

Making Suptech Work: Evidence on the Key Drivers of Adoption

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Abstract This paper examines the institutional drivers of adopting supervisory technology (suptech) by financial authorities worldwide. Using survey data from 112 financial authorities across 97 countries from the State of SupTech Report, we analyse how organisational characteristics and strategic frameworks shape the adoption of suptech initiatives. The analysis employs a two-stage hurdle model to track adoption from proof of concept to prototype, and finally to full deployment. We find that authorities with institution-wide strategies for digital transformation, data governance, and suptech deployment use, on average, about 20 additional applications and face fewer design and implementation challenges. Furthermore, while an authority’s size and institutional mandate are significant factors in initiating advanced projects, the establishment of a dedicated suptech unit is the most critical factor in increasing the number of deployed applications. Finally, we find that public cloud adoption is associated with a higher probability of implementing AI tools, while reliance on in-house development is strongly associated with early-stage AI experimentation.

JEL Codes: G28, O33, C25

Keywords: suptech, financial supervision, technology adoption, financial authorities

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1 Introduction

Financial supervision plays a central role in mitigating market failures inherent to financial intermediation, including asymmetric information, moral hazard, and agency conflicts (Pigou, 1932; Akerlof, 1970; Jensen & Meckling, 1976; Stiglitz & Weiss, 1981). By setting prudential standards and enforcing compliance, supervisory authorities reduce the social costs of excessive risk-taking and limit the abuse of market power. In doing so, supervisors act as centralized monitors, producing and processing information that would be prohibitively costly for dispersed market participants to generate individually (Llewellyn, 1999). The effectiveness of supervision therefore depends fundamentally on the cost, precision, and timeliness of information production.

The rapid digitalisation of financial markets has profoundly altered this supervisory production function. Financial institutions now generate vast quantities of granular, high-frequency data, while new risk domains, such as cyber risk, digital assets, and climate-related exposures, require increasingly sophisticated analytical capabilities. Traditional supervisory tools, designed for periodic reporting and manual review, struggle to process these data flows efficiently. As the marginal cost of private financial innovation declines, the relative technological capacity of supervisors becomes a critical determinant of regulatory effectiveness.

This is where supervisory technology (suptech) plays a crucial role. Suptech refers to financial supervisors' use of advanced technologies, such as artificial intelligence (AI), including machine learning (ML), and cloud computing, to improve how they monitor the market, collect data, and detect risks. After the global financial crisis and the rise of fintech, there is a greater need for agile, data-driven, and effective supervision. Suptech helps supervisors identify emerging risks, reduce information asymmetries, and strengthen compliance. However, suptech adoption has been slow and uneven across jurisdictions and institutional types. While many financial authorities have initiated pilot projects, far fewer have integrated advanced technologies into routine supervisory processes. This heterogeneity raises a fundamental policymakers' question on financial intermediation: What determines the technological capacity of financial supervision? More specifically, which institutional, technological, and organizational mechanisms drive the adoption of suptech by financial authorities?

This paper provides a seminal empirical analysis of the determinants of suptech adoption across financial supervisory authorities worldwide, contributing to this emerging field of research. Given that research involving supervisory data often faces challenges related to confidentiality and limited access, these issues are particularly pronounced in suptech due to the technological aspects, as financial authorities tend to be reluctant to share results from experimental projects. We are closing this data gap by using the 2024 State of SupTech dataset, which was collected by the Cambridge SupTech Lab

in collaboration with Digital Transformation Solutions (DTS). This data set integrates detailed information on suptech deployment, along with organizational characteristics, governance structures, and jurisdiction-level features, providing a global overview of the authorities involved. We model suptech adoption based on two-stage estimate hurdle models that distinguish between the initiation of suptech activity and the intensity of deployment conditional on adoption. Our analysis focuses on three main determinates: organizational capacity (e.g., the presence of dedicated suptech units), strategic framework that includes digital transformation, data governance, and suptech strategies, and enabling infrastructure such as cloud computing.

Our results reveal substantial complementarities across strategic and technological dimensions. Financial authorities that implement integrated digital transformation, data governance, and suptech strategies deploy significantly more supervisory technologies than those that adopt isolated initiatives. In economic terms, institutions adopting all three strategies use, on average, approximately 20 more suptech tools than those without such frameworks. The presence of a dedicated suptech unit is strongly associated with higher deployment intensity, suggesting that organizational specialization translates strategic intent into operational capacity. Cloud infrastructure emerges as a key enabling technology, particularly for AI-based tools, consistent with the view that scalable computational capacity reduces the marginal cost of advanced analytics. At the same time, adoption remains limited in emerging supervisory domains, such as climate risk, cyber risk, and digital assets, highlighting areas where technological upgrading lags behind evolving risk exposures.

This paper contributes to the financial supervision literature by providing seminal evidence and a comprehensive overview of the current state of global suptech (Eisenbach et al., 2022; Degryse et al., 2025; Brynjolfsson & Kazinnik, 2025). It identifies key factors that can help financial authorities advance the development of new supervisory tools and transform their organizations to enhance supervisory capacity, providing crucial insights for policymakers. As foundational work offering an overview of the suptech phenomenon, it provides a basis for future theoretical and empirical research (Goldstein, 2025). In particular, subsequent studies should examine the micro-level adoption of individual suptech tools to assess their efficiency and effectiveness, as well as their impact on financial market risk-taking.

The remainder of the paper is structured as follows. Section 2 links our paper with three strands of the literature: financial supervision, technology adoption, and institutional capacity. Section 3 outlines an analytical framework for suptech adoption, describing the stages of the suptech lifecycle and the main drivers of technological development. Section 4 describes the data collection process and the dataset. Section 5 details the construction of the primary variables and provides some descriptive analysis. Section 6 outlines the empirical strategy, based on hurdle models. Section 7 presents the main results, and

Section 8 concludes by discussing policy implications and avenues for future research.

2 Links with existing policy and academic literature

This section examines how financial supervision is evolving through technology from an economic and policy perspective. Financial supervision is essential for addressing market failures that create risks related to prudential conduct within the financial system. These issues include externalities, asymmetric information, moral hazard, and principal-agent problems (Pigou, 1932; Akerlof, 1970; Stiglitz & Weiss, 1981; Jensen & Meckling, 1976). If left unaddressed, these distortions can undermine market integrity and stability. Financial regulations establish rules of behaviour to mitigate these risks and define acceptable outcomes for firms. Supervision complements regulation by ensuring that firms comply with these rules and intervening when their actions threaten regulatory objectives. This oversight, performed by competent authorities, helps resolve collective action problems and reinforces the financial system’s stability. Llewellyn (1999) describes this as consumers delegating monitoring responsibilities to these authorities to reap the benefits of expertise and economies of scale. Otherwise, consumers would find monitoring of financial firms costly and would likely create a ‘free rider’ problem.

