	Fail to reject. RE preferred
Wooldridge (Serial Corr.)	Chisq = 259.36	16	$<2.2 \times 10^{-16}$	Significant Serial Correlation
Breusch-Pagan (Heteroskedasticity)	BP = 107.5	8	$<2.2 \times 10^{-16}$	Significant Heteroskedasticity
Pesaran CD (Cross-section Dependence)	Z = 28.042	N/A	$<2.2 \times 10^{-16}$	Significant Cross-sectional Dependence

Source: Own calculations via RStudio (version 2025.09.2-418).

Table A3. Comparison of FE (Clustered SEs) and RE (Driscoll-Kraay SEs).

Variable	FE (Clustered Ses) Estimate (<i>p</i> -Value)	RE (Driscoll-Kraay Ses) Estimate (<i>p</i> -Value)
(Intercept)	N/A	26.631 (5.012×10^{-10} ***)
Control.of.Corruption	−1.168 (0.2695)	−1.494 (0.0422 *)
Government.Effectiveness	−0.271 (0.6765)	−0.508 (0.1470)
Rule.of.Law	1.116 (0.2379)	0.759 (0.0739)
Regulatory.Quality	−1.649 (0.0181 *)	−1.584 (0.0539)
New.Technology.Creation	−2.791 (0.0182 *)	−3.373 (0.0005 ***)
New.Technology.Difusion	−8.658 (2.286×10^{-6} ***)	−8.569 (0.0001154 ***)
Old.Technology.Difusion	5.516 (0.1444)	4.763 (0.0407 *)
Development.of.human.skills	−11.832 (1.712×10^{-7} ***)	−12.734 ($<2.2 \times 10^{-16}$ ***)

Significance codes: '***' 0.001, '*' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Table A4. VIF Results and Refined RE Model with Driscoll-Kraay Standard Errors.

Predictor	Initial VIF	Refined Model Estimate (<i>p</i> -Value)
(Intercept)	N/A	25.275 (9.589×10^{-8} ***)
Control.of.Corruption	6.08	−1.890 (0.0031 **)
Regulatory.Quality	5.96	Dropped
New.Technology.Creation	2.88	−3.884 (5.320×10^{-6} ***)
New.Technology.Difusion	1.77	−8.017 (0.0006 ***)
Old.Technology.Difusion	2.59	4.668 (0.0354 *)
Development.of.human.skills	1.78	−12.613 ($<2.2 \times 10^{-16}$ ***)

Significance codes: '***' 0.001, '**' 0.01, '*' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Table A5. Oneway (individual) effect Two-steps model System GMM.

Variable	Coefficients	Estimate Std. Error	z-Value	Pr (> z)
lag(Shadow.Economy, 1)	0.966198	0.011272	85.7134	$<2.2 \times 10^{-16}$ ***
Control.of.Corruption	−0.328141	0.101617	−3.2292	0.001241 **
New.Technology.Creation	−0.774208	0.649954	−1.1912	0.233585
New.Technology.Difusion	0.977014	0.407590	2.3970	0.016528 *
Old.Technology.Difusion	0.927062	0.638730	1.4514	0.146665
Development.of.human.skills	−0.061306	0.292060	−0.2099	0.833738

Sargan test: Chisq (45) = 27.46437 (*p*-value = 0.98175)Autocorrelation test (1): Normal = −3.82649 (*p*-value = 0.00012998)Autocorrelation test (2): Normal = 2.014791 (*p*-value = 0.043927)

Significance codes: '***' 0.001, '**' 0.01, '*' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Table A6. Correlation Matrix of Explanatory Variables (*r*) and *p*-Values (*p*).

	Shadow Economy	New Tech Diffusion	Regulatory Quality	Gov. Effectiveness	Control of Corruption	Rule of Law	Human Skills	New Tech Creation	Old Tech Diffusion
Shadow Economy	1.0 (<i>p</i> = 0)	−0.57 (<i>p</i> = 0.0)	−0.73 (<i>p</i> = 0.0)	−0.78 (<i>p</i> = 0)	−0.78 (<i>p</i> = 0)	−0.79 (<i>p</i> = 0)	−0.37 (<i>p</i> = 0.0)	−0.44 (<i>p</i> = 0)	−0.31 (<i>p</i> = 0.0)
New Tech Diffusion	−0.57 (<i>p</i> = 0)	1.0 (<i>p</i> = 0.0)	0.64 (<i>p</i> = 0.0)	0.64 (<i>p</i> = 0)	0.62 (<i>p</i> = 0)	0.66 (<i>p</i> = 0)	0.16 (<i>p</i> = 0.0004)	0.27 (<i>p</i> = 0)	0.1 (<i>p</i> = 0.0303)

Table A6. Cont.

