The Role of Exchange Rate Regimes in Driving Startup Ecosystem: Evidence from the Financial Infrastructure Channel

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Abstract

Exchange rate regime choices introduce structural trade-offs between financial stability and innovation incentives that shape the startup ecosystem. Utilizing a panel of 40 emerging economies from 2010 to 2024, we overcome data sparsity by deploying non-parametric Machine Learning imputation before constructing customized indices for financial infrastructure, depth, and openness channels. We employ Double Machine Learning Local Projections (DML-LP) to execute a nonlinear causal inference strategy. To prevent traditional fixed effects from mechanically absorbing the treatment variance of sticky exchange rate regimes, we embed the Hybrid-Mundlak controls directly within the DML-LP nuisance equations. Our findings reveal that unexpected transitions toward floating regimes catalyze a creative destruction process that expands financial infrastructure, whereas peg defenses reinforce structural stagnation. Paradoxically, startup depth responds positively to both financial infrastructure expansions and contractions. These dynamics highlight systemic reductions in financial frictions and powerful technological leapfrogging effects. Ultimately, we demonstrate that financial infrastructure serves as the underlying transmission mechanism through which exchange rate regimes shape private capital absorption and mobilization within startup ecosystems.

Keywords: Exchange rate regimes, Startup, Emerging markets, Machine learning, Nonlinear causal inference, Asymmetric shocks

JEL Classification: F31, F33, G24, O16

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1 Introduction

The intensifying competition for technological depth and the structural diversification of growth away from commodity and legacy industries highlight the critical interaction between macroeconomic policy and the development of startup ecosystems. While the classic debate regarding macroeconomic exchange rate regimes is well established (Mundell 1963; Levy-Yeyati and Sturzenegger 2001; Edwards and Yeyati 2005), it is currently being reinvented amid the rapid evolution of fintech capacities and alternative digital ledgers within a highly interconnected international monetary system. Although financial innovations introduce distinct dimensions of systemic financial risk (Allen 2021), this macro financial relationship is reciprocal: exchange rate regimes can also exert a profound impact on the trajectory of domestic financial innovation and technological capacities. Understanding these dynamics adds a critical empirical extension to open-economy macroeconomics by clarifying how exchange rate regimes reshape the domestic institutional landscape to sustain high-velocity technological ventures.

Unlike traditional small and medium-sized enterprises, technology startups operate under a regime of radical uncertainty, characterized by nonlinear scalability and a fundamental reliance on intellectual capital rather than tangible assets. Consequently, nurturing these entrepreneurial frontiers demands highly specialized financial ecosystems capable of efficiently pricing and allocating risk capital. While a substantial body of microeconomic literature has examined localized determinants of startup success such as founder human capital and regional clustering (Colombo and Grilli 2010; Pe'er and Keil 2013), the overarching macro-currency institutional architecture that shapes the transmission channels of this capital remains largely unmapped.

At the apex of this macro-currency architecture sits the choice of the exchange rate regime. Historically evaluated through the narrow lens of the open economy trilemma or short-term shock-absorption capabilities (Fleming 1962; Mundell 1963; Levy-Yeyati and Sturzenegger 2001), the exchange rate regime fundamentally functions as a core financial institutional arrangement. However, the existing literature treats exchange rate policies and startup ecosystems as distinct, insulated domains. This insulation overlooks how the choice of exchange rate regimes creates structural trade-offs for startups via macro financial stability and innovation incentives. On one hand, fixed regimes are observed to stabilize inflation and suppress exchange rate volatility (Levy-Yeyati and Sturzenegger 2001; Kočenda and Valachy 2006), which can mitigate capital costs and prevent the erosion of investment returns. On the other hand, the removal of the implicit currency safety net of the central bank when transitioning to a floating regime mirrors the classic dynamics of creative destruction (Schumpeter 2013), precisely because the private sector is compelled to innovate and develop sophisticated financial infrastructure and markets to minimize risk exposure and maximize transac-

tional velocity. Under a floating regime, innovations that ensure real-time risk management, instant currency conversion, and immediate settlement become matters of structural survival. In return, this high-velocity financial infrastructure conditions the capacity of startup to absorb and mobilize private capital. Specifically, this decentralization correlates with the development of sophisticated hedging instruments, high-frequency exchange rate trading platforms, real-time digital monitoring networks, integrated API rails, and automated clearing systems. The high performance of these financial innovations necessitates and incentivizes the deployment of advanced data centers, modern decentralized ledgers, integrated smart grids, secure transaction protocols, and expanded banking density. Ultimately, this reorientation incentives the private sector toward autonomous risk management and market-driven innovation, reiterating the structural growth mechanics of creative destruction.

We pose a structural paradox: Does a fixed exchange rate regime shield early- and mid-stage startup capital mobilization by suppressing exchange rate uncertainty, or does transitioning to a floating regime accelerate its expansion via creative destruction dynamics? Central to this research is identifying the specific transmission channels bridging macroeconomic exchange rate regimes and microeconomic startup dynamics. We investigate this transmission mechanism through the structural maturation of three distinct institutional financial pillars: financial infrastructure, financial depth, and financial openness.

Deep financial markets offer a liquid initial public offering (IPO) exit channel that incentivizes venture capitalists seeking to maximize capital gains upon exit (Black and Gilson 1998), while a liquid banking sector can trigger hot markets more frequently, supporting the development of the microeconomy. However, traditional credit or legacy equity market capitalization can be structurally ill-suited to finance asset-light, high-velocity technological ventures (Stiglitz and Weiss 1981). Because commercial banks typically ration credit based on physical collateral requirements to mitigate adverse selection, aggregate traditional financial expansion frequently marginalizes early-stage startups. To circumvent this exclusionary boundary, the role of digital financial infrastructure becomes paramount. The proliferation of high-velocity transactional systems, algorithmic data verification, and modernized financial architectures creates an alternative informational ecosystem. Within this framework, digital footprints and data streams substitute physical assets, operating effectively as "information collateral" that generates a verifiable digital audit trail of secure transactions, thereby lowering monitoring costs for investors and relaxing financial constraints for asset-light startups. Alternatively, financial openness connects localized ecosystems to global financial networks, bypassing the structural rigidities of the domestic banking sector while serving as a dynamic support for early-stage startups seeking to capitalize on international markets long before reaching maturity within the theoretical framework of the born-global imperative (Knight and Cavusgil 2004; Oviatt and McDougall 2005).

To empirically test this theoretical tension, we address these gaps through several original contribu-

tions. First, we bridge the divide between macroeconomic exchange rate regimes and the startup microeconomy by identifying specific financial pillars as the primary transmission channels. This shifts the discourse on regime choice beyond traditional macro-stabilization tradeoffs (Eichengreen and Hausmann 1999; Levy-Yeyati and Sturzenegger 2001; Edwards and Yeyati 2005) toward the microstructural development of startup ecosystems and institutional financial maturation.

Second, we construct customized indices for financial infrastructure, financial depth, and financial openness for 40 emerging markets spanning across the MENA region, Africa, Latin America, Eastern Europe, and Asia from 2010 to 2024 and release data as open source. To address data sparsity, we employ a robust missForest imputation approach. Our financial infrastructure index integrates both digital and physical dimensions, while the financial depth index is designed to capture both traditional and derivatives aspects of financial markets. Additionally, the financial openness index specifically captures de facto openness by aggregating cross border asset and liability positions while accounting for economic scale.

Third, we utilize an exponential GARCH (EGARCH) model to capture exchange rate volatility. This approach accounts for asymmetric positive and negative shocks. We incorporate an interaction term between volatility and regime choice to assess how the impact of volatility is conditional on the specific regime in relation to startup depth and our constructed financial indices.

Fourth, we explore robust, complex associations between exchange rate regimes and startup depth via our constructed financial indices by utilizing a Mundlak framework and NARDL estimation as baseline checks. For our nonlinear identification strategy, we employ a Double Machine Learning integrated with Local Projections (DML-LP). This setup leverages non-parametric residualization via machine learning to isolate orthogonalized dynamic responses over a three-year horizon. Specifically, we deploy this DML-LP engine across distinct empirical settings: we estimate the baseline direct, reduced-form effect of the exchange rate regime choice on startup depth. Then, we dissect the underlying transmission channels to identify the asymmetric impulse of the regime choice on our constructed financial indices along the policy-to-mediator channel, followed by the subsequent asymmetric shocks of those intermediate pillars on downstream startup outcomes along the mediator-to-outcome channel.

Fifth, we integrate the Hybrid-Mundlak framework directly within the asymmetric DML-LP architecture. This setup is particularly critical when evaluating the treatment effect of a structurally sticky policy variable, such as an exchange rate regime. By accounting for cross-sectional averages, this approach controls for unobserved time-invariant unobserved heterogeneity while preventing traditional fixed-effects dummies from mechanically absorbing the treatment variance. Consequently, this approach resolves a pervasive identification challenge in macroeconometrics that arises when machine learning estimators are applied to persistent panel data settings.

The remainder of this article is organized as follows: In section 2, we provide a comprehensive literature review; In section 3, we describe the data and methodology; In sections 4 and 5, we present and discuss the empirical results; Finally, we conclude in section 6.

2 Literature Review

The interaction of exchange rate policies on the trajectory of financial innovation and technological capacities introduces complex dynamics and tradeoffs, currently unanswered by the existing literature, which can result in macrofinancial policies disconnected from the real micro-economy. For instance, the growth-stabilization tradeoffs observed to be amplified by exchange rate regimes (Levy-Yeyati and Sturzenegger 2001; Edwards and Yeyati 2005) can enable fixed exchange rate regimes to provide a stable environment for early-stage startups entry and consolidation through inflation stabilization and the anchoring of expectations and capital costs. Conversely, floating exchange rate regimes can catalyze market opportunities for startups by stimulating economic growth and enhancing price competitiveness.

Furthermore, lower exchange rate volatility associated with a fixed regime (Kočenda and Valachy 2006) can facilitate the ability of startup entrepreneurs to secure foreign funds without significant exchange rate risks that erode investment returns. However, this implicit insulation from exchange rate risks can reduce private sector incentives to hedge and innovate, potentially slowing the development of sophisticated financial architecture. In contrast, higher exchange rate risks correlated with the floating regime can incentivize fintech firms to develop new financial instruments, such as derivatives and cross-border payment systems to mitigate these risks. This volatility is shown to be associated with the expansion of market depth (Hajilee and Al Nasser 2017), thereby increasing liquidity in markets. Simultaneously, the floating regime is observed to promote financial inclusion (Chiboub and Sadok 2025), which can establishes the digital infrastructure required for startups to mitigate transactional frictions, expand market accessibility, and maintain a digital footprint to secure external financing. Although the existing literature has focused on how exchange rate fluctuations respond to fintech (Afshan et al. 2024), it overlooks how exchange rate regimes and their associated volatility catalyze fintech innovation.

The institutional development of the financial system serves as a critical mediator in the transmission mechanism connecting exchange rate regimes and startup ecosystems. The quality of domestic institutions determines whether the capacity to support innovative instruments fosters growth or defaults into instability. While some research has explored the broader connection between exchange rates and financial development (Lin and Ye 2011; Hajilee and Al Nasser 2017), the specific causal link between exchange rate regimes and the financial infrastructure and financial depth required by startups remains an unaddressed gap in the

current literature.

Consistent with the impossible trinity framework (Fleming 1962; Mundell 1963), capital account openness related to the floating regime can attract foreign investment in startups. However, such liberalized markets can quickly escalate into capital flight and sudden stops, allowing investors to move funds abroad at the slightest hint of trouble (Stiglitz 2000). In an increasingly multipolar international monetary system characterized by shifting geopolitical spheres and the emergence of new monetary technologies, a floating regime may enable sufficient flexibility to pivot between different ledgers and geopolitical financial networks, whereas a fixed regime might constrain a country's alignment to a specific monetary anchor, limiting its flexibility to adopt alternative decentralized ledgers or shifting geopolitical poles.

Furthermore, the floating regime is observed to act as a vital shock absorber (Edwards and Yeyati 2005) by allowing the exchange rate to adjust to external shocks and global liquidity shortages. This flexibility can maintain international price-competitiveness via lower entry capital costs for foreign investors and increased exports, which in turn can fosters startup development. However, the fixed regime may allow for the superior management of financial shocks associated with 'original sin', where debt is heavily denominated in foreign currencies (Eichengreen and Hausmann 1999), protecting the financial system and firms from a debt collapse during a period of currency stress.

Despite these conflicting theoretical channels, which suggest a complex transmission pattern between exchange rate regimes and startup development mediated by the financial system, no studies were found that rigorously investigate the interplay between different exchange rate regimes and startup depth. This highlights a critical gap in the literature, which traditionally treats exchange rate policies and startups as two distinct worlds. Such transmission mechanisms likely involve nonlinearities and conditional effects that remain undetected by standard linear models.

Although the literature offers broad indices that measure financial development (e.g., Svirydzenka 2016), these existing metrics exhibit compositional gaps that limit their capacity to capture the digital financial infrastructure and derivative instruments available to startups in emerging markets. Furthermore, traditional financial openness indices still rely on de jure capital account openness, such as the Chinn-Ito index (Chinn and Ito 2006; Chinn and Ito 2008), while countries may report high levels of formal openness and simultaneously impose strict capital controls that limit actual mobility. To address these data gaps, we construct customized indices for de facto financial openness, financial depth, and financial infrastructure. These metrics are specifically designed to capture the critical dimensions necessary for startup ecosystems across 40 emerging markets from 2010 to 2024.

3 Methodology

3.1 Data and variables

We study 40 emerging economies from 2010 to 2024, a sample selected for both theoretical necessity and empirical rigor. Unlike advanced economies, emerging markets provide significant institutional heterogeneity and a diverse array of de facto exchange rate regimes, coupled with a higher susceptibility to original sin and balance sheet vulnerabilities. This environment offers an ideal laboratory to robustly test the innovation and stabilization paradox amplified by exchange rate policies on startups. Our sample, which spans diverse regions across the MENA region, Africa, and Asia, Latin America, and Eastern Europe, provides sufficient degrees of freedom and cross-sectional diversity to ensure that our findings represent a global systemic trend rather than the idiosyncratic dynamics of a single country, offering broad implications for emerging markets.

To ensure that our results reflect market-driven responses to macrofinancial policies, we exclude countries experiencing extreme extra-economic shocks or systemic institutional failures. For instance, we omit Ukraine and Russia due to the distortionary effects of wartime mobilization on capital allocation. Similarly, we exclude countries suffering from total banking system collapses, such as Lebanon and Venezuela. Finally, the sample is restricted to jurisdictions with consistent and harmonized reporting of startup investments in databases.