The academic literature on financial supervision in the banking sector is quite limited due to data availability and confidentiality issues. This literature serves as our reference point for studying the suptech phenomenon and its impact on the organisational structure of financial authorities. One strand addresses the determinants of supervisory practices, focusing on the internal information flows that shape monitoring and reporting activities, which are fundamental to supervisory actions such as enforcement. Another strand examines the effects of enforcement actions on market risk-taking behaviour. Ultimately, the focus will shift to technology’s impact on supervisory practices.

Supervisors’ will and ability to act are essential to effective financial supervision (Adrian et al, 2023). Clarity of mandate, strong operational independence and accountability, adequate resources, and legal protection for supervisors enable this will and ability to act. These factors are captured in the first two Core Principles for Effective Banking Supervision developed by the Basel Committee on Banking Supervision (BCBS) and the Insurance Core Principles developed by the International Association of Insurance Supervisors (IAIS). These principles serve as minimum standards for banking and insurance supervision. Studies show that the supervisory architecture and governance, which determine independence and accountability, influence the effectiveness of financial supervision (Masciandaro et al., 2008; Dincer & Eichengreen, 2012).

The literature shows the impact of enforcement actions on banks’ risk-taking. Stringent supervision through enforcement action and direct on-site inspections reduces banks’ fragility and risk exposure (Bassett et al., 2015). Delis et al. (2019) and Deli et al.

(2011, 2016) show that enforcement actions against banks can strengthen their financial stability by reducing risk-weighted assets and nonperforming loan ratios. While there is no observed increase in the level of regulatory capital, the results suggest that enforcement actions improve banks' overall health. Even supervisory scrutiny, actions that fall short of enforcement actions, reduces bank risk-taking (Degryse et al., 2025).

Financial supervisors must have a basis for conducting enforcement actions or introducing preventive measures. Supervisors' monitoring activities provide that basis, and their effectiveness depends on how authorities deploy resources, particularly the skills, processes, technologies, techniques, and tools available to them. Eisenbach et al. (2022) demonstrate that the allocation of supervisory resources scales almost proportionally with bank size. They discuss the potential benefits of technological economies of scale and scope in supervision. The deployment of supervisory resources should enable monitoring activities to provide timely and reliable information about financial institutions' condition and risk profile. Traditionally, such information was obtained from regulatory reports, public disclosures, and on-site examinations. For instance, Hirtle and Lopez (1999) show that the frequency of on-site examinations should depend on how quickly private supervisory information erodes in value. Now, supervisors also use alternative sources of information, such as market data, news articles, and social media (Alonso-Robisco et al., 2025).

Financial authorities are constantly improving their monitoring activities to enhance the quality and timeliness of information and improve the insights available to them. This involves continuously developing supervisory staff capacity (Crisanto et al., 2022), using new technologies to enhance regulatory reporting and data collection (Crisanto et al., 2020), and upgrading IT infrastructure and data architecture (di Castri et al., 2019). Authorities have also explored, developed, and deployed new technologies to benefit from advances in data analytics (Coelho et al., 2019; Beerman et al., 2021; Garcia Ocampo et al., 2022). For example, supervisors increasingly use ML to analyse large volumes of structured and unstructured data. In this context, Brynjolfsson & Kazinnik (2025) propose a comprehensive framework to understand how AI, especially large language models (LLMs), can enhance supervisory authorities' strategic and operational capabilities. AI tools can transform supervisory workflows by improving data collection, speeding up signal extraction, and enabling more accurate and timely risk assessments. Empirical analysis indicates that these tools could enhance a significant portion of supervisory tasks, particularly those involving analytical and decision-making functions. However, this transformation requires investment in data infrastructure, workforce upskilling, and robust governance mechanisms to manage the risks of integrating AI into supervisory processes.

The term "suptech", short for supervisory technology, was coined by the Monetary Authority of Singapore in 2017 to describe its strategic adoption of financial technology. A dual objective drove the initiative: to enhance the effectiveness of its supervisory

processes while simultaneously reducing the compliance burden imposed on regulated firms (Menon, 2017). Broeders and Prenio (2018) later formalised the term with the now widely used definition of suptech: supervisory authorities’ use of innovative technologies to support supervision. The emphasis on innovative technologies is crucial, as it positions suptech as the supervisory equivalent of fintech in the private sector. This distinguishes it from the more “legacy-based” systems supervisors have long used, and instead refers specifically to modern tools involving AI/ML and big data (di Castri et al., 2019). Supervisory authorities worldwide are actively pursuing suptech initiatives to address common supervision challenges, such as the growing complexity of risks and limited supervisory capacity (Prenio et al., 2024). Global adoption of suptech is expanding rapidly, with 171 financial authorities across 107 countries reporting live implementations by 2024, up from just 54 agencies in 2022 (Barasa et al., 2025). However, only a few authorities have reported that suptech has become integral to their supervisory processes (Prenio, 2024). Several factors affect the success of suptech initiatives. Strong board and senior management support is key, as this shapes resource allocation. Support from top management also enables the development of institution-wide strategies for suptech adoption and the governance arrangements needed to implement them.

3 An analytical framework for Suptech adoption

Suptech adoption has been heterogeneous across countries and different types of organisations. To study the factors and mechanisms behind the adoption of suptech, we take a micro approach, looking at the lifecycle of technological development. This perspective allows for a more granular understanding of how institutional dynamics, resource availability, and strategic policy frameworks affect the trajectory of suptech implementation.

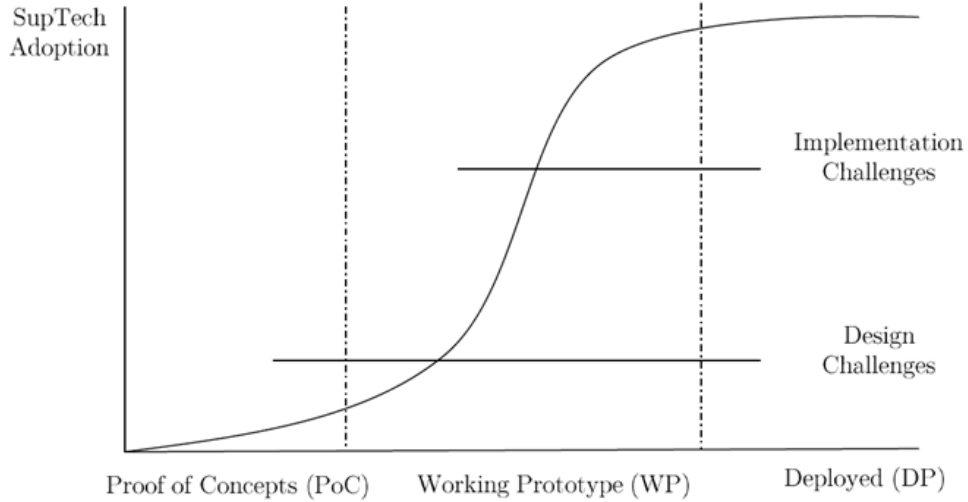
Figure 1 illustrates financial authorities’ lifecycle of suptech adoption, mapped along a typical technology diffusion curve within the organisation. It distinguishes three levels of suptech activity: Proof of Concept (PoC), which explores the technical feasibility of a proposed tool or application; Working Prototype (WP), where a functional model demonstrates a tool’s design, features, and user interface; and Deployed Solutions (DP), indicating fully implemented and operational tools/applications within supervisory processes. The figure highlights how design challenges dominate the early stages, while implementation challenges become more significant as tools move toward full deployment.