	Shadow Economy	New Tech Diffusion	Regulatory Quality	Gov. Effectiveness	Control of Corruption	Rule of Law	Human Skills	New Tech Creation	Old Tech Diffusion
Regulatory Quality	−0.73 ($p = 0$)	0.64 ($p = 0.0$)	1.0 ($p = 0.0$)	0.88 ($p = 0$)	0.9 ($p = 0$)	0.91 ($p = 0$)	0.22 ($p = 0.0$)	0.31 ($p = 0$)	0.18 ($p = 0.0001$)
Gov. Effectiveness	−0.78 ($p = 0$)	0.64 ($p = 0.0$)	0.88 ($p = 0.0$)	1.0 ($p = 0$)	0.94 ($p = 0$)	0.95 ($p = 0$)	0.26 ($p = 0.0$)	0.27 ($p = 0$)	0.22 ($p = 0.0$)
Control of Corruption	−0.78 ($p = 0$)	0.62 ($p = 0.0$)	0.9 ($p = 0.0$)	0.94 ($p = 0$)	1.0 ($p = 0$)	0.95 ($p = 0$)	0.32 ($p = 0.0$)	0.33 ($p = 0$)	0.25 ($p = 0.0$)
Rule of Law	−0.79 ($p = 0$)	0.66 ($p = 0.0$)	0.91 ($p = 0.0$)	0.95 ($p = 0$)	0.95 ($p = 0$)	1.0 ($p = 0$)	0.28 ($p = 0.0$)	0.28 ($p = 0$)	0.23 ($p = 0.0$)
Human Skills	−0.37 ($p = 0$)	0.16 ($p = 0.0008$)	0.22 ($p = 0.0$)	0.26 ($p = 0$)	0.32 ($p = 0$)	0.28 ($p = 0$)	1.0 ($p = 0.0$)	0.6 ($p = 0$)	0.58 ($p = 0.0$)
New Tech Creation	−0.44 ($p = 0$)	0.27 ($p = 0.0$)	0.31 ($p = 0.0$)	0.27 ($p = 0$)	0.33 ($p = 0$)	0.28 ($p = 0$)	0.6 ($p = 0.0$)	1.0 ($p = 0$)	0.76 ($p = 0.0$)
Old Tech Diffusion	−0.31 ($p = 0$)	0.1 ($p = 0.0303$)	0.18 ($p = 0.0002$)	0.22 ($p = 0$)	0.25 ($p = 0$)	0.23 ($p = 0$)	0.58 ($p = 0.0$)	0.76 ($p = 0$)	1.0 ($p = 0.0$)

Source: Own calculations via RStudio (version 2025.09.2-418).

Table A7. Random Effects 2008–2021 (Full Model).

Variable	VIF	Estimate	Std. Error	t Value	Pr ($> t $)	Significance
(Intercept)		24.96627	1.29732	19.2445	$<2.2 \times 10^{-16}$	***
Control.of.Corruption	1.885338	−2.74345	0.540722	−5.0737	6.07×10^{-7}	***
New.Technology.Creation	3.011254	−0.86907	0.399326	−2.1763	0.0301	*
New.Technology.Difusion	1.807557	−3.1239	1.466052	−2.1308	0.0337	*
Old.Technology.Difusion	2.702253	0.446423	1.433022	0.3115	0.7556	
Development.of.human.skills	1.750472	−7.5534	1.950519	−3.8725	0.0001	***
R^2		0.606211				

Significance codes: '***' 0.001, '*' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Table A8. Random Effects 2008–2021 (Intermediate Model).

Variable	VIF	Estimate	Std. Error	t Value	Pr ($> t $)	Significance
(Intercept)		25.18934	0.765521	32.9048	$<2.2 \times 10^{-16}$	***
Control.of.Corruption	1.868306	−2.77338	0.51539	−5.3811	1.28×10^{-7}	***
New.Technology.Creation	1.694898	−0.85395	0.352749	−2.4208	0.0159	*
New.Technology.Difusion	1.753471	−3.06245	1.599906	−1.9141	0.0563	
Development.of.human.skills	1.69227	−7.59814	1.956133	−3.8843	0.0001	***
R^2		0.607277				

Significance codes: '***' 0.001, '*' 0.05. Source: Own calculations via RStudio (version 2025.09.2-418).

Table A9. Random Effects 2008–2021 (Reduced Model).

Variable	VIF	Estimate	Std. Error	t value	Pr ($> t $)	Significance
(Intercept)		24.26651	0.837472	28.9759	$<2.2 \times 10^{-16}$	***
Control.of.Corruption	1.155256	−2.98236	0.530662	−5.6201	3.65×10^{-8}	***
New.Technology.Creation	1.641864	−0.20966	0.629233	−0.3332	0.7392	
Development.of.human.skills	1.635052	−7.16996	2.053161	−3.4922	0.0005	***
R^2		0.598765				

Significance codes: '***' 0.001. Source: Own calculations via RStudio (version 2025.09.2-418).

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