We select the 2010 to 2024 timeframe to capture a distinct epoch of technological advancement, specifically the transformation of the global fintech sector and the emergence of digital financial infrastructure such as distributed ledgers and banking-as-a-service (BaaS) platforms. This period also encompasses the COVID-19 pandemic and the subsequent recovery, both of which were characterized by significant shifts in digital transition and financial access. We utilize annual observations because startup data and financial system metrics in emerging economies are difficult to collect at higher frequencies while maintaining the strict harmonization required for panel data analysis.

While data from domestic reporting agencies may appear to offer local granularity, these registries vary significantly in their definitions and reporting methodologies. For instance, some jurisdictions categorize any new venture (including traditional service-based businesses, such as laundromats) as a "startup," which leads to biased estimates. To ensure a uniform, standardized, and innovation-led definition across our sample, we utilize the Dealroom database (Dealroom.co 2026). Dealroom data is widely adopted for research and policy analysis by international organizations such as the OECD, providing an established benchmark for venture capital studies. The provider employs a multi-layered data collection strategy (utilizing automated machine learning algorithms to harvest public records combined with manual expert verification) to isolate technology-driven ventures. This approach ensures that startup entries are measured in a consistent manner

across our diverse 40-country panel.

To capture early- and mid-stage and innovation-sensitive startup activity, while avoiding large investment outliers that can distort the perceived health of the sector, we restrict the dataset to early- and mid-stage technological ventures. Specifically, we retain Pre-Seed, Seed, Series A, and Series B rounds, while excluding outside-tech tags, mature-stage firms, SPAC private placement rounds, and government grants. This filtering strategy prevents instances where a single massive funding round or a public subsidy creates a false signal of a thriving ecosystem while the broader startup environment remains constrained. Furthermore, we refine the investor profile by focusing on venture capital, corporate venture, private equity, family offices, and angel funds. Our primary dependent variable, Startup Depth (SD), is defined as the natural logarithm of the ratio of total startup investment value to nominal GDP, as specified in Equation 1. We utilize this log-ratio transformation to mitigate the influence of extreme outliers and to ensure cross-country comparability by accounting for variations in economic scale across our panel. Nominal GDP data (in current USD) is sourced from the IMF World Economic Outlook (IMF 2025c).

$$SD_{i,t} = \ln\left(1 + \frac{\text{Investment Value}_{i,t}}{\text{Nominal GDP}_{i,t}}\right) \tag{1}$$

Where: i is the country; t is the year.

Furthermore, we construct a Startup Deal Intensity (SDI) metric by calculating the ratio of annual startup deal counts to nominal GDP (per billion current USD) and applying a log transformation. This indicator, which follows the same filtering criteria as our primary analysis (Dealroom.co 2026), serves as a robustness check to differentiate between liquidity available for startup and the frequency of funding rounds directed to venture activity.

To preserve statistical power and avoid the loss of observations in our primary dependent variable due to missing data, we employ the machine learning-based missForest approach (Stekhoven and Bühlmann 2012) to impute values using nonlinear patterns. This method is superior to linear imputation, which is often prone to error and the creation of artificial relationships in diverse panels. By using auxiliary predictors, the missForest algorithm can detect complex, nonlinear patterns during the imputation process.

To maintain analytical rigor, the predictive fidelity of this nonlinear procedure is verified through a Masked-Data Validation approach. In this procedure, we extract a representative complete-case subset of the panel and randomly mask 10% of the observations. We then utilize the algorithm to recover these values and evaluate the results using the Normalized Root Mean Square Error (NRMSE). The NRMSE quantifies the deviation between imputed and observed values relative to the standard deviation of the data.

This metric ensures that our auxiliary macrofinancial helpers provide a robust signal for predicting missing values, effectively distinguishing fundamental trends from idiosyncratic noise. Finally, we also provide a sensitivity analysis in the appendix by reporting baseline results without the imputed observations to ensure the robustness of our primary findings. Table 12 (in Appendix) details the specific auxiliary predictors and covariates utilized within the missForest framework.

We employ the International Monetary Fund's de facto classification system (IMF 2025a) to determine the exchange rate regimes of the countries in our sample. To prevent overfitting and mitigate potential biases arising from the sparse distribution of observations across sub-categories, we consolidate these arrangements into a binary framework. The floating regime ($Regime_{i,t} = 1$) encompasses both free and managed floats. Conversely, the fixed regime ($Regime_{i,t} = 0$) aggregates hard pegs, soft pegs, and intermediate residual arrangements.

Furthermore, we control for economic performance by utilizing annual Real GDP (constant 2015 USD) sourced from the World Bank (WBG 2025b), which we subsequently log-transform to account for scale effects. We also control for stability by using annual inflation rates from the IMF World Economic Outlook database (IMF 2025c).

Rather than using a simple standard deviation to measure exchange rate volatility, we construct an annual metric that captures volatility clusters and asymmetric responses to shocks using an Exponential GARCH (EGARCH) model (Nelson 1991). We utilize daily frequency data extracted from the Yahoo Finance database (Yahoo Finance 2026) and calculate daily log-returns before estimating an EGARCH(1,1) specification. This model accounts for the leverage effect by enabling positive and negative shocks to influence future exchange rate volatility differently.

From this estimation, we extract the daily conditional variance and convert it into a harmonized annual metric by calculating the square root of the sum of daily variances for each calendar year. To ensure that currency crises and hyperinflationary outliers do not lead to overfitting in the machine learning process, we apply a targeted Winsorization (Tukey 1960; Angrist and Pischke 2009) that caps outliers at a value of 10. This approach preserves the ranking of volatility across the panel and stabilizes the estimation, preventing the extreme noise of a specific country's currency collapse from obscuring broader patterns in the sample. The conditional variance equation is defined in Equation 2 as:

$$\ln(\sigma_t^2) = \omega + \alpha \left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2) \tag{2}$$

Where γ captures the asymmetry or leverage effect. If $\gamma \neq 0$, it indicates that shocks have an asymmetric

impact on volatility.

3.2 Index Construction

3.2.1 Financial infrastructure index

We construct a customized index to capture financial infrastructure using Principal Component Analysis (PCA) (Pearson 1901; Jolliffe and Cadima 2016). This granular approach addresses a critical gap in the literature; specifically, it accounts for both financial access and transactional velocity, while traditional institutional metrics (e.g., Svirydzenka 2016) capture baseline access, the dimension of transactional velocity remains overlooked. We integrate these dimensions into a composite index while simultaneously developing two distinct sub-indices:

The Physical Access Sub-index: While startups rely predominantly on the digital sphere, they also operate within broader and informal settings where cash transactions remain a primary mode of payment in emerging markets. Physical pillars, such as ATMs and commercial bank branches, serve as critical withdrawals points and physical settlement layers that ensure customer trust and facilitate integration into regional value chains. This physical dimension also represents the gateway for currency to be digitized and injected into the formal financial system, ensuring an off-ramp and on-ramp mechanism between fiat and digital currencies.

The Digital Access Sub-index: This framework tracks the digital dimension by moving beyond simple institutional presence. We triangulate supply-side data measuring infrastructure intensity with demand-side data measuring reach via ownership rates to capture the true depth of digital financial access within the adult population. By also accounting for digital transaction rates, we target the functional capacity for e-commerce and SaaS payments, which are vital for modern startups. We specifically excluded mobile money agents and mobile-only accounts as these indicators compromised the quality of the factor loadings due to low correlation and structural data gaps. This selection process ensures a coherent and robust construct of transactional readiness rather than a collection of uncorrelated technological proxies.

The Integrated Financial Infrastructure Index: Finally, we combine these sub-indices with ICT intensity (measured as ICT service exports to nominal GDP) and internet usage rates (WBG 2025b). This multidimensional approach incorporates physical and digital financial access points with information and communication technology maturity and internet connectivity. This integrated measure is more suitable for tracking the technological readiness of entrepreneurs than traditional, purely physical indicators. Table 1 summarizes these indices details.

Table 1: Hierarchical Construction of Financial Infrastructure Index

Index Layer	Components / Pillars	Source
Block 1: Physical Access (Sub-index)	Bank Branches (per 100k adults)	IMF 2025b
	ATMs (per 100k adults)	IMF 2025b
Block 2: Digital Access (Sub-index)	Card Ownership (Credit/Debit)	WBG 2025a
	Total Cards (Credit/Debit) (per 100k adults)	IMF 2025b
	Deposit Accounts	IMF 2025b
	Digital Transaction Volume	IMF 2025b
Block 3: Integrated Index (Main Variable)	Physical Access Sub-index	Block 1 PCA
	Digital Access Sub-index	Block 2 PCA
	ICT Service Exports (% GDP)	WBG 2025b
	Internet Usage (% Population)	WBG 2025b

Source: Author's calculations based on the IMF IMF 2025b and WBG WBG 2025b databases.

Note: All indices are constructed using PCA. Raw variables are log-transformed and standardized before PCA. The final Integrated Index is rescaled to a [0, 100] range for interpretability.

To mitigate sample attrition and maintain the information density of our panel, we implement the missForest algorithm (Stekhoven and Bühlmann 2012). This non-parametric approach leverages auxiliary macrofinancial helpers specified in Table 13 (Appendix) to provide a robust predictive signal, while accounting for potential nonlinearities between variables.

3.2.2 Financial depth index

We construct a financial depth index that extends beyond traditional metrics, such as private credit and stock market capitalization, to incorporate sophisticated financial instruments like derivatives. These instruments are vital as they facilitate the hedging of exchange rate and interest rate risks, which provides a strategic buffer for startups operating in volatile emerging markets. This financial depth index ultimately focuses on the availability and sophistication of raising and managing that capital.

By incorporating stock market capitalization, private credit, and derivatives intensity, we proxy for a financial continuum that supports the evolutionary stages of startup growth, moving from credit intermediated scaling to market based liquidity and exit opportunities. Moreover, the inclusion of derivatives captures a layer of systemic sophistication that reduces the cost of capital and facilitates risk-sharing for the entire financial ecosystem, directly benefiting startups' investors and clients. Derivatives intensity is operationalized using asset and liability derivatives from the External Wealth of Nations database (Milesi-Ferretti 2026), as formally defined in Equation 3:

$$\text{Derivatives Intensity}_{i,t} = \ln\left(1 + \frac{\text{Deriv. Assets}_{i,t} + \text{Deriv. Liabilities}_{i,t}}{\text{Nominal GDP}_{i,t}}\right) \tag{3}$$

We maintain financial infrastructure and financial depth as separate indices to preserve granularity and prevent the dilution of distinct institutional dimensions. Table 2 details the target variables while Table 14 (Appendix) shows auxiliary helpers employed in the missForest.

Table 2: Operationalization of the Financial Depth Index

Dimension	**Indicator / Pillar**	**Data Source**
Financial Depth	Stock Market Capitalization (% GDP)	WBG 2025b
	Private Credit to the Private Sector (% GDP)	WBG 2025b
	Derivatives Intensity	Milesi-Ferretti 2026

Source: Author's calculations based on External Wealth of Nations (Milesi-Ferretti 2026) and WBG (WBG 2025b) data.

Note: All indicators are log-transformed and standardized prior to PCA. The resulting index is rescaled to a $[0, 100]$ range for interpretability.

3.2.3 Financial openness index

Rather than relying on traditional de jure capital account openness indices (e.g., Chinn and Ito 2006), which may fail to capture actual capital mobility in the presence of administrative de facto controls, we construct a volume-based measure of financial integration. Following the methodology of the External Wealth of Nations database (Milesi-Ferretti 2026, we calculate overall financial openness (Equation 4) and equity openness (Equation 5). These ratios, which aggregate cross-border asset and liability positions relative to the scale of the economy, measure the actual degree of country's financial integration and exposure to global markets.

$$\text{Financial Openness}_{i,t} = \ln\left(1 + \frac{\text{Total Assets}_{i,t} + \text{Total Liabilities}_{i,t}}{\text{Nominal GDP}_{i,t}}\right) \tag{4}$$

$$\text{Equity Openness}_{i,t} = \ln\left(1 + \frac{(FDI_A + FDI_L)_{i,t} + (PE_A + PE_L)_{i,t}}{\text{Nominal GDP}_{i,t}}\right) \tag{5}$$

Where FDI: Foreign Direct Investments, PE: portfolio equity, A: assets, and L: liabilities

We construct the financial openness index using PCA on variables shown in Table 3:

Table 3: Operationalization of the Financial Openness Index

Indicator	**Source**	**Estimation**
De Facto Openness	Milesi-Ferretti 2026	Equation 4
Equity Openness	Milesi-Ferretti 2026	Equation 5

Source: Authors' calculations based on the External Wealth of Nations database (Milesi-Ferretti 2026).

Note: Component variables are log-transformed and standardized prior to PCA. The resulting index is subsequently rescaled to a $[0, 100]$ range.

3.3 Model and approach

We examine the complex nonlinear transmission mechanisms between exchange rate regimes (macro-level policy), the financial system (institutional intermediary), and startup activity (micro-level outcomes). Our multi-stage empirical strategy characterizes the nonlinear identification and association across these dimensions.

First, we establish a link between exchange rate regimes and startup depth. Given that exchange rate regimes exhibit low temporal variation and transitions are rare policy events, a standard country-fixed effects estimator would likely absorb the primary institutional variation. Consequently, we employ a Mundlak specification (Mundlak 1978; Badi H Baltagi 2023), which allows us to identify the between-country institutional effects while addressing whether country-specific heterogeneity and the regressors are correlated.

As specified in Equation 6, we incorporate the group-level means of our time-varying predictors to ensure the consistency of our coefficients. Such a hybrid approach yields results equivalent to a fixed effects estimator for time-varying variables while preserving the identification of time-invariant factors. We utilize clustered standard errors at the country level to account for within-unit correlation and incorporates time-fixed effects to control for unobserved global shocks (Wooldridge 2010; Badi Hani Baltagi et al. 2008).

Our baseline specification includes the mean-centered exchange rate volatility (estimated via $EGARCH(1,1)$) and an interaction term between the regime choice and volatility. This interaction allows us to determine whether the institutional impact of the policy regime is conditional upon the intensity of currency shocks. Finally, we control for economic scale and macroeconomic stability by including the first-difference of the natural logarithm of Real GDP and the annual inflation rate.

$$\begin{aligned} SD_{i,t} = \alpha &+ \beta_1 Regime_{i,t} + \beta_2(Vol_{i,t} - \overline{Vol}) + \beta_3[Regime_{i,t} \times (Vol_{i,t} - \overline{Vol})] \\ &+ \gamma_1 \Delta \ln RGDP_{i,t} + \gamma_2 infl_{i,t} \\ &+ \lambda_1 \overline{Vol}_i + \lambda_2 \overline{\Delta \ln RGDP}_i + \lambda_3 \overline{infl}_i + \delta_t + \mu_i + \epsilon_{i,t} \end{aligned} \tag{6}$$

Where: SD: Startup Depth

$Regime$: Binary dummy (0 for fixed, 1 for float)

$(Vol_{i,t} - \overline{Vol})$: Mean-centered exchange rate volatility

$Regime_{i,t} \times (Vol_{i,t} - \overline{Vol})$: The interaction term

$\Delta lnRGDP$: First-differenced natural logarithm of GDP (constant 2015 USD)

$infl$: Annual inflation rate

$\overline{Vol}_i, \overline{\Delta \ln RGDP}_i, \overline{infl}_i$: Country-specific time-averages (Mundlak terms)

δ: Time fixed effects

μ_i: Random country-specific effect.