Suptech adoption typically begins at the PoC stage, where authorities face feasibility challenges such as technological constraints, data availability, legal constraints, and internal capacity limitations. PoCs are primarily used to identify potential application areas, assess possible efficiency gains within organisational processes, and evaluate the resources needed to scale solutions. As solutions evolve from WPs to DPs, adoption accelerates significantly. However, implementation challenges, such as data quality, shortages of personnel with

adequate technical skills, and budget constraints, become more prominent and often represent the primary barriers to suptech adoption (Barasa et al., 2024).¹

Several regulatory bodies are transitioning from isolated pilot projects to comprehensive strategies that provide a unified vision and institutional coherence. By embedding digital initiatives within broader governance structures, financial authorities can enhance operational consistency, support workforce development, and ensure technological alignment to overcome challenges such as cultural inertia, siloed operations, fragmented data systems, and limited technical capacity. Digital transformation, data governance, and suptech strategies thus represent three distinct yet interdependent pillars of modern supervisory practice. Each contributes uniquely to the development of effective, technology-enabled oversight.

Figure 1: Suptech lifecycle



As described in Barasa et al. (2024), the journey toward effective suptech adoption is built upon three distinct yet interdependent strategic pillars. First, an institution-wide digital transformation strategy provides a roadmap for modernising operations, infrastructure, and workforce capabilities, integrating technology, data, and human capital under a unified institutional vision. It often serves as an umbrella framework for suptech and data governance strategies, fostering agility and coherence in response to evolving market and technological conditions. Second, an institution-wide data governance strategy establishes protocols for data management, quality, security, and ethical use across all functions, supporting AI-readiness and suptech deployment through robust architecture and stewardship frameworks. Overseen by senior data leaders, the data governance

¹To analyse the mechanisms underlying the institutional factors that drive the adoption of suptech by financial authorities, we consider several dimensions: i) idiosyncratic characteristics (i.e., size and type of the financial authority, the country where they operate), ii) the adoption of strategic frameworks for enabling innovation, iii) organisational models for designing, developing, and deploying applications and iv) the presence of complementary technologies that help scale adoption.

strategy promotes interoperability and safeguards privacy and fairness. Third, a suptech strategy provides structured plans for harnessing new technologies to enhance supervisory efficiency and effectiveness. Prenio (2024) argues that a successful suptech strategy covering experimentation, development, and deployment-related issues is more likely to succeed. By outlining how tools will be rolled out, building user skills, and ensuring seamless integration with existing supervisory systems, these strategies can overcome common barriers to adoption.

The interaction among these strategic elements is synergistic: i) digital transformation removes technological, structural, and cultural barriers to innovation; ii) data governance ensures high-integrity inputs; and iii) suptech delivers measurable improvements, reinforcing the case for continued reform. Together, they form a reinforcing cycle that supports resilient, scalable, and future-ready supervisory innovation. Financial authorities may pursue different strategic approaches: a standalone suptech strategy with a clear roadmap for integrating advanced technologies into supervisory operations; embedding suptech within broader institutional strategies for data governance or digital transformation. A data governance strategy, for example, may focus on managing institutional data effectively while enabling advanced analytics for supervisory purposes. These strategies are not mutually exclusive but complementary, offering multiple viable pathways for financial authorities to support innovation and institutional development.

To translate high-level strategies into deployed applications, financial authorities tend to adopt an operational model for managing innovation. This model reflects organisational constraints and directly influences the management of resources, skills, and procurement. We focus on three approaches: A decentralised model is the most common, where individual business units develop solutions; this approach offers flexibility and domain-specific relevance but can limit scalability and lead to redundancies if not supported by proper suptech strategies (Beerman et al, 2021). A centralised hub model places ownership of all initiatives within a single unit (e.g., a dedicated suptech unit or IT unit) to ensure standardisation and alignment with institutional goals. A hybrid "hub-and-spoke" model balances central oversight with departmental expertise by allowing each supervision unit to experiment and develop suptech applications it needs, supported by the central hub.

Finally, we examine the role of cloud computing in deploying suptech tools, particularly AI-based ones. Cloud services offer the flexibility, scalability, and computing power required for real-time analytics, forecasting, and automated supervisory functions. Around one-third of financial authorities currently use hybrid and public cloud services, indicating that adoption remains cautious due to concerns about data privacy, cybersecurity, and data sovereignty (Barasa et al., 2024). Reluctance to change legacy IT infrastructures, fragmented data architectures, and bureaucratic constraints also impede the effective adoption of AI, even though cloud-based architectures - particularly data lakes and schema-on-read models - offer a promising path toward unified, real-time access to diverse

data sources across institutional silos. Despite these trade-offs, the growing need for scalable infrastructure is expected to accelerate cloud adoption as authorities strive to balance security, compliance, and performance while modernising supervisory, policy, and analytical functions (Araujo et al., 2025; Kazinnik & Brynjolfsson, 2025; Prenio, 2025).

4 Data, variables, and descriptive analysis

Data sources. The econometric analysis in this paper draws on anonymised data from the Cambridge SupTech Lab and DTS’s State of SupTech Survey 2024 ². This survey, typically completed by senior staff in financial authorities worldwide, is a comprehensive, multi-dimensional tool designed to provide a global overview of suptech adoption and implementation. The analysis is based on responses from 112 financial authorities across 97 countries and six continents, ensuring a diverse and globally representative sample. The participants include central banks, banking, insurance, securities, capital markets regulators, and other financial supervisory bodies. Around two-thirds of the respondents are from emerging markets and developing economies, ensuring all perspectives from regions often underrepresented in global discussions on financial supervision modernisation. The 56-question survey includes a mix of multiple-choice, matrix-style, and open-ended questions, many of which are conditional on earlier responses.

The survey was conducted in two parts. The first mandatory section collects essential data on the suptech landscape, including strategies or roadmaps for data governance, digital transformation, and suptech. It also explores the number and types of suptech applications, the organisational models supporting their development, and the challenges encountered during design and implementation. This section further identifies the supervisory areas where suptech is applied, such as AML, consumer protection, digital assets, and climate risk supervision, along with questions on the effectiveness of tools, funding sources, and the enabling technologies and data science methods used in supervisory processes. The optional second section allows respondents to provide more detailed insights into governance structures, data management practices, collaborative efforts, and strategic plans. It includes questions on the level of AI and generative AI adoption, ethical frameworks, Environmental, Social, and Governance (ESG) oversight, and challenges in using both structured and unstructured data. It also covers the agency’s internal capacity-building efforts, available skill sets, and collaboration with peer authorities. The two-tier approach of the survey enables us to capture the institutional characteristics of financial authorities, the extent of suptech adoption, and the maturity of tools across their

²The data used in this analysis were provided exclusively for research purposes in aggregated form, in accordance with the confidentiality terms established with State of SupTech Survey participants. No individual or institution-level responses were shared or disclosed, and all analyses were conducted in a manner that preserves the anonymity and integrity of participating authorities.

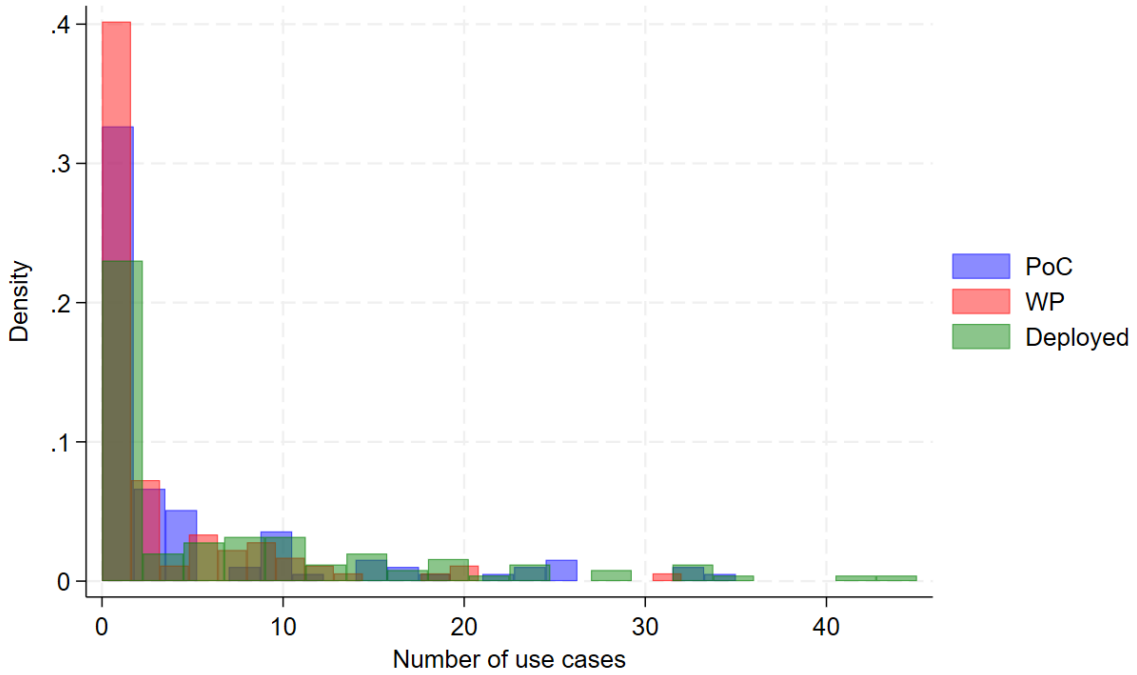
lifecycle.

To better understand the institutional conditions underpinning suptech activity, the survey includes questions on: (1) the existence of formally implemented strategies for data governance, digital transformation, or suptech; (2) the organisational model for innovation (i.e. decentralised, centralised, or hub-and-spoke); (3) the technological and data foundations (e.g. whether the authority has implemented cloud services); (4) reported challenges, including public procurement barriers, legal uncertainty, and internal skill shortages; and (5) collaboration with external providers such as vendors. The size of each authority was measured using scraped employment data from the official’s LinkedIn profile and cross-checked with institutional sources. Finally, this authority-level dataset was merged with IMF cross-country indicators on financial development, supervisory independence, and state capacity. We use two broad-based indices that Svirydzenka (2016) created for financial development, providing a more comprehensive measure than traditional indicators. In particular, we use different decomposition indices that capture the development of financial institutions and financial markets at a more granular level.³ Specifically, we consider measures for these decomposed indices, including depth, access, and efficiency. Merging the dataset with IMF indices reduces the sample to 112 financial authorities, as data for some smaller jurisdictions are unavailable in the IMF indices.

Variable description: To measure adoption, our main variables are counts of suptech use cases developed by each authority at three stages of the technological lifecycle: PoC, WP, and DP. This approach distinguishes between early-stage experimentation and full operational integration. The count variables are constructed from 104 predefined use cases (See Appendix, table A4) across 13 supervisory areas. For each use case, respondents report the stage of development. $Y_{is} \in \{0, 1, 2, \dots, 104\}$ denotes the number of areas where authority i has a suptech project at the maturity stage $s \in \{\text{PoC}, \text{WP}, \text{DP}\}$. The 13 supervisory areas are further grouped into four broader categories: (i) financial stability oversight and prudential supervision, (ii) licensing and compliance, (iii) supervision of emerging risks, and (iv) consumer protection and conduct supervision. This structure allows for detailed analysis of suptech adoption both across and within supervisory domains and development stages.

³The Financial Development Index by Svirydzenka (2016) captures the multidimensional nature of financial systems through two main components, Financial Institutions (FI) and Financial Markets (FM), each decomposed into Depth (FID/FMD), Access (FIA/FMA), and Efficiency (FIE/FME). The FI index reflects the development of banks, insurers, and other financial intermediaries, while the FM index measures the development of stock and bond markets. Within Financial Institutions, Depth (FID) includes private-sector credit, pension fund assets, mutual fund assets, and insurance premiums to GDP; Access (FIA) captures bank branches and ATMs per 100,000 adults; and Efficiency (FIE) comprises net interest margin, lending–deposit spread, non-interest income to total income, overhead costs to total assets, return on assets, and return on equity. Within Financial Markets, Depth (FMD) covers stock market capitalization, stocks traded, and international and total debt securities of governments, financial, and nonfinancial corporations to GDP; Access (FMA) measures the share of market capitalization outside the top 10 companies and the total number of debt issuers (domestic and external, financial and nonfinancial); and Efficiency (FME) is represented by the stock market turnover ratio (stocks traded to capitalization).

Figure 2: Distribution of Suptech Activity - All use cases



Source: Cambridge SupTech Lab and DTS, authors' calculations.