$\epsilon_{i,t}$:Error term clustered at the country level

Second, we identify the transmission channels through which these regimes influence the financial indices using the Hybrid-Mundlak specification. Our estimation strategy incorporates time-fixed effects and clusters standard errors at the country level, as formalized in Equation 7:

$$\begin{aligned} FinIndex_{i,t} = \alpha &+ \beta_1 Regime_{i,t} + \beta_2(Vol_{i,t} - \overline{Vol}) \\ &+ \beta_3[Regime_{i,t} \times (Vol_{i,t} - \overline{Vol})] \\ &+ \gamma_1 \Delta \ln RGDP_{i,t} + \gamma_2 infl_{i,t} \\ &+ \lambda_1 \overline{Vol}_i + \lambda_2 \overline{\Delta \ln RGDP}_i + \lambda_3 \overline{infl}_i + \delta_t + \mu_i + \epsilon_{i,t} \end{aligned} \tag{7}$$

Where: $FinIndex$: Our constructed financial indices(see subsection 3.2)

We transition to a Nonlinear Autoregressive Distributed Lag (NARDL) framework (Shin, Yu, and Greenwood-Nimmo 2014) to examine the dynamics between financial indices and startup depth. As shown in Equation 8, we incorporate country fixed effects, as supported by the Mundlak 1978 procedure, and clustered standard errors. By focusing on within-country variation, we isolate the asymmetric impact of financial shocks while controlling for time-invariant unobservable characteristics such as geography, legal origin, or national culture. The choice of this asymmetric framework over a linear baseline is validated via a Wald test (Wald 1943) reported in the results section.

$$\begin{aligned} \Delta SD_{i,t} = \alpha_i &+ \rho SD_{i,t-1} + \theta^+ Findex^+_{i,t-1} + \theta^- Findex^-_{i,t-1} \\ &+ \beta^+ \Delta Findex^+_{i,t} + \beta^- \Delta Findex^-_{i,t} \\ &+ \gamma_1 \ln RGDP_{i,t} + \gamma_2 infl_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{8}$$

Where $\Delta SD_{i,t}$: Differenced Startup Depth

$SD_{i,t-1}$: Lagged level of Startup Depth

$Findex^+_{i,t-1}$ and $Findex^-_{i,t-1}$: long-run partial sums

$\Delta Findex^+_{i,t}$ and $\Delta Findex^-_{i,t}$: short-run asymmetric shocks

α_i: Country fixed effects

ρ: The speed of adjustment parameter

Following Shin, Yu, and Greenwood-Nimmo 2014, we decompose the financial indices into positive ($Findex^+$)

and negative ($Findex^{-}$) partial sums to capture the asymmetric effect of financial shocks, as shown in Equations 9 and 10.

$$Findex_t^{+} = \sum_{j=1}^{t} \Delta Findex_j^{+} = \sum_{j=1}^{t} \max(\Delta Findex_j, 0) \tag{9}$$

$$Findex_t^{-} = \sum_{j=1}^{t} \Delta Findex_j^{-} = \sum_{j=1}^{t} \min(\Delta Findex_j, 0) \tag{10}$$

This tiered approach reduces omitted variable bias while avoiding saturating the model with an excessive number of variables that could dilute the estimated effects or introduce multicollinearity, a critical consideration given the limited degrees of freedom in our sample. Finally, to validate the use of nonlinear models over linear counterparts, we employ the Wald test to evaluate the null hypothesis of symmetry between positive and negative shocks of financial indices (Wald 1943).

To transition from baseline association to a causal identification strategy, we implement a Double Machine Learning (DML) framework (Chernozhukov et al. 2018) integrated with Local Projections (LP) (Jordà 2005). We select this approach over the traditional Difference-in-Differences (DiD) method (Angrist and Pischke 2009), as DiD typically requires a parallel trends assumption and a large pool of treatment transitions. Given that exchange rate regime shifts are rare, sticky macro policy events in our sample. The DML-LP configuration optimizes causal identification in this framework, circumventing the requirement for a discrete, untreated control group by establishing a counterfactual baseline via continuous treatment residuals. Consistent with Chernozhukov et al. 2018, we employ a double residualization (orthogonalization) procedure to purge the influence of macroeconomic confounders from both the treatment and outcome variables. Under this setup, the counterfactual baseline corresponds to a treatment residual of zero, representing the control state in the absence of an unexpected shock.

This process involves the estimation of two separate non-parametric nuisance models. First, a Random Forest regressor ($n = 100$, $max_depth = 5$) (Breiman 2001) estimates the conditional expectation of the treatment given the covariates, which corresponds to the propensity score in the case of a binary treatment variable. Second, a parallel Random Forest model ($n = 100$, $max_depth = 5$) estimates expectation of the outcome variable based on the same covariates. While the specific control vectors are detailed in appendix, we explicitly integrate a Hybrid-Mundlak framework within our first- stage DML-LP architecture when analyzing structurally persistent treatments such as exchange rate regimes. This configuration is employed to circumvent omitted variable bias and prevent the absorption of the treatment effect itself. In practice, we introduce a Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends (Year dummies) in the first-stage DML nuisance equation. This approach effectively preserves the meaningful within-country variation necessary to identify the direct effect of treatments while

partialling out macro shocks.

The subtraction of these machine-learning expectations from the observed values yields orthogonalized residuals ($\tilde{T}$ and $\tilde{Y}$) that are, by construction, uncorrelated with macroeconomic confounders. This orthogonalization ensures that the treatment residual is independent of the controls, replicating a quasi-experimental setting where the remaining variance of the treatment framework can be considered as an exogenous shock. Standard errors are clustered at the country level to ensure robustness against potential autocorrelation and heteroskedasticity. We apply this specific residualization procedure to evaluate both the direct impact and the underlying transmission mechanisms following this estimation strategy:

$$\text{Exchange Rate Regime} \rightarrow \text{Startup Depth}$$

By partialling out the complex, nonlinear confounding factors that drive regime selection, this DML framework systematically minimizes selection bias and endogeneity risks. This approach offers a rigorous alternative identification strategy when valid external instrumental variables are unavailable across a heterogeneous global panel. Finding a valid common instrument for a diverse 40-country panel remains structurally unfeasible. Moreover, we evaluate the DML-LP framework using predetermined covariates lagged at $t-1$ to mitigate potential reverse causality and simultaneity bias.

For the sticky exchange rate regime serving as the treatment variable, Equation 11 specifies the final DML estimation, while Equations 12 and 13 define the treatment and outcome nuisance models, respectively. This framework is consistent with the Neyman orthogonality properties established by Chernozhukov et al. 2018, while embedding a Hybrid-Mundlak transformation inside the non-parametric first-stage nuisance equations:

$$\tilde{Y}_{i,t+h} = \beta_h \tilde{T}_{i,t} + \epsilon_{i,t+h} \tag{11}$$

Where $\tilde{Y}$ and $\tilde{T}$: orthogonalized residuals at horizon h. The nuisance models are estimated non-parametrically as:

$$T_{i,t} = g_1(X_{i,t}, \bar{X}_i, \mathbf{L}_k X_{i,t}, \tau_i t) + \tilde{T}_{i,t} \tag{12}$$

$$Y_{i,t+h} = f_1(X_{i,t}, \bar{X}_i, \mathbf{L}_k X_{i,t}, \tau_i t) + \tilde{Y}_{i,t+h} \tag{13}$$

Where:$T_{i,t}$: sticky exchange rate regime

$Y_{i,t+h}$: the downstream startup depth

$g_1(\cdot)$ and $f_1(\cdot)$: the non-parametric machine learning mapping functions

$X_{i,t}$: the vector of time-varying control variables

$\bar{X}_i$: the cross-sectional country-specific means of the covariate vector

$\mathbf{L}_k X_{i,t}$: a matrix of k pre-treatment historical lags

$\tau_i t$: country-specific continuous linear time trends

When dissecting the relationship to uncover the underlying transmission mechanisms, a linear orthogonalized residualization fails to capture the distinct transmission channels linking exchange rate regimes to startup depth, stemming from an aggregate dilution effect. Thus, following (Kilian and Vigfusson 2011; Tenreyro and Thwaites 2016), we extend our second-stage estimation to capture asymmetric shocks. By partitioning the orthogonalized residuals into directional vectors, this framework enables positive innovations (unexpected transitions toward a floating regime or an expansion in a financial mediator index) and negative innovations (unexpected defense of a fixed regime or a contraction in a financial index) to trace entirely independent nonlinear dynamic trajectories. We implement this specific configuration by extending the baseline linear model in Equation (11) into an asymmetric specification in Equation (14) across both upstream and downstream transmission channels following this estimation strategy:

$$\underset{(\tilde{T}^+_{i,t},\, \tilde{T}^-_{i,t})}{\text{Asymmetric Policy Shocks}} \rightarrow \underset{(\tilde{M}^+_{i,t},\, \tilde{M}^-_{i,t})}{\text{Asymmetric Mediators}} \rightarrow \text{Startup Depth}$$

$$\tilde{Y}_{i,t+h} = \beta^+_h \tilde{Z}^+_{i,t} + \beta^-_h \tilde{Z}^-_{i,t} + \epsilon_{i,t+h} \tag{14}$$

Where $\tilde{Z}_{i,t}$: generalized notation of either the orthogonalized policy residual ($\tilde{T}_{i,t}$) or the mediator residual ($\tilde{M}_{i,t}$) depending on the estimation. These innovations are partitioned into positive and negative components via a zero-bound indicator threshold:

$$\tilde{Z}^+_{i,t} = \max(\tilde{Z}_{i,t}, 0) \quad \text{and} \quad \tilde{Z}^-_{i,t} = \min(\tilde{Z}_{i,t}, 0) \tag{15}$$

Where $\tilde{T}^+_{i,t}$: unexpected floating transition shocks

$\tilde{T}^-_{i,t}$: unexpected peg defense shocks

$\tilde{M}^+_{i,t}$: unexpected expansionary shocks to a financial index

$\tilde{M}_{i,t}^{-}$: unexpected contractionary shocks to a financial index

β_h^+/β_h^-: directional dynamic responses at horizon h

Following the Local Projections (LP) framework of Jordà 2005, we shift the outcome residuals forward by horizons h (from 0 to 3 years) to map the short-term impact of the treatment, while preserving sufficient degrees of freedom. This approach generates a dynamic causal response, visualized through an Impulse Response Function (IRF). The LP framework allows for the smooth integration of the non-parametric residuals generated via DML and exhibits significant robustness to model misspecification compared to traditional structural models. In the placebo test with results detailed in the Appendix, we shift the outcome residuals backward by horizons h (from 0 to -2 years).

3.4 Descriptive statistics and Preliminary Analysis

To maintain data integrity and prevent observation sparsity, we addressed missing values using the MissForest algorithm, a non-parametric machine learning approach. Table 4 confirms the reliability of this procedure by reporting the Normalized Root Mean Square Error (NRMSE).

Table 4: Imputation Accuracy: MissForest NRMSE Results

Variable/Index	NRMSE
Financial Infrastructure Index	0.0432
Physical access sub-Index	0.0426
Digital access sub-Index	0.1370
Financial Depth Index	0.0326
Startup Depth	0.0537

Source: Authors' Calculations

The NRMSE results in Table 4 indicate high imputation accuracy, with values ranging from 0.032 to 0.137, which are below the conservative threshold of 0.15 for non-parametric settings (Stekhoven and Bühlmann 2012). These low error margins suggest that the imputed observations do not introduce significant noise into our structural estimations. To further ensure the stability of our findings, we also conduct robustness checks using the non-imputed dataset.

The structural integrity of our constructed indices is validated through (PCA). In Table 15 (Appendix), the PCA diagnostic results for the index construction are statistically reliable. The eigenvalues consistently exceed the Kaiser threshold of 1.0, justifying the use of the first principal component in all cases (Kaiser 1974). The positive factor loadings, combined with a high proportion of variance explained (ranging from 60.65% to 97.82%), suggest that these composite indices capture the vast majority of the underlying information. Furthermore, the significant Bartlett's test (Bartlett 1950) results and KMO scores (Kaiser 1974)

above 0.50 indicate that the variables are sufficiently correlated for meaningful factor extraction. Notably, in bivariate configurations, the KMO reaches the mathematical boundary of 0.50 by default, in accordance with identification requirements. The descriptive statistics of our panel of 40 emerging economies spanning from 2010 to 2024 are presented in Table 5:

Table 5: Summary Statistics of Main Variables

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Startup Depth (SD)	600	4.905	2.358	0.000	10.430
Financial Infrastructure Index	600	64.255	18.640	0.000	100.000
Financial Depth Index	600	47.314	20.904	0.000	100.000
Financial Openness Index	600	31.206	15.316	0.000	100.000
Regime (Float = 1)	600	0.530	0.500	0.000	1.000
Exchange rate volatility (centered)	600	-0.000	2.985	-2.263	7.728
$\ln RGDP$	600	25.909	1.317	22.518	28.877
$\Delta \ln RGDP$	600	0.035	0.035	-0.157	0.179
Inflation	600	6.590	12.884	-2.523	219.885
Startup Deal Intensity	600	0.131	0.166	0.000	1.319

Source: Authors' calculations.

Notes: Δ refers to the first-difference operator. To prevent the loss of 2010 observations, 2009 $RGDP$ data was utilized to calculate the initial differences. Indices are normalized on a 0 to 100 scale.

The descriptive statistics reveal a well-balanced distribution of regime arrangements within our panel. The mean of 0.530 for the regime indicator suggests that 53% of the observations are characterized by floating arrangements, providing sufficient variation for our empirical specifications. Similarly, Startup Depth, with a mean of 4.902 and a standard deviation of 2.360, exhibits sufficient variation ranging from a minimum of 0.000 to a maximum of 10.430. This spread reflects the wide disparity of entrepreneurial development across our panel.

Our constructed financial indices range from 0 to 100, a scaling that facilitates standardized comparisons between disparate financial systems. We observe substantial standard deviations across these indices, specifically 18.6 for infrastructure and 20.9 for depth. These figures highlight significant heterogeneity in financial maturity across our 40-country sample, which accounts for everything from embryonic financial ecosystems to highly sophisticated markets.

Exchange rate volatility, estimated via an $EGARCH(1,1)$ process, has been mean-centered to ensure that the coefficients in the subsequent interaction models remain directly interpretable at the sample average. The standard deviation of 2.98 relative to the centered mean indicates substantial currency instability throughout the sample period.