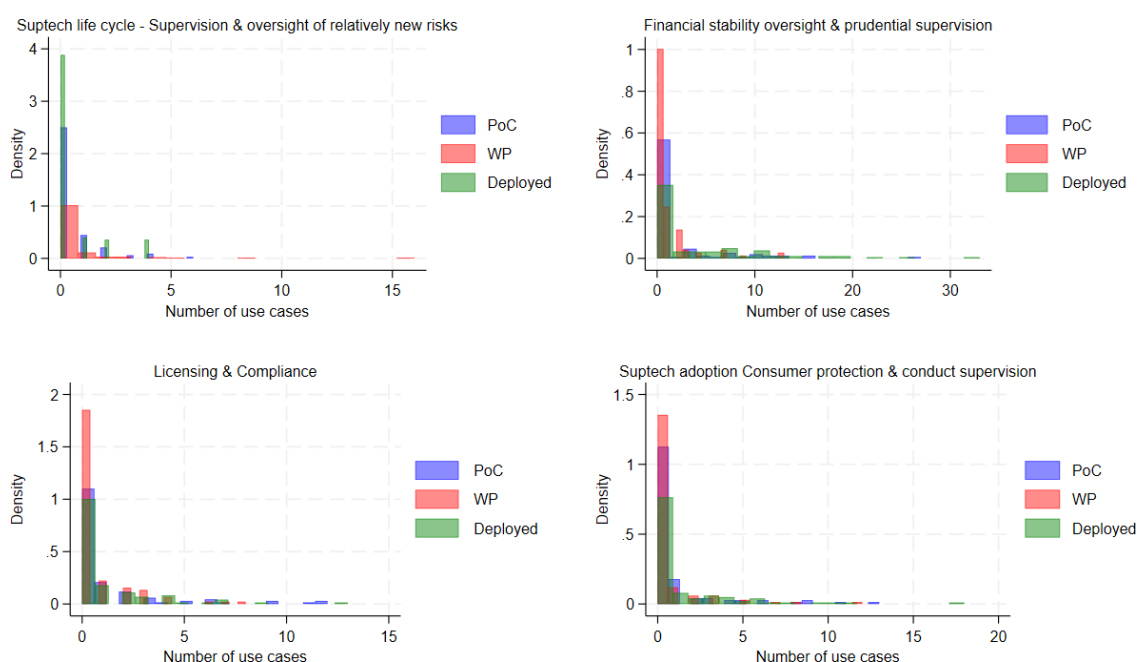
Figure 2 illustrates the distribution of suptech tools across the three stages of development over the suptech lifecycle. These distributions provide a preliminary overview of suptech maturity and reveal salient patterns in its diffusion across supervisory areas. Across all three stages, the distributions are distinctly right-skewed, with a pronounced spike at zero, indicating that many authorities report no suptech activity. The combination of excess zeros and skewed count distributions highlights the need for an empirical approach to distinguish between the decision to adopt suptech and the extent of implementation. To address these features, our econometric analysis will employ a hurdle model, which separately estimates: (i) the probability that an authority adopts at least one suptech tool; and (ii) the number of tools adopted, conditional on adoption. This methodology is well-suited to our data structure and will be discussed in detail in the next section.

Figure 3 shows the distribution of the suptech activity variables, PoC, WP, and DP, across the four main supervisory areas, clustered into four categories. Although the histograms reveal some similarities across the distributions, suggesting a degree of consistency in suptech activity across supervisory categories, their differing modes and dispersion point to notable variation in adoption intensity and progression. Suptech deployment is most advanced in financial stability oversight and prudential supervision, which records the highest incidence of deployed tools.

By contrast, the supervision of emerging risks - including climate and environmental

risks, cyber threats, and risks related to digital assets - shows relatively few instances of full deployment, indicating slower technological integration despite their growing importance. This may reflect limited data availability in these areas. The licensing and compliance category exhibits a more uniform distribution across PoC, WP, and DP stages, suggesting a relatively balanced development trajectory. In contrast, consumer protection and conduct supervision remain concentrated in the PoC and WP stages, with comparatively limited evidence of deployment. This pattern reflects ongoing experimentation and tool development in this area and highlights slower progression toward full operational integration.

Figure 3: Distribution of Suptech Activity across Supervisory Categories



Source: Cambridge SupTech Lab and DTS, authors' calculations.

Table 1 summarises descriptive statistics for the variables used in the empirical analysis. The final sample comprises 112 supervisory authorities that submitted the survey by March 2025, after manually excluding implausible outliers and observations missing from the IMF database. Dependent variables reveal substantial heterogeneity: the average number of PoC initiatives is 4.65 (SD = 8.035, max = 35), suggesting widespread early-stage experimentation alongside a subset of highly active adopters. WPs exhibit a lower average (mean = 2.795, SD = 5.166, max = 32), while DPs show the highest mean and significant variation (mean = 6.929, SD = 10.029, max = 45). The variable Challenges is a count variable that captures the number of challenges faced by the financial authority during

the design and implementation of a supotech project, along with its relevant decomposition. It averages 7.830 ($SD = 4.640$), with dispersion underscoring divergent institutional capacities. The type of supervisory authorities in the sample is distributed as follows: Standalone Banking Supervisors at 49.1%, Central Banks at 30.4%. The remaining 20.5% fall under the category of Other Supervisory Authorities, which includes sector-specific authorities like security and financial market or insurance entities. The sample distribution is geographically concentrated in Latin America, the Caribbean (LAC), Europe, and Central Asia (ECA) regions, accounting for 30.4% and 29.5% of the sample respondents, respectively. Other regions, such as East Asia and Pacific (EAP), Middle East and North Africa (MENA), South Asia (SA), and Sub-Saharan Africa (SSA), have smaller representation, and North America (NA) represents 3.6% of the sample.

The data on organisational models reveal that the IT-Centred model is the most prevalent, adopted by 40.2% of the authorities. The Hub & Spoke model is also common, used by 28.6% of the authorities. The Centralised Hub model is less frequent at 17%, while 14.3% of the authorities report using other organisational models. These figures provide preliminary insight into the different governance and operational structures supervisory authorities have to manage supotech initiatives.

Independent variables capture organisational and technological characteristics. The number of employees is, on average, 336.86. Measured as the natural logarithm, as in the regressions, it averages 5.818 with a range between 3.401 and 9.903. Looking more deeply at the institutional characteristics of authorities, 51% have a dedicated supotech unit, while 26% have a supotech strategy. The percentage of authorities with data governance is 35% and digital transformation strategies in place are 34%. Furthermore, the sub-sample analysis collected through the optional questions shows limited adoption of more advanced technologies. While 40% of the authorities have implemented private cloud solutions, only 11% use public cloud infrastructure. Similarly, AI deployment has a mean of only 6.6%, but this number increases to 41% if initial phases of AI exploration are included.

Data on supotech sourcing models show that a hybrid approach is the most common strategy among authorities with at least one active or developing supotech application. Over half of these authorities report using a mix of both in-house development and external vendors. An in-house approach, where tools are built internally, is the second most prevalent strategy, adopted by 31% of the authorities. Finally, relying exclusively on external solutions, such as hiring vendors or purchasing software, is the least common method, used by only 15% of the sample.

Two key insights summarise this preliminary data analysis. First, the right-skewed distributions of PoC, WP, and DP variables, with means far below the median, are consistent with the hurdle model’s assumption of zero-inflated count processes, where initiation and scale are distinct decisions. Second, limited adoption of enabling infrastructures, such as cloud computing and AI, and relatively few formal strategies, suggest institutional

and technological barriers may constrain suptech implementation. This heterogeneity motivates our empirical approach, which explicitly models the dual decision structure of adoption.

Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
<i>Suptech life cycl</i>					
Proof-of-Concept	112	4.652	8.035	0	35
Working Prototype	112	2.795	5.166	0	32
Deployed Solution	112	6.929	10.029	0	45
Size (ln employees)	112	5.818	1.288	3.401	9.903
Suptech Unit	112	0.509	0.502	0	1
<i>Agency type</i>					
Standalone Banking Supervisors	112	0.491	0.502	0	1
Central Banks	112	0.304	0.462	0	1
Other Supervisory Authorities	112	0.205	0.406	0	1
<i>IMF income classification</i>					
Advanced Economies (AEs)	112	0.321	0.469	0	1
Emerging and Developing (EMDEs)	112	0.679	0.469	0	1
<i>World regions¹</i>					
EAP	112	0.107	0.311	0	1
ECA	112	0.295	0.458	0	1
LAC	112	0.304	0.462	0	1
MENA	112	0.062	0.243	0	1
NA	112	0.036	0.186	0	1
SA	112	0.071	0.259	0	1
SSA	112	0.125	0.332	0	1
<i>Cloud type</i>					
No Cloud	45	0.289	0.458	0	1
Public	45	0.111	0.318	0	1
Private	45	0.400	0.495	0	1
Hybrid	45	0.200	0.405	0	1
<i>Sourcing (buy vs build)</i>					
In-House	70	0.314	0.468	0	1
Hybrid	70	0.543	0.502	0	1
External	70	0.143	0.352	0	1
<i>Organisational models</i>					
IT-Centred	112	0.402	0.492	0	1
Centralised Hub	112	0.170	0.377	0	1
Hub & Spoke	112	0.286	0.454	0	1
Other organisational models	112	0.143	0.351	0	1
<i>Strategies</i>					
Data Governance	112	0.348	0.479	0	1
Digital Transformation	112	0.339	0.476	0	1
Suptech	112	0.259	0.440	0	1
<i>Challenges</i>					
Challenges	112	7.830	4.640	0	20
Design	112	3.205	2.019	0	9
Implementation	112	4.625	2.774	0	12
<i>AI</i>					
AI	76	0.408	0.495	0	1
AI early-stage	76	0.342	0.478	0	1
AI deployed	76	0.066	0.250	0	1
<i>IMF indices²</i>					
Financial institutions depth (FID)	112	0.475	0.193	0.081	0.959
Financial institutions access (FIA)	112	0.398	0.212	0.014	0.864
Financial institutions' efficiency (FIE)	112	0.594	0.090	0.225	0.799
Financial markets depth (FMD)	112	0.328	0.280	0.019	1
Financial markets access (FMA)	112	0.254	0.295	0	1
Financial markets efficiency (FME)	112	0.195	0.301	0	1

¹ Economies are classified following the World Bank definition.² Based on Svirydenka (2016).

5 Empirical strategy

This study employs a hurdle model, a specialised count data regression framework, to analyse suptech adoption, a context characterised by excessive zero observations and overdispersion, where the variance exceeds the mean (Cragg, 1971; Mullahy, 1986). Hurdle models are well-suited to situations where the outcome is frequently zero (e.g., no adoption) yet exhibits meaningful variation among positive values. Compared to zero-inflated models, they offer greater flexibility in capturing both excess zeros and the conditional distribution of non-zero observations (Gurmu, 1999; Feng, 2021). This approach is particularly appropriate for suptech data, where many authorities report no adoption, as shown in Figure 2. The model comprises two distinct steps. The first step employs a binary logistic regression to estimate the probability of crossing a hurdle or threshold (i.e., transitioning from non-adoption to adoption). Here, the dependent variable is binary, distinguishing zeros (no adoption) from positive counts (adoption). Conditional on crossing this hurdle, the second step estimates the intensity of adoption using a zero-truncated negative binomial model, which accounts for overdispersion in positive counts while explicitly excluding zeros. This two-step approach disentangles the decision to adopt suptech tools from the subsequent decision on how many tools to adopt, offering nuanced insights into the adoption process.

The hurdle model’s statistical appropriateness is further underscored by its alignment with institutional dynamics of suptech adoption. Initial adoption often reflects a discrete institutional choice, while subsequent tool adoption may depend on heterogeneous resource constraints, regulatory needs, technological capacities, and factors captured by the truncated count model. By addressing excess zeros and overdispersion, the framework mitigates bias in parameter estimates that could arise under standard Poisson or negative binomial specifications, thereby enhancing empirical reliability.

The formal hurdle model for suptech adoption based on the previous specification of our main independent variables, let $Y_{is} \in \{0, 1, 2, \dots, 104\}$ denote the number of areas where a suptech project has been developed by the supervisory authority i , at the maturity stage $s \in \{\text{PoC}, \text{WP}, \text{DP}\}$. The hurdle model decomposes the outcome distribution into two steps:

$$\Pr(Y_i^s = y) = \begin{cases} \pi_i^s, & \text{if } y = 0 \\ (1 - \pi_i^s) \cdot \frac{f(y; \mu_i^s, \alpha^s)}{1 - f(0; \mu_i^s, \alpha^s)}, & \text{if } y > 0 \end{cases} \quad (1)$$

where π_i^s is the probability of observing a structural zero, $f(y; \mu_i^s, \alpha^s)$ is the negative binomial probability mass function, $\mu_i^s = \exp(Z_i \gamma^s)$ is the expected count, α^s is the overdispersion parameter estimated from the data.

The first step models the probability that an authority undertakes any suptech project

in a specific supervisory area using a logistic regression:

$$\Pr(Y_{is} > 0) = \frac{\exp(X_i\beta_s)}{1 + \exp(X_i\beta_s)} \quad (2)$$

The first step of the hurdle model remains consistent across specifications. The selection of variables in this step is based on the assumption that they are exogenous and not influenced by suptech adoption. Specifically, the model includes variables that describe the characteristics of the supervisory authority, as well as the financial development context of each jurisdiction and broader regional features that are not directly tied to suptech. The regression model of the first step is represented by the following logit specification, structured as follows:

$$Y_{i,c}^{0,1} = g_1 \text{Size}_i + g_2 \text{Authority Type}_i + g_3 \text{Region}_c + g_4 \text{IMF Indices}_c + \varepsilon_{i,c} \quad (3)$$

where i is the supervisory authority in country c , Size is measured as the natural logarithm of the number of employees, Authority Type is a categorical variable for the type of authority, with central banks as the point of comparison. Region is a vector of regional dummies based on the World Bank classification, with EAP as the reference category. IMF Indices captures financial development indicators for cross-country variation in financial system characteristics. A more comprehensive description of all variables is provided in the Appendix, Table A3.