Finally, the macroeconomic environment exhibits significant heterogeneity, characterized by high variability in both inflation and output growth. While the average inflation rate stands at 6.59%, the maximum value of 219.9% reflects hyperinflationary episodes, such as the inflationary spikes observed in Argentina

during 2023–2024. Similarly, first-differenced real GDP yields a mean growth rate of 3.5% but exhibits substantial variability ranging from -15.7% to 17.9%. Such volatility underscores the necessity of employing clustered standard errors and robust estimators to prevent domestic shocks from biasing the broader structural results.

Table 16 (in Appendix) shows VIF values below the threshold of 5, confirming that multicollinearity does not artificially inflate the standard errors of our estimates. Table 17 (Appendix) reveals relatively low correlations (below 0.34) between the explanatory variables and startup activity. The financial indices exhibit moderate inter-correlations, ranging from 0.39 to 0.64, which justifies their inclusion as distinct variables that capture separate dimensions of the financial system rather than a single redundant indicator.

4 Results

We initiate the results section by evaluating the integration properties of the variables using the Im-Pesaran-Shin (IPS) panel unit root test (Im, Pesaran, and Shin 2003), as presented in Table 6. While the Nonlinear Autoregressive Distributed Lag (NARDL) approach is capable of accommodating variables integrated of order zero $I(0)$ or one $I(1)$, it strictly requires that no variable is integrated of order $I(2)$ or higher to confirm the F-bounds test validity. Given the relatively short time dimension of our panel ($T = 15$), we specify a fixed lag length of one instead of relying on automated statistical selection criteria that might unnecessarily exhaust the available degrees of freedom. Furthermore, the DML framework flexibly accommodates variables in levels during the first step, ensuring that the second step local projections operate on stationary, purified residuals.

Table 6: Panel Unit Root Test Results (Im-Pesaran-Shin)

Variable	Intercept Stat.	p-value	Integration
Startup Depth	-7.244	0.000***	$I(0)$
Financial Infrastructure Index	-3.303	0.001***	$I(0)$
Financial Depth Index	-3.336	0.000***	$I(0)$
Financial Openness Index	-3.255	0.001***	$I(0)$
Exchange Rate Volatility	-8.089	0.000***	$I(0)$
ln $RGDP$	-10.643	0.000***	$I(1)$
Inflation	-7.300	0.000***	$I(0)$
Startup Deal Intensity	-2.641	0.000***	$I(0)$

Source: Authors' calculations.

Notes: ***Significance levels: p < 1%. Test specification includes an intercept. Capped values in the Exchange Rate Volatility series were excluded to avoid undefined results

Having confirmed the integration properties of our variables, we proceed with our empirical analysis. Results of the direct effect and transmission channels involving the Hybrid Mundlak framework with regimes

on startup depth and financial indices is in Table 7:

Table 7: Hybrid Mundlak specification of exchange rate regimes on startup depth and financial indices

Variable	(1) Startup Depth	(2) F.Infrastructure	(3) F.Depth	(4) F.Openness
Main Variables				
Regime (Float = 1)	0.961**	9.235***	12.613***	5.552*
	(0.375)	(3.379)	(3.762)	(2.948)
ER Volatility	0.143	−1.111	−0.695	0.920
	(0.109)	(1.234)	(1.628)	(0.867)
Regime × Volatility	−0.08	0.851	0.344	−0.131
	(0.077)	(1.249)	(1.789)	(0.952)
Δ ln Real GDP	−4.652∗	8.436	−11.285	−10.564
	(3.199)	(17.589)	(14.315)	(8.096)
Inflation	−0.002	0.050**	0.013	0.030**
	(0.004)	(0.023)	(0.025)	(0.014)
Mundlak Terms				
Mean Volatility	−0.013	−0.547	−0.254	−1.257 ∗ ∗
	(0.113)	(0.842)	(1.301)	(0.643)
Mean Δ ln Real GDP	-0.405	−481.520 ∗ ∗∗	−255.113	−397.640 ∗ ∗∗
	(15.853)	(150.855)	(173.131)	(104.636)
Mean Inflation	0.005	−0.020	−1.101 ∗ ∗∗	−0.641 ∗ ∗∗
	(0.014)	(0.282)	(0.277)	(0.173)
Intercept	2.574***	63.95***	57.700***	44.604***
	(0.683)	(7.010)	(7.429)	(4.494)
Year Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE (Country)	Yes	Yes	Yes	Yes
R^2	0.361	0.434	0.358	0.330
Observations	600	600	600	600

Notes: Standard errors (in parentheses) are clustered at the country level. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' calculations.

The significance of the Mundlak group-mean terms indicates a correlation between the unobserved country effects and the regressors. This result invalidates the assumption required for a Random Effects model and justifies the use of the Mundlak hybrid approach to estimate time-invariant variables like exchange rate regimes.

The coefficients for the floating regime are positive and statistically significant. These findings suggest that a flexible exchange rate is associated with higher levels of startup depth (0.961**), financial infrastructure (9.235**), and financial depth (12.614***) in these emerging markets, whereas its association with de facto financial openness is statistically less robust (5.552*). Conversely, exchange rate volatility and its interaction with the regime are consistently insignificant across all specifications, suggesting that the impact of currency shocks on the financial system is not conditional upon the policy regime. Finally, the use of standard errors clustered at the country level ensures the robustness of these estimates against autocorrelation and heteroskedasticity.

Table 8 reports the NARDL estimation results between financial indices and startup depth, supplemented by Wald tests for long-asymmetry and the Mundlak-Wald diagnostic for model specification:

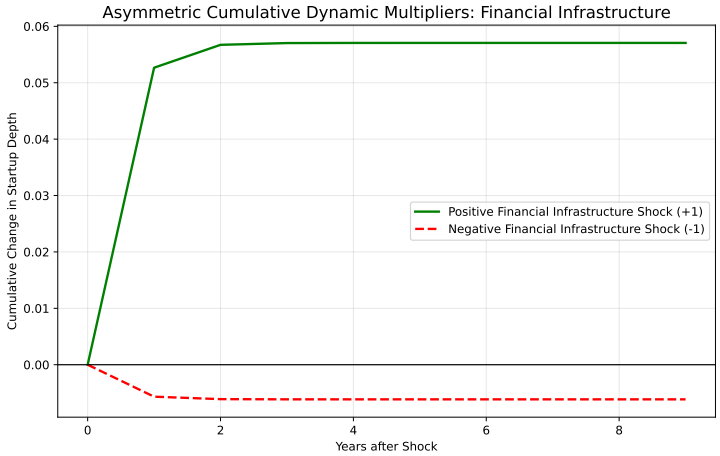
Table 8: NARDL Panel Estimates: Asymmetric Impacts of Financial Indices

DV: $\Delta StartupDepth$	(1) **Fin. Infrastructure**	(2) **Fin. Depth**	(3) **Fin. Openness**
Long-Run Dynamics (Lags in Levels)			
$StartupDepth_{t-1}$ (ρ)	$-0.923 * **$	$-0.974 * **$	$-1.000 * **$
	(0.061)	(0.047)	(0.051)
$Index^{+}_{t-1}$	0.053**	0.087***	0.143***
	(0.026)	(0.021)	(0.036)
$Index^{-}_{t-1}$	-0.006	0.001	-0.007
	(0.025)	(0.020)	(0.044)
Short-Run Dynamics (Differences)			
$\Delta Index^{+}_{t}$	0.026	0.020	0.041
	(0.044)	(0.027)	(0.050)
$\Delta Index^{-}_{t}$	0.001	-0.009	-0.092
	(0.008)	(0.023)	(0.071)
Control Variables			
$\ln RealGDP$	3.580***	3.724***	3.212***
	(1.276)	(1.060)	(1.029)
Inflation	0.003	-0.001	$-0.006 * *$
	(0.003)	(0.002)	(0.003)
Diagnostics			
Intercept	$-92.573 * **$	$-96.036 * **$	$-82.30 * **$
	(34.299)	(25.337)	(27.600)
Country Fixed-Effects	Yes	Yes	Yes
Wald Test (LR Asymmetry)	2.923*	12.387***	14.591***
Mundlak-Wald (FE Confirm)	102.85***	98.73***	124.53***
R^2	0.505	0.527	0.532
Observations	600	600	600

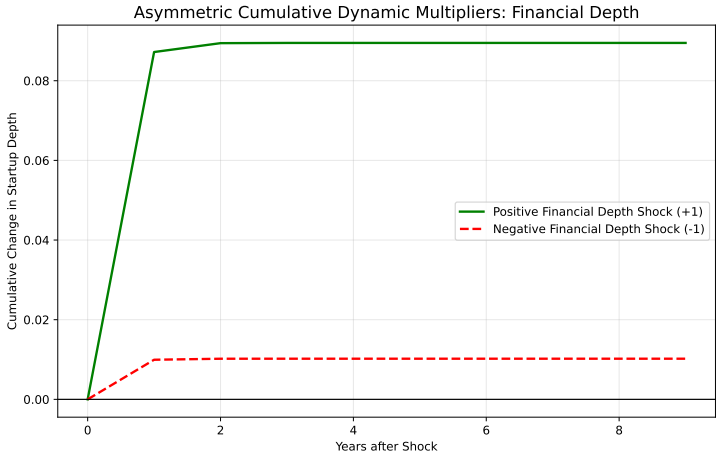
Source: Authors' calculations.

Notes: Standard errors (in parentheses) are clustered at the country level. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. $Index^{+}$ and $Index^{-}$ show the partial sums of positive and negative shocks.

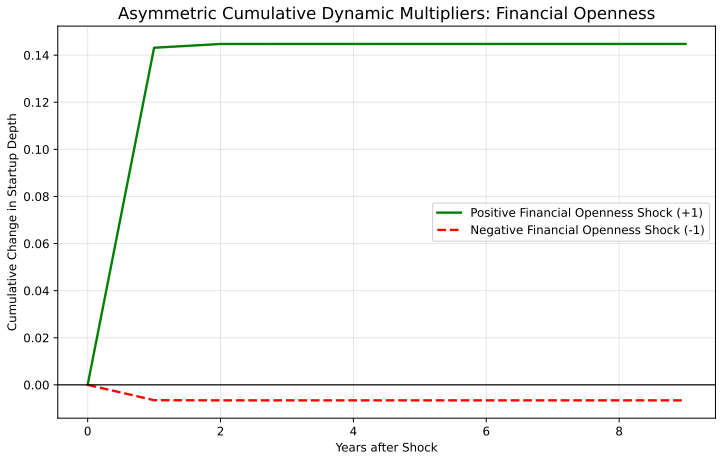
The NARDL results show robust evidence of long-run asymmetric associations between financial development and the startup ecosystem. Notably, the positive partial sums indicate that expansions in financial infrastructure, financial depth, and financial openness are associated with increases in startup depth (0.053**), (0.087***), and (0.143***), respectively. In contrast, the insignificant negative partial sums suggest a lack of statistical link between financial contractions and startup depth. This asymmetry is validated by the Wald test, which confirms that positive and negative changes in the financial system show divergent associations with startup depth. These findings demonstrate that while a developed financial system offers a conducive environment that associates with startup maturation, the ecosystem exhibits resilience during financial contraction. The error correction mechanism suggests a highly dynamic speed of adjustment in the startup ecosystem, where temporary deviations are rapidly corrected. The Mundlak-Wald test favors the fixed effects specification by rejecting the null of random effects. Figure 1 illustrates the asymmetrical divergence between financial expansion and its contraction over the 10-year horizon:



(a) Financial Infrastructure



(b) Financial Depth



(c) Financial Openness

Figure 1: NARDL Dynamic Multipliers: Asymmetric Shocks on Startup Depth. *Note: Green line for the cumulative positive shocks; Red dashed line for the cumulative negative shocks. Source: Authors' calculations*

In the following step, we move beyond association to isolate dynamic nonlinear responses using a Double Machine Learning with Local Projection (DML-LP) framework within distinct channels. By utilizing this approach with standard errors clustered at the country level, we isolate the impact of exchange rate regimes transitions on startup depth. Crucially, it clarifies the transmission mechanism running from regimes to financial indices and track their subsequent effect on startup depth. These dynamic responses estimated via local projections are illustrated in Figures 2 through 5:

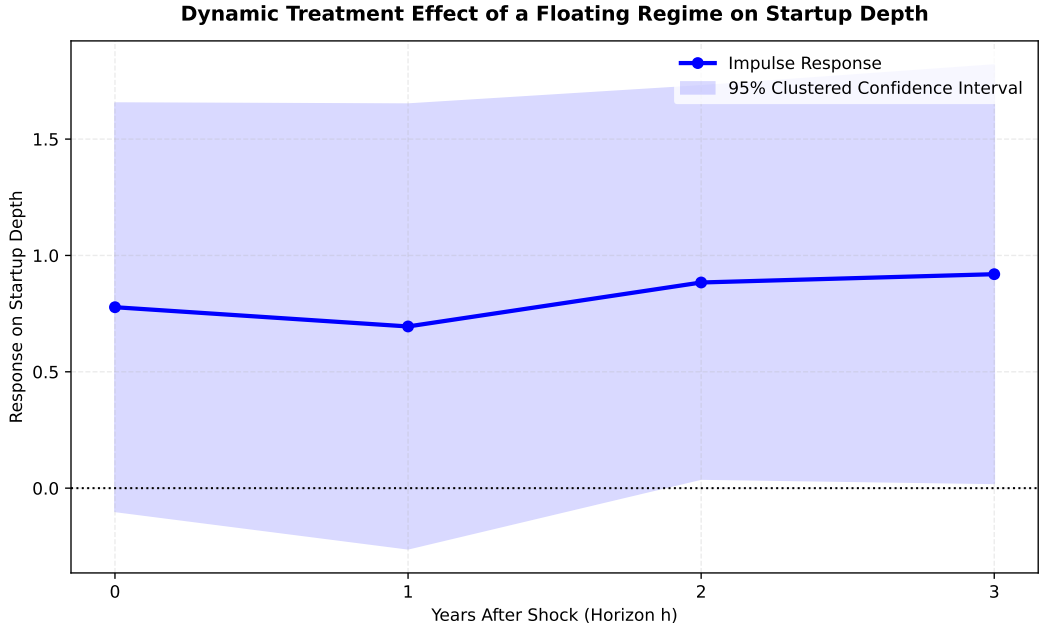
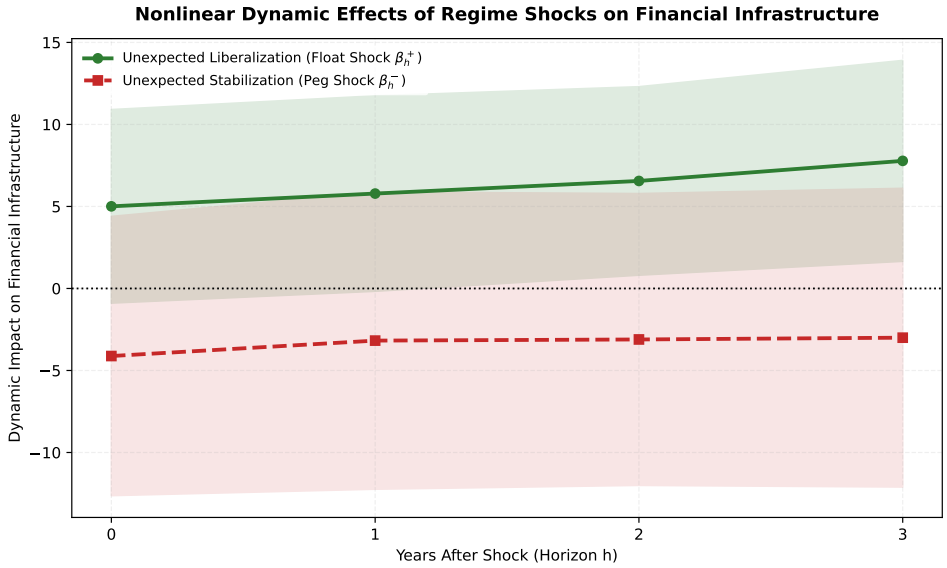
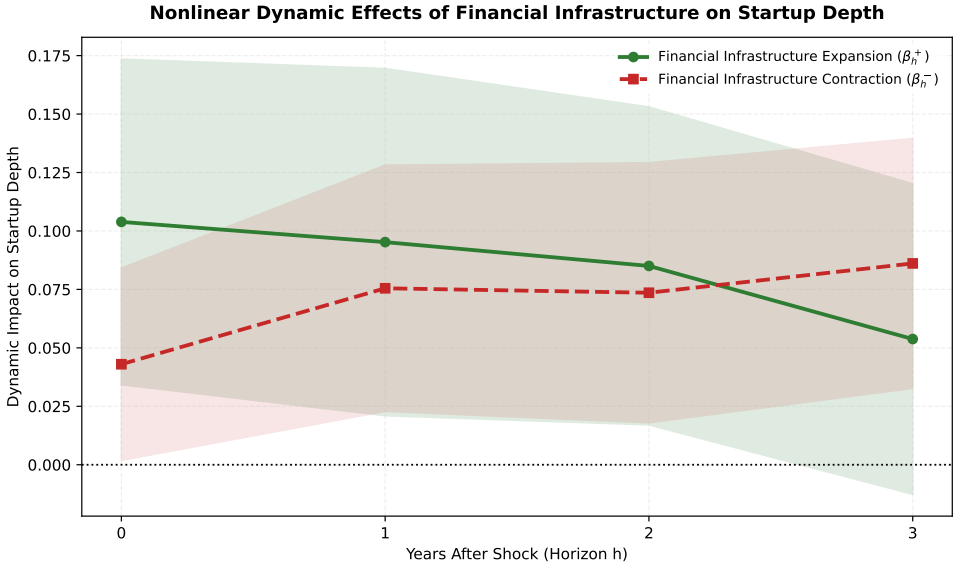


Figure 2: Local Projection Impulse Responses: Dynamic Response of Startup Depth to a Floating Regime Transition. *Note: Colored areas illustrate 95% confidence intervals. The model utilizes the Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends. Constant included in the second-stage local projection. Standard errors clustered at the country level. Source: Authors' calculations*

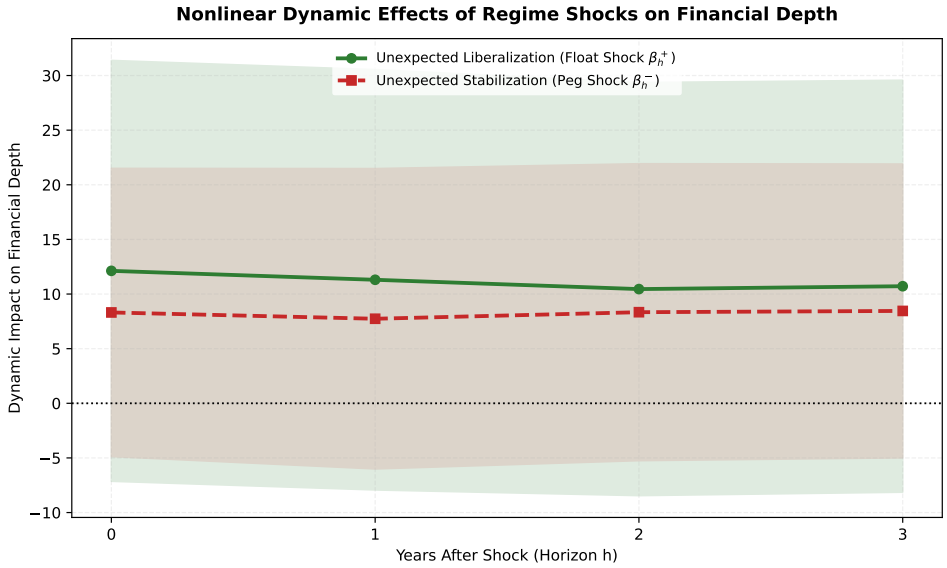


(a) Regime → Financial Infrastructure

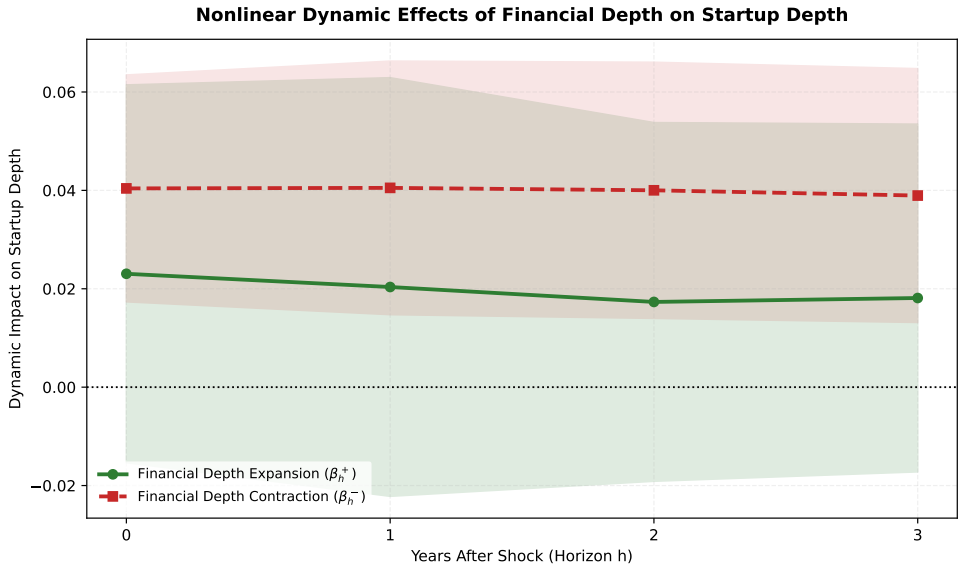


(b) Financial Infrastructure → Startup Depth

Figure 3: Local Projections Impulse Responses: Sequential Transmission from Floating Regime Transitions to Startup Depth via Financial Infrastructure *Note: Colored areas illustrate 95% confidence intervals. Standard errors clustered at the country level. We utilize a Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends in the first-stage DML nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations*

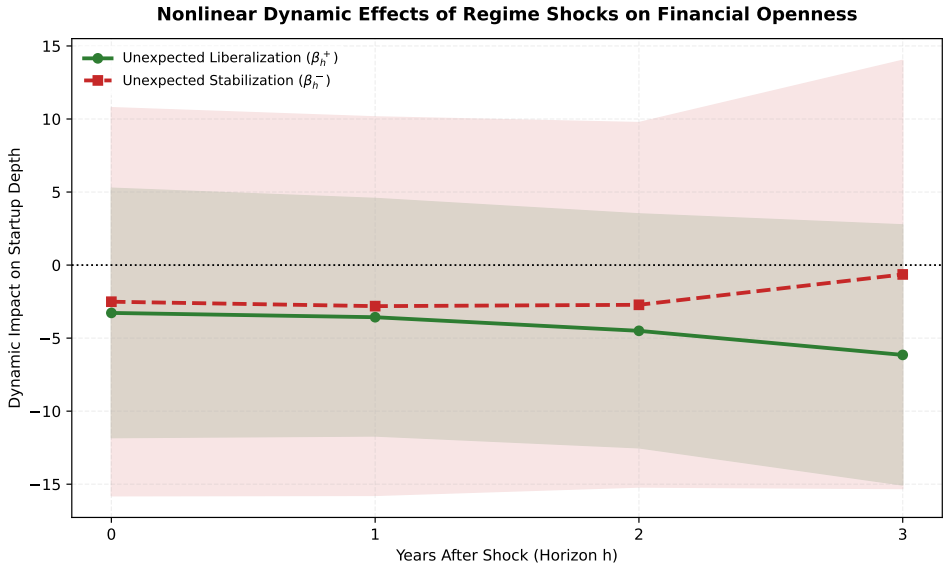


(a) Regime → Financial Depth

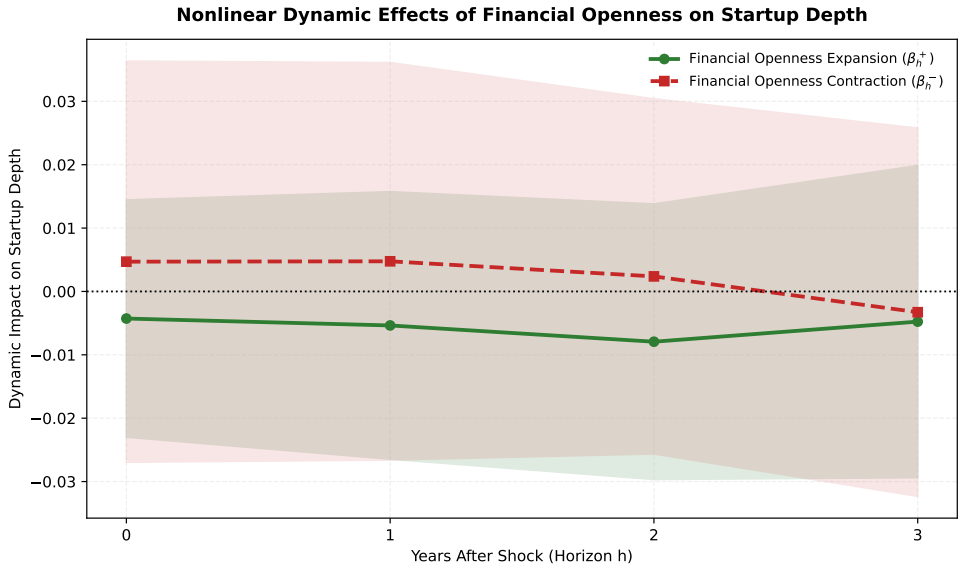


(b) Financial Depth → Startup Depth

Figure 4: Local Projections Impulse Responses: Sequential Transmission from Floating Regime Transitions to Startup Depth via Financial Depth *Note: Colored areas illustrate 95% confidence intervals. Standard errors clustered at the country level. We utilize a Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends in the first-stage DML nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations*



(a) Regime → Financial Openness



(b) Financial Openness → Startup Depth

Figure 5: Local Projections Impulse Responses: Sequential Transmission from Floating Regime Transitions to Startup Depth via Financial Openness *Note: Colored areas illustrate 95% confidence intervals. Standard errors clustered at the country level. We utilize a Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends in the first-stage DML nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations*

We observe in the DML-LP results that a transition to a floating exchange rate regime generates a positive, statistically significant response in startup depth by the second year, peaking at the third year ($h = 3$: 0.9194**). When evaluating the underlying transmission mechanism through standard linear models,

the aggregate treatment framework fail to uncover a significant effect on intermediate variables. However, by deploying a nonlinear specification that partition positive and negative policy shocks, we document that an unexpected shift toward a floating regime expands the financial infrastructure index, peaking in the third year ($h = 3$: $\beta_h^+ = 7.7788^{***}$). In contrast, an unexpected defense of a pegged regime results in financial infrastructure stagnation. Throughout this policy-to-mediator channels, the dynamic responses of the financial depth and financial openness channels remain statistically insignificant across projection horizons.

Regarding the downstream mediator-to-outcome channels, we observe that a one-unit expansion in financial infrastructure exerts a statistically significant positive impact on startup depth, peaking immediately ($h = 0$: $\beta_h^+ = 0.1039^{***}$) before gradually decaying. Crucially, contractionary shocks to both financial infrastructure and financial depth induce a leapfrogging effect within the startup depth, triggering sustained, statistically significant positive reallocations that peak in the third year for financial infrastructure contractions ($h = 3$: $\beta_h^- = 0.0861^{***}$) and the second year for financial depth contractions ($h = 2$: $\beta_h^- = 0.0405^{***}$). Conversely, expansionary shocks in financial depth and nonlinear variations in financial openness do not exhibit a statistically impact on startup depth. In sum, our empirical findings indicate that transitioning toward a floating regime expands startup investment depth. Furthermore, our decomposition isolates financial infrastructure as the primary transmission mechanism linking regime choice to startup capital absorption, whereas alternative channels remain disconnected.

Tables 9 to 11 present the results of the robustness checks for our DML-LP utilizing the Lasso linear regularizer (Tibshirani 1996; Hastie 2009) and the Extreme Gradient Boosting (XGBoost) learners (Chen and Guestrin 2016) to validate our estimates.