The second step employs zero-truncated negative binomial models, conditional on $Y_{is} > 0$. It estimates the number of areas where suptech projects are being developed, using the same explanatory variables from the first step, supplemented by additional characteristics relevant to suptech within supervisory agencies. The model is specified as follows:

$$\begin{aligned} Y_{i,c}^s = & r_1 \text{Size}_i + r_2 \text{Authority Type}_i + r_3 \text{Strategies}_i + \\ & + r_4 \text{Organisation}_i + r_5 \text{Suptech Unit}_i + r_6 \text{Economic Development}_c + \\ & + r_7 \text{Region}_c + r_8 \text{IMF Indices}_c + \varepsilon_{i,c} \end{aligned} \quad (4)$$

where, for each authority i in country c , Organisation is a categorical variable capturing the organisational model adopted for developing suptech tools, distinguishing between decentralised (reference), centralised hub, hybrid hub-and-spoke, and other specified arrangements. Suptech Unit is a dummy variable equal to 1 if the authority has a dedicated suptech unit, and 0 otherwise. Economic Development is a vector of economic development dummies that distinguishes between advanced and developing countries. Strategies is a vector of dummy variables indicating whether the authority has adopted a suptech strategy, a data governance strategy, or a digital transformation strategy.

We further extend the empirical analysis in equation (4) to examine factors mediating the challenges a financial authority faces in adopting and developing suptech tools. The new dependent variable is constructed by counting the number of design and implementation challenges reported in the complete survey classification (see Table A2 in the Appendix). Unlike PoC, WP, and DP variables, its distribution is not markedly right-skewed toward zero. This allows us to apply a standard Poisson count model to estimate the second step of the hurdle model. This additional analysis will further assess how strategic frameworks influence the adoption of suptech by examining how structured implementation approaches can reduce barriers to technological development.

The final part of our analysis examines the relationship between AI project activity, cloud technologies, and sourcing models adopted by the authority to develop suptech applications. To this end, we compute a linear probability model where our independent variables have a different specification and decomposition of the AI measure by the stage of maturity. First, we use an aggregate specification, $Y_i = 1$, that is, a binary variable that captures any level of maturity in using AI tools, ranging from initial exploration and research to pilot projects with limited deployment, to fully deployed AI-based suptech tools by authority i . We then decompose this aggregate measure into two components. The first captures early-stage AI engagement, defined as initial exploration, research, and pilot projects with limited deployment. The second isolates cases of full deployment, identifying authorities that have operationalised AI-based suptech tools. In detail, the model specification is:

$$Y_i = \begin{cases} 1 & \text{if authority } i \text{ has any AI-based SupTech tools (from early-stage to full deployed);} \\ 0 & \text{otherwise.} \end{cases}$$

$$\Pr(Y_i = 1 \mid X_i) = X_i' \beta + \varepsilon_i \quad (5)$$

where:

$$X_i' = [\text{CloudType}_i, \text{SourceModel}_i, \text{Controls}_i]$$

The X_i' includes three types of variables for each authority i . `CloudType` is a categorical variable that distinguishes between private, public, and hybrid models. These cloud-type indicators allow us to test whether specific deployment environments are more conducive to AI experimentation and uptake. `SourceModel` is a set of dummies designed to capture how AI tools are developed, acquired, or created through a hybrid approach in collaboration with consultants or external providers, whether in-house, procured from external vendors, or developed through a combination of these methods. Additionally, the model includes the same `Controls` used in previous regressions, capturing the institutional and organisational characteristics of the financial authority, regions and financial development.

6 Results

This section presents the results of our empirical analysis, starting with the baseline hurdle model that focuses on idiosyncratic organisational characteristics. Table 2 reports the marginal effect estimates from our model. Columns (1), (3), and (5) show the results for the first step (the logit model), which captures the likelihood of an authority initiating at least one suptech project at the PoC, WP, and DP stages, respectively. Columns (2), (4), and (6) report the corresponding estimates from the second step (the count model), which estimates the number of suptech tools adopted, conditional on having at least one.

Table 2: Baseline results

Variables	Panel A: PoC		Panel B: WP		Panel C: DP	
	(1) Logit	(2) Count	(3) Logit	(4) Count	(5) Logit	(6) Count
Size	0.0415 (0.0514)	-0.5591 (1.0376)	0.0874* (0.0458)	1.1887 (0.7525)	-0.0071 (0.0480)	0.0755 (1.1699)
Other Supervisory Authorities	-0.0538 (0.1207)	-3.0038 (2.2470)	0.1026 (0.1177)	0.8859 (1.3633)	0.1234 (0.1220)	1.5172 (2.4809)
Standalone Banking Supervisor	0.2162 (0.1345)	3.2880 (3.3554)	0.2465* (0.1335)	2.7439 (1.9755)	0.2337* (0.1323)	4.5168 (3.5554)
Centralised Hub		-2.0102 (2.5246)		-2.1591 (1.7342)		1.8158 (3.4438)
Hub & Spoke		-3.5086* (1.9554)		-1.4639 (1.4570)		-0.4054 (2.3130)
Other org. model		10.3785 (13.1780)		-2.0345 (1.8210)		-3.6580 (2.7938)
Suptech unit		3.8027** (1.8571)		0.8988 (0.8961)		6.5262*** (2.0389)
EMDEs		-0.7636 (2.2174)		-2.3609* (1.3144)		-0.8798 (3.2594)
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes
IMF Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Economic dev. controls	No	Yes	No	Yes	No	Yes
Observations	112	112	112	112	112	112
Pseudo R2	0.165	0.165	0.199	0.199	0.128	0.128

Note: The table presents the marginal effect results from the baseline specification of the hurdle model, as specified in equation (3). Columns (1), (3), and (5) report the marginal effects of the probability model of surpassing the zero threshold. These coefficients indicate the likelihood of initiating a PoC, WP, or DP project. Columns (2), (4), and (6) present the marginal effects of the hurdle counting model specified in equation (4). The different specifications of models include controls for: IMF indices: FID, FIA, FIE, FMD, FMA, FME; regional area dummies: EAP, ECA, LAC, MENA, NA, SA, and SSA; Economic development dummies: ADs and EMDEs. Robust standard errors are reported in parentheses. Statistical significance is denoted as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A key finding is that the size of a financial authority is a significant factor in the early stages of development, specifically for WP. A larger authority is more likely to initiate projects at the prototype stage. However, size does not show a statistically significant

effect on the number of tools developed once the adoption process has begun. The type of financial authority is also a critical determinant. Standalone banking supervisors are significantly more likely than central banks (the reference category) to initiate suptech projects that reach the more advanced WP and deployment stages. In contrast to central banks, the supervision function in authorities that are standalone banking supervisors does not have to compete with other functions for resources. Compared to authorities that are classified as “Other Supervisory Authorities”, standalone banking supervisors also tend to have more resources, may have more flexibility in how they deploy these resources and may be less constrained by public procurement rules than supervisory authorities attached to government ministries.