Table 9: Dynamic Response of a Floating Regime Transition on Startup Depth

Estimator	**Horizon 0**	**Horizon 1**	**Horizon 2**	**Horizon 3**
Random Forest	0.7776*	0.6948	0.8838**	0.9194**
	(0.4336)	(0.4723)	(0.4175)	(0.4443)
Lasso	0.8789**	0.8632**	0.9917**	0.9871**
	(0.3844)	(0.4020)	(0.3904)	(0.3816)
XGBoost	1.0779**	1.0084*	1.1412**	1.1574**
	(0.4953)	(0.5319)	(0.5053)	(0.4963)

Notes: Local Projections Coefficients. Standard errors clustered at the country level (in parentheses). Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Random Forest is the baseline DML estimator, while Lasso and XGBoost serve as robustness checks. All models utilize the Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends. Constant included in each second-stage local projections. Source: Authors' calculations

Table 10: Dynamic Nonlinear Response of Financial Indices to Regime Shocks Across DML Estimators

Shock Domain / Channel	Horizon 0	Horizon 1	Horizon 2	Horizon 3
PANEL B: Financial Infrastructure Channel				
Random Forest				
Float Shock (β_h^+)	5.0070*	5.7858*	6.5549**	7.7788**
	(2.9182)	(2.9470)	(2.8421)	(3.0289)
Peg Defense (β_h^-)	-4.1192	-3.1784	-3.1092	-3.0009
	(4.2092)	(4.4806)	(4.3996)	(4.5031)
Lasso				
Float Shock (β_h^+)	24.6597***	24.7766***	24.7557***	24.6504***
	(8.8584)	(8.7659)	(8.6632)	(8.8074)
Peg Defense (β_h^-)	-12.4454	(9.5186)	-11.9646	-10.8948
	(9.5186)	(9.1264)	(9.0905)	(9.8780)
XGBoost				
Float Shock (β_h^+)	5.3283	4.9927	5.2833	5.9333
	(4.7054)	(4.8509)	(4.6123)	(4.7627)
Peg Defense (β_h^-)	0.8760	1.6592	1.2921	1.3843
	(4.5593)	(4.8397)	(4.9259)	(5.2785)
PANEL C: Financial Depth Channel				
Random Forest				
Float Shock (β_h^+)	12.1221	11.3046	10.4534	10.7162
	(9.5240)	(9.5126)	(9.3485)	(9.3237)
Peg Defense (β_h^-)	8.3142	7.7377	8.3381	8.4538
	(6.5218)	(6.7976)	(6.7203)	(6.6502)
Lasso				
Float Shock (β_h^+)	15.7155	16.5681	18.3657	21.2273
	(17.5750)	(18.2025)	(18.7651)	(20.5006)
Peg Defense (β_h^-)	-3.6223	-4.7561	-6.4879	-10.9771
	(14.2590)	(14.5723)	(14.9930)	(17.3316)
XGBoost				
Float Shock (β_h^+)	14.8284*	14.6626*	15.2330*	15.0724*
	(8.3824)	(8.2685)	(8.4409)	(8.6774)
Peg Defense (β_h^-)	12.8699	12.2294	11.4441	10.6083
	(7.6486)	(7.4430)	(7.7126)	(8.2842)
PANEL A: Financial Openness Channel				
Random Forest				
Float Shock (β_h^+)	-3.2748	-3.5684	-4.5006	-6.1495
	(4.2184)	(4.0174)	(3.9564)	(4.3991)
Peg Defense (β_h^-)	-2.5081	-2.8102	-2.7194	-0.6403
	(6.5644)	(6.4027)	(6.1643)	(7.2445)
Lasso				
Float Shock (β_h^+)	16.3456	15.4624	15.4612	14.9943
	(10.9310)	(11.5336)	(12.0489)	(12.7875)
Peg Defense (β_h^-)	-10.4056	-10.2956	-11.2155	-10.5031
	(8.2183)	(8.5340)	(8.8562)	(9.9942)
XGBoost				
Float Shock (β_h^+)	-2.1195	-1.9896	-2.3267	-3.4238
	(7.2112)	(7.1674)	(7.1440)	(8.1829)
Peg Defense (β_h^-)	-0.9774	-2.9328	-2.3267	-3.4238
	(8.5429)	(8.5799)	(8.3805)	(10.8172)

Notes: Local Projections Coefficients. Standard errors clustered at the country level. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. All models utilize the Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends. Constant included in each second-stage local projections. Constant included in each second-stage local projections. Source: Authors' calculations

Table 11: Dynamic Nonlinear Response of Financial Indices on Startup Depth Across MultiModel DML-LP Channels

Mediator Shock / Estimator	Horizon 0	Horizon 1	Horizon 2	Horizon 3
PANEL A: Financial Infrastructure Channel				
Random Forest				
Expansion (β^+)	0.1039***	0.0952**	0.0850**	0.0538
	(0.0344)	(0.0367)	(0.0336)	(0.0328)
Contraction (β^-)	0.0430**	0.0755***	0.0736**	0.0861***
	(0.0203)	(0.0260)	(0.0275)	(0.0264)
Lasso				
Expansion (β^+)	0.0340	0.0283	0.0276	0.0348
	(0.0208)	(0.0222)	(0.0214)	(0.0214)
Contraction (β^-)	0.0554**	0.0632**	0.0612**	0.0539**
	(0.0241)	(0.0240)	(0.0252)	(0.0243)
XGBoost				
Expansion (β^+)	0.1087***	0.1041***	0.0852***	0.0729**
	(0.0291)	(0.0350)	(0.0312)	(0.0337)
Contraction (β^-)	0.0472**	0.0896***	0.0989***	0.0919***
	(0.0231)	(0.0322)	(0.0334)	(0.0338)
PANEL B: Financial Depth Channel				
Random Forest				
Expansion (β^+)	0.0230	0.0204	0.0173	0.0181
	(0.0190)	(0.0210)	(0.0180)	(0.0175)
Contraction (β^-)	0.0404***	0.0405***	0.0400***	0.0389***
	(0.0114)	(0.0127)	(0.0129)	(0.0128)
Lasso				
Expansion (β^+)	0.0052	0.0015	0.0024	0.0043
	(0.0130)	(0.0133)	(0.0132)	(0.0125)
Contraction (β^-)	0.0386***	0.0327***	0.0361***	0.0313***
	(0.0058)	(0.0075)	(0.0074)	(0.0078)
XGBoost				
Expansion (β^+)	0.0293	0.0294	0.0283	0.0253
	(0.0199)	(0.0214)	(0.0206)	(0.0197)
Contraction (β^-)	0.0226	0.0276	0.0318	0.0317
	(0.0285)	(0.0316)	(0.0326)	(0.0315)
PANEL C: Financial Openness Channel				
Random Forest				
Expansion (β^+)	-0.0043	-0.0054	-0.0079	-0.0048
	(0.0093)	(0.0104)	(0.0108)	(0.0122)
Contraction (β^-)	0.0047	0.0048	0.0024	-0.0033
	(0.0157)	(0.0155)	(0.0139)	(0.0144)
Lasso				
Expansion (β^+)	-0.0116	-0.0137	-0.0192*	-0.0166
	(0.0080)	(0.0093)	(0.0097)	(0.0104)
Contraction (β^-)	0.0034	0.0105	0.0101	0.0113
	(0.0178)	(0.0183)	(0.0181)	(0.0170)
XGBoost				
Expansion (β^+)	0.0021	-0.0030	-0.0028	-0.0033
	(0.0089)	(0.0109)	(0.0126)	(0.0116)
Contraction (β^-)	-0.0030	-0.0051	0.0068	-0.0011
	(0.0279)	(0.0310)	(0.0308)	(0.0304)

Notes: Local Projections Coefficients. Standard errors clustered at the country level (in parentheses). Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. All models utilize the Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous time trends. Constant included in each second-stage local projections. Source: Authors' calculations

The baseline results remain highly stable in both sign and statistical significance across alternative DML estimators, specifically Lasso and XGBoost. The direct response of startup depth to a floating regime

transition holds robustly across all model specifications peaking at distinct horizons ($h = 3$ for Random Forest: 0.9194**, $h = 2$ for Lasso: 0.9917***, $h = 3$ for XGBoost: 1.1574**). This consistency indicates that our causal identification strategy is highly robust and verifies that the baseline findings are not artifacts of model misspecification inherent to the Random Forest estimator. Moreover, evaluating the asymmetric transmission responses provides additional empirical validation for the primary financial infrastructure channel. We observe that the expansion of financial infrastructure following an unexpected shift toward a floating regime is robust under Lasso ($h = 3$: Random Forest: $\beta_h^+ = 7.7788$***, Lasso: $\beta_h^+ = 24.6504$***) through it lacks statistical significance under XGBoost. The subsequent translation of this infrastructure expansion into a positive response for startup depth is captured by XGBoost ($h = 0$: Random Forest: $\beta_h^+ = 0.1039$***, XGBoost: $\beta_h^+ = 0.1087$***), but does emerge under Lasso. Crucially, the contraction in financial infrastructure that positively impact startup depth is confirmed by all these alternative learners ($h = 3$: Random Forest: $\beta_h^- = 0.0861$***, $h = 2$: Lasso: $\beta_h^- = 0.0632$***, $h = 2$: XGBoost: $\beta_h^- = 0.0989$**). Similarly, the contraction in financial depth that expands startup depth holds robustly under Lasso ($h = 2$: Random Forest: $\beta_h^- = 0.0405$***, Lasso: $\beta_h^- = 0.0386$***) but loses significance under XGBoost. Conversely, other mechanisms remain insignificant across both baseline and alternative model settings.

To further validate these findings, we conduct leading placebo tests to evaluate the presence of pre-existing trends prior to the treatment shock. We utilize the raw datasets, excluding the imputations generated by the missForest algorithm. We also assess the generalization of our findings by replacing the primary dependent variable, startup depth (SD), with startup deal count intensity (SDI). In Table 12, we report the summary of these robustness checks, while we offer detailed results in the appendix.

Table 12: Robustness Checks Summary: Alternative Proxies and Data Specifications

Robustness Strategy	**Hybrid Mundlak**	**NARDL**	**DML-LP**
Placebo Tests	N/A	N/A	Non-significant
Startup Deal Intensity	Discontinued significant association for regimes.	Maintained sign and significance; emergent short-run dynamics in financial openness.	Discontinued significance in the direct effect; Financial Infrastructure maintains significance; Financial openness emerges as a significant channel
No Data Imputation	Maintained sign and significance; Financial infrastructure attenuated by the proxy.	Maintained sign and significance; emergent short-run dynamics in financial infrastructure transmission.	Maintained sign and significance in direct regime effect; Financial infrastructure attenuated by proxy, discontinuing this mechanism at the policy-to-mediator level; Financial depth emerging as a significant channel

Notes: Standard errors across all specifications are clustered at the country level. In the non-imputed specification, the digital access sub-index within financial infrastructure is proxy-replaced with mobile cellular subscriptions to mitigate structural data attrition. Source: Authors' calculations.

Table 12 presents a synthesis of our robustness checks. We observe that placebo tests of exchange rate regime transitions on startup depth and financial infrastructure yield non-significant responses, reinforcing

our nonlinear identification strategy and confirming the absence of anticipation effects or pre-existing trends.

Moreover, substituting our primary dependent variable with the alternative startup deal intensity proxy confirms the validity of the underlying transmission mechanisms, as the pass-through effect operates robustly through the financial infrastructure and financial openness channels within the DML-LP framework. These insights suggest that a floating regime does not influence deal frequency in a vacuum, but are instead transmitted via these catalyzed financial pillars.

Furthermore, evaluating the non-imputed dataset demonstrates that our results remain structurally stable under listwise deletion. To mitigate structural data attrition in the raw sample, the digital financial access sub-index within financial infrastructure index was proxy-replaced with mobile cellular subscriptions scaled per 1,000 adults. While this substitution attenuates the cross-sectional significance of the financial infrastructure channel within the policy-to-mediator at the Hybrid-Mundlak and DML-LP frameworks, this channel remains invariant in driving startup activity. Crucially, the direct response between regime transition and startup depth remains robust.

5 Discussion

We observe that a transition toward floating exchange rate regimes acts as critical catalyst for startup depth by fostering financial expansion in infrastructure and openness. This institutional shift addresses the structural tradeoff between macrofinancial stability and the innovation required for the growth of the startup ecosystem.

Our empirical findings indicate that an unexpected transition to a floating regime serves as a primary driver of financial infrastructure expansion, whereas the unexpected defense of a fixed regime results in financial stagnation. This aligns closely with literature demonstrating that exchange rate flexibility can enhance financial inclusion (Chiboub and Sadok 2025). By dismantling the implicit currency subsidies inherent in fixed anchors, a floating arrangement reconfigures private sector risk management and innovation incentives, correlating with an adaptation away from legacy financial architectures that echoes the theoretical framework of creative destruction (Schumpeter 2013). Ultimately, this process accelerates transactional velocity and expands financial access, providing pathways that condition the capacity of startups to absorb private capital allocations.

While prior literature establishes that access to formal bank finance is a significant determinant of startup rates in developing economies (Naudé et al. 2008), our results indicate that financial infrastructure integrating both digital and physical dimensions conditions the capacity of startups to attract private investment. This dual connectivity reduces financial frictions and lowers entry barriers by offering the structural

channels necessary for both capital initiation and subsequent scaling. Notably, the interaction of digital financial networks, financial access, secure transaction protocols, and banking density facilitates high-velocity technological venture development while systematically lowering operational transaction costs. Furthermore, this integrated infrastructure can mitigate risks arising from information asymmetry, by acting as a form of 'information collateral' that generates a verifiable digital audit trail of secure transactions, thereby lowering monitoring costs for investors and relaxes financial constraints for asset-light startups.

Crucially, our nonlinear findings reveal that startup depth responds positively to financial infrastructure contractions, signaling a powerful leapfrogging effect where capital is reallocated toward alternative startups out of structural necessity. When legacy financial rails stagnate in emerging markets, the innovation of startups to bypass these infrastructure bottlenecks becomes critical and creates high-growth opportunities through the development of parallel fintech solutions; such as digital remittances, money transfers, mobile wallets, peer-to-peer capital networking, and automated B2B clearing tools. This workaround to fill the structural vacuum piques investor interest, which ultimately drives alternative capital allocations toward funding these startups.

Similarly, we observe that while financial depth expansions exert no statistically significant effect on startup depth, a contraction in traditional financial depth yields a positive effect on startup investment depth. This divergence occurs because traditional banking credits frequently exclude collateral-constrained startups (Schmalz, Sraer, and Thesmar 2017) and stock markets architecture in emerging markets remains structurally oriented toward large-scale, asset-heavy companies. While classical studies show that deep stock markets offer a liquid initial public offering (IPO) exit channel that incentivizes venture capitalists seeking to maximize capital gains upon exit (Black and Gilson 1998), our findings centered on emerging markets reveal that a contraction in traditional financial market depth drives a portfolio reallocation toward high-velocity technological ventures to capture alternative yields despite elevated risk profiles.

We acknowledge several limitations common in international macroeconomics: First, the reliance on low frequency annual datasets across 40 emerging markets constrains the degrees of freedom available for estimation. This is particularly relevant for the machine learning framework that benefits from larger sample sizes. However, the variables required for this analysis are rarely available at higher frequencies. We avoid interpolation to monthly variations to prevent the introduction of spurious correlations or artificial relationships. Instead, we maximize the available information by incorporating a comprehensive panel of 40 countries. Second, the geographic breadth of studying various emerging markets results in a high degree of data sparsity. To mitigate the loss of valuable information, we utilize the missForest imputation method and report a robust normalized root mean square error. We further ensure the validity of our findings by providing non-imputed results in the Appendix. Third, the Dealroom database may under report startup investments

in specific developing regions where data transparency is restricted. Nevertheless, relying on a uniform third party reporter ensures harmonized observations across countries, thereby avoiding the methodology biases inherent in varying local definitions and classifications.

Despite these drawbacks, our empirical findings indicate that transitioning toward a floating exchange rate regime expands startup investment depth and catalyzes institutional financial maturity, thereby bounding the empirical relevance of the fear of floating hypothesis (Calvo and Reinhart 2002; Kočenda and Valachy 2006). While international venture capital funds are highly sensitive to foreign exchange volatility due to the potential erosion of investment returns, we find no statistically significant association between baseline volatility levels and startup depth. This outcome suggests that the institutional impact of the floating regime is far more consequential than secondary operational effects such as volatility. Moreover, although financial openness is traditionally viewed as a dynamic support for early-stage startups seeking to capitalize on international markets long before reaching maturity within the theoretical framework of the born-global imperative (Knight and Cavusgil 2004; Oviatt and McDougall 2005), we find no robust evidence that this integration connects domestic startups to global financial network to secure the external resources necessary to compete at the technological frontier.

The expansion of fintech architecture facilitates capital mobility, structurally eroding the enforcement efficacy of traditional de jure capital controls. This technological shift reinforces the two-corner hypothesis, which posits that soft peg regimes become increasingly unstable under higher capital mobility (Summers 2000; Fischer 2001). By demonstrating that exchange rate regimes operate via the expansion of high-velocity technological ventures, our results suggest that modern fintech advancements accelerates the structural transition away from intermediate soft pegs toward the corners of the impossible trinity framework (Fleming 1962; Mundell 1963).

6 Conclusion

We introduce a novel empirical dimension to the long-standing debate on the choice of exchange rate regimes by shifting the analytical focus toward startup ecosystem depth and institutional financial maturation. By integrating a Hybrid-Mundlak framework and NARDL estimations to map complex associations alongside a DML-LP identification strategy with embedded Hybrid-Mundlak terms, we observe that floating exchange rate regimes catalyze startup investment depth across forty emerging markets through specific financial maturation channels. Dismantling the implicit currency subsidies inherent to fixed anchors fundamentally alters private-sector innovation incentives, correlating with a structural adaptation away from legacy financial architectures that allows startups to leverage enhanced transactional velocity and expanded financial access

to absorb private capital allocations.

Crucially, our findings uncover vital nonlinear interactions within these transmission mechanisms. Within the policy-to-mediator framework, an unexpected defense of the fixed peg results in financial infrastructure stagnation, whereas an unexpected transition toward a floating regime results in a structural expansion of the financial infrastructure index. This financial infrastructure channel emerges as a robust mechanism that consistently condition the capacity of early- and mid-stage startups to absorb capital. Furthermore, our findings demonstrate that both financial infrastructure expansions and contractions drive downstream startup depth, revealing a systemic reduction in financial frictions and a powerful technological leapfrogging effect. While financial depth expansion exert no statistically significant response, a contraction in financial depth drives a reallocation of venture capital toward high-velocity technological ventures. Ultimately, these insights indicate that exchange rate regimes operate primarily through the financial infrastructure channel to promote innovation incentives in emerging market ecosystems.

Data Availability Statement

Replication data and code are available upon request and will be made publicly accessible via an open-source repository upon publication.

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Appendix

A Appendix

A.1 Auxiliary Helpers in MissForest Strategy

Table 13: MissForest Imputation Strategy: Target Variables and Auxiliary Predictors

Target Variable	**Auxiliary Predictors**	**Source**
Startup Depth	Startup Deal Intensity	Dealroom.co 2026
	Real GDP per capita	WBG 2025b
	Inflation	IMF 2025c
	Real Interest Rates	WBG 2025b
	Year trend	

Source: Authors' calculations using data from Dealroom.co 2026, IMF 2025c, and WBG 2025b

Note: Real GDP per capita, startup depth, and startup deal intensity are log transformed. Intensity measures are calculated by normalizing raw deal counts by nominal GDP.

Table 14: MissForest Imputation Strategy and Auxiliary Predictors

Imputation Target	**Auxiliary Predictors (missForest Helpers)**
Physical Pillars	Lagged values $(t-1)$, ln(Real GDP per capita) (WBG 2025b), Inflation(IMF 2025c), Real Interest Rates (WBG 2025b), ln(Adult Population) (WBG 2025b), Urbanization (WBG 2025b), World Bank secondary density measures (ATM and bank branches) (WBG 2025a), ln(Private Credit/GDP) (WBG 2025b), ln(M_2/GDP) (WBG 2025b), Year Trend.
Digital Pillars	Lagged values $(t-1)$, ln(Real GDP per capita)(WBG 2025b), ln(Adult Population)(WBG 2025b), Real Interest Rates(WBG 2025b), Inflation (IMF 2025c), Physical Access Index, Fixed Broadband (WBG 2025b), Internet Users (WBG 2025b), ln(M_2/GDP) (WBG 2025b), ln(Private Credit/GDP) (WBG 2025b), ln(Mobile Subscriptions) (WBG 2025b), Active Mobile Money (IMF 2025b), Urbanization(WBG 2025b), Year Trend.
Integrated Index	Year Trend, Fixed Broadband (WBG 2025b), ICT Goods Exports (% of total exports) (WBG 2025b).

Source: Author's calculations based on the IMF (IMF 2025b) and WBG (WBG 2025b; WBG 2025a) databases.

Table 15: missForest Imputation Strategy for Financial Depth Pillars

Target Variable	**Auxiliary Predictors (missForest Helpers)**	**Source**
Stock Market Cap.	Equity-to-Debt Ratio	Milesi-Ferretti 2026
Private Credit	M_2/GDP	WBG 2025b
	Real Interest Rates	WBG 2025b
Derivatives Intensity	Portfolio Equity Liabilities Ratio	Milesi-Ferretti 2026

Source: Author's calculations using data from WBG 2025b and External Wealth of Nations (Milesi-Ferretti 2026) data.

Note: Stock market Cap., Private Credit, and M_2/GDP are logged. The Equity-to-Debt ratio is calculated as the sum of Foreign Direct Investment (FDI) and Portfolio equity liabilities divided by total external debt liabilities, following Milesi-Ferretti 2026 data.

A.2 Detailed Tables of Preliminary Analysis

Table 16: Principal Component Analysis (PCA) Validation

Index and Variables	**Loading**	**Eigenvalue**	**Var. %**	**KMO**
Physical Access Sub-Index		1.649	82.33%	0.500
Commercial Bank Branches	0.707			
ATMs	0.707			
Bartlett's test p-value: 0.000				
Digital Access Sub-Index		3.961	65.91%	0.780
Credit card	0.413			
Debit card	0.402			
Own a credit card	0.399			
Own a debit card	0.455			
Deposit accounts	0.329			
Mobile/Internet banking transactions	0.440			
Bartlett's test p-value: 0.000				
Financial Depth Index		1.822	60.65%	0.591
Stock market capitalization	0.607			
Private credit to GDP	0.640			
Derivatives intensity	0.472			
Bartlett's test p-value: 0.000				
Financial Infrastructure Index		2.436	60.81%	0.667
ICT intensity	0.256			
Internet usage (% population)	0.553			
Physical Access Sub-Index	0.519			
Digital Access Sub-Index	0.599			
Bartlett's test p-value: 0.000				
Financial Openness Index		1.960	97.82%	0.500
De Facto Openness	0.707			
Equity Openness	0.707			
Bartlett's test p-value: 0.000				

Source: Authors' Calculations

Table 17: Multicollinearity Diagnostics: Variance Inflation Factor (VIF)

Variable	VIF
Financial Infrastructure Index	2.006
Financial Depth Index	2.104
Financial Openness Index	2.716
$\ln RGDP$	1.701
$\Delta \ln RGDP$	1.097
Inflation	1.157
Exchange Rate Volatility (centered)	1.169
Startup Deal Intensity	1.321
Regime (Float = 1)	1.269

Source: Authors' calculations

Notes: A constant was included in the estimation but is omitted from the table for brevity

Table 18: Correlation Matrix of Key Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Startup Depth	1.000									
(2) F.Infrastructure	0.336	1.000								
(3) F.Depth	0.223	0.393	1.000							
(4) F.Openness	0.161	0.512	0.636	1.000						
(5) Volatility	0.098	-0.334	-0.236	-0.226	1.000					
(6) Regime (Float=1)	0.203	0.326	0.358	0.266	-0.076	1.000				
(7) $\ln RGDP$	0.111	0.138	0.064	-0.287	-0.101	0.207	1.000			
(8) $\Delta \ln RGDP$	-0.115	-0.260	-0.120	-0.218	0.111	-0.074	-0.013	1.000		
(9) Inflation	0.077	0.051	-0.269	-0.158	0.072	-0.069	0.146	-0.085	1.000	
(10) Startup Deal Intensity	0.605	0.326	0.087	0.204	-0.021	0.101	-0.289	-0.055	-0.018	1.000

Source: Authors' calculations.

A.3 Matrix of Control Variable Layout across DML-LP

Table 19: **Matrix of Control Variable Layouts across DML-LP**

	Policy to Mediator			**Mediator to Outcome**			**Direct Effect**
Control Variable	**Depth**	**Infra.**	**Open**	**Depth**	**Infra.**	**Open**	**Regime**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline Macroeconomic Controls							
Real GDP Growth	✓	✓	✓	✓	✓	✓	✓
Inflation Rate	✓	✓	✓	✓	✓	✓	✓
Real Interest Rate	✓	✓	✓	✓	✓	✓	✓
Log GDP per Capita	✓	✓	✓	✓	✓	✓	✓
Panel B: Alternate Channel Financial Indices							
Financial Depth	–	✓	✓	–	✓	✓	–
Financial Infrastructure	✓	–	✓	✓	–	✓	–
Financial Openness	✓	✓	–	✓	✓	–	–
Panel C: Monetary and Institutional Demographics							
Broad Money Supply (% of GDP)	–	–	–	–	–	–	✓
Urbanization Rate	✓	✓	✓	✓	✓	✓	✓

Notes: Columns 1 to 3 show the policy-to-mediator specifications, columns 4 to 6 indicate the mediator-to-outcome channels, and column 7 tracks the direct treatment effect. Checkmarks (✓) show the active inclusion of the covariate array, while markers (−) indicate deliberate exclusions implemented to avoid multi-collinearity or post-treatment bias. Furthermore, we incorporate a Hybrid-Mundlak configuration containing pre-treatment lags, cross-sectional country means, and continuous country-specific time trends within the first stage nuisance equations.

A.4 Robustness Analysis using Placebo Tests

Table 20: Symmetric DML-LP Estimates of Regime Shocks on Startup Depth

Horizon (h)	**Coefficient** (β_h)	**Std. Error**	p**-value**	**95% Conf. Interval**	
Placebo Domain					
−2	0.841*	0.439	0.063	−0.048	1.730
−1	0.741*	0.436	0.097	−0.140	1.623
Impact Domain					
0	0.778*	0.434	0.081	−0.099	1.655
1	0.695	0.472	0.149	−0.260	1.650
2	0.884**	0.417	0.041	0.039	1.728
3	0.919**	0.444	0.045	0.021	1.818

Notes: Standard errors clustered at the country level (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models utilize the Hybrid-Mundlak controls in the first-stage nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations

Table 21: Asymmetric DML-LP Estimates of Regime Shocks on Financial Infrastructure

	Unexpected Liberalization (β_h^+)			**Unexpected Stabilization** (β_h^-)		
Horizon (h)	**Coef.**	**Std. Err.**	p**-value**	**Coef.**	**Std. Err.**	p**-value**
Placebo Domain						
-2	5.270	3.158	0.103	-5.978	4.590	0.200
-1	5.237	3.128	0.102	-5.246	4.401	0.240
Impact Domain						
0	5.007*	2.918	0.094	-4.119	4.209	0.334
1	5.786*	2.947	0.057	-3.178	4.481	0.482
2	6.555**	2.842	0.026	-3.109	4.400	0.484
3	7.779**	3.029	0.014	-3.001	4.503	0.509

Notes: Standard errors clustered at the country level (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models utilize the Hybrid-Mundlak controls in the first-stage nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations

A.5 Robustness Analysis Excluding Data imputation

Table 22. Exchange Rate Regimes on Startup Depth and Financial Indices Excluding Data imputation

Variables	(1) **Startup Depth**	(2) **Fin. Depth**	(3) **Fin. Openness**	(4) **Fin. Infra.**
Regime (Floating = 1)	1.1122***	17.0897***	7.0582**	2.7524
	(0.388)	(4.391)	(3.060)	(2.179)
ER Volatility (Centered)	0.1712	−1.9699	0.0933	−1.6256**
	(0.158)	(1.399)	(0.899)	(0.644)
Regime × Volatility	−0.1103	2.0272	0.4735	1.6521***
	(0.078)	(1.677)	(0.965)	(0.594)
Δ ln Real GDP	−1.2694	−44.9213**	−28.0058***	−4.6252
	(3.644)	(21.698)	(9.499)	(11.703)
Inflation	0.0035	0.0176	0.0411	0.0048
	(0.016)	(0.110)	(0.045)	(0.063)
Mundlak Means				
Mean ER Volatility	−0.0104	−0.6047	−1.1070	−0.6327
	(0.160)	(1.348)	(0.719)	(0.455)
Mean Δ ln Real GDP	12.8525	−84.9294	−352.9942***	−229.9204***
	(15.169)	(172.315)	(130.085)	(84.043)
Mean Inflation	0.0188	−1.4576***	−0.6913***	0.2446
	(0.033)	(0.357)	(0.227)	(0.259)
Intercept	1.9202***	53.0213***	42.7716***	32.1586***
	(0.654)	(8.132)	(5.488)	(3.781)
Time Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE (Country)	Yes	Yes	Yes	Yes
R squared	0.406	0.439	0.335	0.473
Observations	600	600	600	600

Notes. Standard errors in parentheses are clustered at the country level. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' calculations.

Table 23. NARDL estimates: Asymmetric effects on startup depth Excluding Data imputation

Variable	(1) Fin. Infra.	(2) Fin. Depth	(3) Fin. Openness
Adjustment Dynamics			
Startup Depth (t.1)	-1.0976***	-1.0713***	-1.0594***
	(0.109)	(0.098)	(0.080)
Long Run Dynamics			
Pillar (+) (t.1)	0.1649***	0.1514***	0.2424***
	(0.055)	(0.032)	(0.041)
Pillar (-) (t.1)	-0.0441	-0.0399	0.0956
	(0.102)	(0.046)	(0.089)
Short Run Dynamics			
Δ Pillar (+)	0.0077	0.0295	0.0636
	(0.083)	(0.053)	(0.090)
Δ Pillar (-)	-0.2637**	-0.0443	0.0155
	(0.112)	(0.046)	(0.078)
Controls and Intercept			
ln Real GDP	4.1384**	2.9876***	4.3731***
	(1.818)	(1.087)	(1.236)
Inflation	0.0041	-0.0153*	-0.0078
	(0.008)	(0.009)	(0.008)
Intercept	-107.7779**	-76.1801***	-112.9796***
	(48.691)	(29.242)	(33.322)
Diagnostics			
Wald Asymmetry (χ^2)	7.9288***	26.0352***	2.9742*
	[p=0.0048]	[p=0.0000]	[p=0.0846]
Mundlak Wald Stat	84.16***	83.25***	120.52***
	[p=0.0000]	[p=0.0000]	[p=0.0000]
R squared	0.578	0.607	0.605

Notes. Standard errors in parentheses are clustered at the country level. P-values of diagnostic tests are in square brackets. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' calculations

Table 24. Baseline Direct Impact of Transitioning to the Floating on Startup Depth Excluding Data Imputation

Estimator	Horizon 0	Horizon 1	Horizon 2	Horizon 3
Random Forest	0.9771**	1.0594**	1.2699***	1.1972***
	(0.4383)	(0.4171)	(0.3787)	(0.3713)
Lasso	0.8751**	0.8205*	0.9283**	0.9124**
	(0.3912)	(0.4105)	(0.3903)	(0.3807)
XGBoost	0.6541	0.6035	0.7599	0.8077
	(0.5270)	(0.5578)	(0.5435)	(0.5118)

Notes: Local Projections Coefficients. Standard errors clustered at the country level (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models utilize the Hybrid-Mundlak configuration in the first-stage nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations

Table 25. Asymmetric Response of Policy-to-Mediators Excluding Data Imputation

Shock Domain / Estimator	Horizon 0	Horizon 1	Horizon 2	Horizon 3
PANEL A: Financial Depth Channel				
Random Forest				
Float Shock (β_h^+)	22.0457*	22.0678*	22.8521*	31.8125***
	(11.3368)	(11.6744)	(11.3489)	(10.8397)
Peg Defense (β_h^-)	13.1384*	15.1417**	14.5281**	18.1296*
	(6.7101)	(6.8887)	(6.9148)	(9.1463)
Lasso				
Float Shock (β_h^+)	30.8645**	33.9239***	37.0075***	41.2238**
	(11.6447)	(11.6028)	(11.7803)	(16.2458)
Peg Defense (β_h^-)	11.3760	8.8253	6.8792	-0.9317
	(7.3659)	(7.4958)	(7.3881)	(7.0680)
XGBoost				
Float Shock (β_h^+)	33.0126**	36.1886**	33.7289**	37.6890**
	(12.3557)	(14.1941)	(14.2891)	(15.3038)
Peg Defense (β_h^-)	11.2267	10.8859	12.8490*	13.1525
	(6.9712)	(7.2130)	(7.3270)	(8.7549)
PANEL B: Financial Infrastructure Channel				
Random Forest				
Float Shock (β_h^+)	2.7447	2.3507	2.2369	1.4123
	(3.2778)	(2.7015)	(2.4414)	(2.5090)
Peg Defense (β_h^-)	-6.8152	-5.3153	-4.4925	-4.1955
	(4.6767)	(4.2601)	(4.7716)	(4.9034)
Lasso				
Float Shock (β_h^+)	7.3449	6.9201	7.2815	6.9930
	(5.6757)	(5.9191)	(5.7393)	(5.6747)
Peg Defense (β_h^-)	-2.7082	1.0358	1.2038	1.1033
	(6.5565)	(9.3104)	(9.4720)	(9.7183)
XGBoost				
Float Shock (β_h^+)	-0.1525	0.4859	-0.6862	-1.0044
	(3.1702)	(2.7239)	(2.6105)	(2.7278)
Peg Defense (β_h^-)	-4.5280	-4.9163	-3.6995	-2.5440
	(5.8395)	(5.2160)	(5.8544)	(6.2447)
PANEL C: Financial Openness Channel				
Random Forest				
Float Shock (β_h^+)	-3.7517	-2.7042	-3.1526	-5.5893
	(5.9078)	(5.6201)	(5.6398)	(6.0623)
Peg Defense (β_h^-)	1.6027	0.6289	1.2827	4.4121
	(7.3738)	(7.3993)	(7.5288)	(9.2300)
Lasso				
Float Shock (β_h^+)	-10.0657	-10.5771	-10.2540	-13.4836
	(18.5885)	(18.9179)	(19.2778)	(23.0904)
Peg Defense (β_h^-)	6.7892	6.9389	6.4991	9.8071
	(11.9933)	(12.0973)	(12.0158)	(15.6241)
XGBoost				
Float Shock (β_h^+)	-5.4829	-6.6443	-6.9108	-8.8828
	(9.5082)	(9.7836)	(9.7495)	(10.6055)
Peg Defense (β_h^-)	4.3072	3.6515	3.7278	6.8106
	(9.6425)	(9.6727)	(9.6895)	(11.4626)

Notes: Local Projections Coefficients. Standard errors clustered at the country level (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models utilize the Hybrid-Mundlak configuration in the first-stage nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations

Table 26. Asymmetric Response of Mediators-to-Outcome Excluding Data Imputation

Mediator Shock / Estimator	Horizon 0	Horizon 1	Horizon 2	Horizon 3
PANEL A: Financial Infrastructure Channel				
Random Forest				
Expansion (β^+)	0.0621**	0.0626*	0.0640*	0.0685*
	(0.0298)	(0.0354)	(0.0350)	(0.0349)
Contraction (β^-)	0.0157	0.0157	0.0147	0.0296
	(0.0295)	(0.0334)	(0.0300)	(0.0292)
Lasso				
Expansion (β^+)	0.0073	-0.0515	-0.0472	0.0294
	(0.0255)	(0.0324)	(0.0304)	(0.0238)
Contraction (β^-)	0.1473***	0.1662***	0.1147**	0.1640
	(0.0517)	(0.0548)	(0.0512)	(0.0979)
XGBoost				
Expansion (β^+)	0.0758*	0.0922**	0.0666	0.0845*
	(0.0378)	(0.0443)	(0.0481)	(0.0435)
Contraction (β^-)	0.0274	0.0138	0.0141	0.0310
	(0.0498)	(0.0443)	(0.0433)	(0.0510)
PANEL B: Financial Depth Channel				
Random Forest				
Expansion (β^+)	0.0381*	0.0349*	0.0298	0.0354*
	(0.0197)	(0.0200)	(0.0200)	(0.0192)
Contraction (β^-)	0.0207	0.0341	0.0428	0.0424*
	(0.0238)	(0.0269)	(0.0264)	(0.0243)
Lasso				
Expansion (β^+)	0.0397**	0.0365**	0.0338**	0.0290*
	(0.0176)	(0.0171)	(0.0163)	(0.0154)
Contraction (β^-)	0.0294	0.0312	0.0349	0.0343
	(0.0338)	(0.0369)	(0.0354)	(0.0266)
XGBoost				
Expansion (β^+)	0.0400**	0.0305*	0.0266	0.0252
	(0.0164)	(0.0155)	(0.0158)	(0.0161)
Contraction (β^-)	0.0622*	0.0797**	0.0831**	0.0775**
	(0.0332)	(0.0374)	(0.0378)	(0.0314)
PANEL C: Financial Openness Channel				
Random Forest				
Expansion (β^+)	-0.0097	-0.0022	0.0053	-0.0005
	(0.0127)	(0.0128)	(0.0132)	(0.0127)
Contraction (β^-)	-0.0666	-0.0799*	-0.0884*	-0.0601*
	(0.0395)	(0.0447)	(0.0453)	(0.0354)
Lasso				
Expansion (β^+)	-0.0060	-0.0039	-0.0009	-0.0031
	(0.0159)	(0.0138)	(0.0121)	(0.0136)
Contraction (β^-)	-0.0528**	-0.0500*	-0.0397	-0.0482*
	(0.0242)	(0.0250)	(0.0253)	(0.0257)
XGBoost				
Expansion (β^+)	-0.0169	-0.0148	-0.0118	-0.0132
	(0.0169)	(0.0208)	(0.0214)	(0.0158)
Contraction (β^-)	-0.0258	-0.0349	-0.0383	-0.0220
	(0.0646)	(0.0708)	(0.0698)	(0.0699)

Notes: Local Projections Coefficients. Standard errors clustered at the country level (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models utilize the Hybrid-Mundlak controls in the first-stage nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations

A.6 Startup Deal Intensity Alternative

Table 27. Hybrid Mundlak Framework: Exchange Rate Regimes on Startup Deal Intensity

Variable	**Coefficient**	**Standard Error**
Intercept	0.052	(0.046)
Main Determinants		
Regime (Floating = 1)	0.028	(0.031)
ER Volatility (Centered)	0.003	(0.010)
Regime × ER Volatility	−0.009	(0.010)
Δ ln Real GDP	−0.194	(0.234)
Inflation	$2.615e-05$	(0.000)
Mundlak Time Invariant Terms		
Mean ER Volatility	0.001	(0.008)
Mean Δ ln Real GDP	−1.04	(1.084)
Mean Inflation	−0.002**	(0.001)
R squared	0.219	
Observations	600	
Time FE	Yes	
Clustered SE (Country)	Yes	

Notes. Standard errors in parentheses are clustered at the country level. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. Source: Authors' calculations.

Table 28. NARDL Estimates: Financial Pillars and Startup Deal Intensity

Variable	(1) **F.Infrastructure**	(2) **F.Depth**	(3) **F.Openness**
Intercept	−1.341***	−1.636***	−0.643***
	(1.269)	(0.769)	(0.833)
Long Run Dynamics			
Startup Deal Intensity ($t-1$)	−0.451***	−0.479***	−0.527***
	(0.104)	(0.115)	(0.125)
Financial Pillar (+) ($t-1$)	0.001*	0.002***	0.004**
	(0.001)	(0.001)	(0.015)
Financial Pillar (-) ($t-1$)	0.000	0.001	−0.000
	(0.001)	(0.001)	(0.945)
Short Run Dynamics			
Δ Financial Pillar (+)	0.004**	0.002	0.010***
	(0.002)	(0.000)	(0.004)
Δ Financial Pillar (-)	0.000	−0.001	−0.008***
	(0.000)	(0.001)	(0.245)
Control Variables			
log Real GDP	0.05*	0.062***	0.024***
	(0.05)	(0.029)	(0.031)
Inflation	−0.000	−0.000	−0.000***
	(0.000)	(0.000)	(0.000)
Diagnostics			
R squared	0.27	0.27	0.28
Wald Test (Asymmetry)	1.12	0.48	1.127
	[p=0.289]	[p=0.486]	[p=0.288]
Mundlak Wald Test	31.11***	34.55***	34.65***
	[p=0.000]	[p=0.000]	[p=0.000]
Country FE	Yes	Yes	Yes
Clustered SE (Country)	Yes	Yes	Yes

Notes. Standard errors in parentheses are clustered at the country level. P-values of diagnostic tests are in square brackets. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. Country fixed effects incorporated in all models via within transformation. Source: Authors' calculations

Table 29. Direct Policy Effect Using Startup Deal Intensity as an Alternative Dependent Variable

Estimator	**Horizon 0**	**Horizon 1**	**Horizon 2**	**Horizon 3**
Random Forest	-0.0001	-0.0034	0.0045	0.0143
	(0.0348)	(0.0399)	(0.0428)	(0.0454)
Lasso	0.0283	0.0286	0.0338	0.0426
	(0.0360)	(0.0375)	(0.0396)	(0.0408)
XGBoost	0.0063	0.0101	0.0187	0.0267
	(0.0362)	(0.0374)	(0.0367)	(0.0418)

Notes: Local Projections Coefficients. Standard errors clustered at the country level (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models utilize the Hybrid-Mundlak controls in the first-stage nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations

Table 30. Transmission Mechanisms Using Startup Deal Intensity as an Alternative Dependent Variable

Mediator Shock / Estimator	Horizon 0	Horizon 1	Horizon 2	Horizon 3
PANEL A: Financial Infrastructure Channel				
Random Forest				
Expansion (β^+)	0.0112**	0.0123**	0.0125**	0.0125**
	(0.0050)	(0.0052)	(0.0054)	(0.0055)
Contraction (β^-)	0.0032	0.0042*	0.0053**	0.0072**
	(0.0021)	(0.0023)	(0.0026)	(0.0031)
Lasso				
Expansion (β^+)	0.0010	0.0011	0.0011	0.0012
	(0.0022)	(0.0023)	(0.0024)	(0.0024)
Contraction (β^-)	0.0036***	0.0042***	0.0050***	0.0054***
	(0.0012)	(0.0014)	(0.0016)	(0.0018)
XGBoost				
Expansion (β^+)	0.0098***	0.0093**	0.0103***	0.0104***
	(0.0035)	(0.0035)	(0.0038)	(0.0038)
Contraction (β^-)	0.0036	0.0051	0.0060	0.0062
	(0.0027)	(0.0031)	(0.0038)	(0.0037)
PANEL B: Financial Depth Channel				
Random Forest				
Expansion (β^+)	-0.0007	-0.0013	-0.0015	-0.0017
	(0.0014)	(0.0016)	(0.0016)	(0.0018)
Contraction (β^-)	0.0028	0.0028	0.0032	0.0036
	(0.0018)	(0.0018)	(0.0019)	(0.0023)
Lasso				
Expansion (β^+)	-0.0018*	-0.0019*	-0.0020*	-0.0022*
	(0.0010)	(0.0011)	(0.0011)	(0.0012)
Contraction (β^-)	0.0001	0.0002	0.0003	0.0004
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
XGBoost				
Expansion (β^+)	-0.0016	-0.0016	-0.0021	-0.0018
	(0.0018)	(0.0019)	(0.0019)	(0.0020)
Contraction (β^-)	0.0029	0.0024	0.0032	0.0032
	(0.0025)	(0.0026)	(0.0026)	(0.0026)
PANEL C: Financial Openness Channel				
Random Forest				
Expansion (β^+)	0.0017**	0.0017**	0.0017*	0.0016
	(0.0008)	(0.0008)	(0.0009)	(0.0010)
Contraction (β^-)	0.0028	0.0028	0.0029	0.0034
	(0.0021)	(0.0020)	(0.0020)	(0.0025)
Lasso				
Expansion (β^+)	0.0002	0.0002	0.0000	0.0000
	(0.0009)	(0.0009)	(0.0009)	(0.0010)
Contraction (β^-)	0.0016	0.0018	0.0019	0.0017
	(0.0017)	(0.0018)	(0.0019)	(0.0018)
XGBoost				
Expansion (β^+)	0.0016**	0.0019**	0.0017**	0.0017*
	(0.0008)	(0.0009)	(0.0008)	(0.0010)
Contraction (β^-)	0.0024	0.0026	0.0031	0.0030
	(0.0028)	(0.0030)	(0.0032)	(0.0033)

Notes: Local Projections Coefficients. Standard errors clustered at the country level (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models utilize the Hybrid-Mundlak controls in the first-stage nuisance equation. Constant included in each second-stage local projections. Source: Authors' calculations