Regarding the organisational models for development, adopting a Hub & Spoke model is associated with significantly fewer projects in the initial PoC stage compared to a fully decentralised approach. The evidence highlights that there is no significant difference in the organisational models for suptech development, regardless of the unique characteristics of each authority and its IT infrastructure configuration. Moreover, the most crucial organisational driver is the presence of a dedicated suptech unit, which suggests centralisation. Authorities with a dedicated unit have, on average, 3.8 more PoC tools and 6.5 more deployed tools than those without one. These highly significant results underscore that a formal allocation of resources and expertise is a powerful enabler for starting and, most importantly, successfully deploying suptech applications. Furthermore, the analysis shows that authorities in EMDEs tend to have a significantly lower number of suptech tools in the WP stage than those in advanced economies, holding other factors constant.

The second part of our analysis investigates the impact of strategic frameworks on the suptech lifecycle. Building on the baseline model, we examine the individual effects of having a suptech, data governance, or digital transformation strategy and their possible interactions. The first three columns of Table 3 present the results from the hurdle model specification described in equation (4). Looking at the individual phases of the suptech lifecycle, the estimates for the PoC phase in column (1) show a positive and significant effect of adopting the suptech strategy, with almost seven applications, but a negative and significant effect is detected for deployed solutions (column 3). This suggests that having a suptech strategy is essential for initiating the planning and development of tools to improve supervisory processes. This also confirms the findings in Prenio (2024) that suptech strategies tend to focus too much on experimentation at the expense of actual implementation.

Table 3: Role of Strategies

Variables	Panel A: SupTech life cycle			Panel B: Challenges		
	(1) PoC	(2) WP	(3) DP	(4) All	(5) Design	(6) Implement.
Data Governance (DG)	3.3402 (3.2639)	0.2920 (1.5323)	−8.1191*** (3.0923)	−0.0922 (0.1949)	−0.0811 (0.1875)	−0.0991 (0.2066)
Suptech Strategy (SS)	6.9472* (4.0660)	−1.4176 (2.0975)	−8.3290* (4.7885)	0.1322 (0.1762)	0.3481* (0.2062)	−0.0188 (0.1778)
Data Transformation (DT)	2.0089 (2.9608)	−0.5593 (1.3078)	−9.4392* (5.4451)	−0.0822 (0.2033)	−0.0026 (0.2490)	−0.1359 (0.1817)
DG x SS	−9.0255 (6.4135)	−0.2456 (2.2596)	15.4170*** (5.9392)	0.2053 (0.3253)	0.0030 (0.3302)	0.3458 (0.3416)
DG x DT	−8.7055* (5.0754)	−3.1271 (2.7840)	16.4407** (7.0643)	0.5186 (0.3283)	0.4282 (0.3630)	0.5804* (0.3236)
SS x DT	−11.7870* (6.1222)	−0.3591 (2.7013)	16.9943** (7.4905)	0.2323 (0.3690)	−0.0062 (0.3832)	0.3945 (0.3812)
DT x SS x DG	−13.3499* (7.0110)	−0.6751 (2.6297)	24.2895*** (8.1856)	−1.4302** (0.5570)	−1.1591** (0.5664)	−1.6169*** (0.5819)
Authority characteristics	Yes	Yes	Yes	Yes	Yes	Yes
IMF Indices	Yes	Yes	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	112	112	112	112	112	112
Pseudo R2	0.187	0.221	0.155	0.10	0.0842	0.1051

Note: The table from column (1) to (3) shows the marginal effects from the hurdle counting model in equation (4), which are estimated separately for three types of suptech activity. In these model specifications, we included several interactions among the strategy dummies related to strategies (Digital Transformation, Suptech and Data Governance Strategy). Columns (4) to (6) report the results of the estimation of the Poisson model with both aggregate and disaggregated challenge independent variables, following the same specifications presented in the previous part of the table. The different specifications of estimation models include controls for: authority-specific characteristics that include: suptech unit, size, organisational models (IT-centred centralised hub, hub & spoke, other org. model), agency type (standalone banking supervisors, central banks and other supervisory authorities), the IMF indices: FID, FIA, FIE, FMD, FMA, FME; regional area dummies: EAP, ECA, LAC, MENA, NA, SA, and SSA; Economic development dummies: ADs and EMDEs. Robust standard errors are reported in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The analysis also reveals that when strategies are combined, the effect becomes negative on PoC. The interaction terms for combinations are all negative and statistically significant. This suggests that while a focused suptech strategy helps kickstart early-stage experimentation, authorities implementing multiple, more complex strategic frameworks simultaneously may initiate fewer PoC projects, possibly because their efforts are directed towards more mature applications. For the Working Prototype stage, none of the individual strategies or their interactions show a statistically significant effect on the number of projects. This indicates that these high-level strategies do not significantly explain the variation in the number of projects in the intermediate development phase.

In contrast, the results for deployed solutions offer the strongest and most significant insights. Individually, each of the three strategies (DG, DT and SS) is associated with a significantly lower number of deployed applications. This suggests that implementing any single strategy in isolation is insufficient for achieving full deployment. The key finding is

the powerful synergistic effect when strategies are combined. All two-way interactions (DG x SS, DG x DT, SS x DT) and the triple interaction (DT x SS x DG) have large, positive, and highly statistically significant coefficients. For instance, authorities implementing all three strategies see an increase of approximately 24.3 deployed tools, which is significant at the $p < 0.01$ level. This provides strong evidence that successful, large-scale suptech deployment is not driven by any single plan but by a comprehensive and integrated strategic approach that combines data, technology, and institutional transformation.

The results in columns (4) to (6) are derived from a Poisson count model and examine the relationship between the number of challenges authorities face and their strategic frameworks. Column (4), which considers the total number of challenges, shows that most individual strategies and two-way interactions do not have a statistically significant effect. However, the triple interaction term (DT x SS x DG) is negative and highly significant, indicating that authorities implementing all three strategies report, on average, 1.43 fewer challenges overall. This finding is further clarified by decomposing the challenges. In column (5), focusing on Design Challenges, having a standalone Suptech Strategy (SS) is associated with a slight increase in reported challenges. Nevertheless, the triple interaction term (DT x SS x DG) is negative and significant, suggesting that having all three strategies in place reduces, on average, of 1.16 design-related challenges. The most relevant effect is in column (6), which looks at Implementation Challenges. The triple interaction term (DT x SS x DG) is again negative and highly significant, showing that authorities with all three strategies report 1.62 fewer implementation challenges. This provides strong evidence that while individual strategies may have a limited impact, a comprehensive and integrated strategic approach is instrumental in mitigating the most critical barriers that arise during the deployment and scaling of suptech solutions.

Table 4 shows results from a linear probability model exploring correlations between an authority’s infrastructure choices and its AI adoption. The first three columns present the results for the baseline linear probability model, indicating that the presence of a dedicated Suptech Unit significantly increases the likelihood of AI use overall, corroborating our previous findings. In contrast, the efficiency of financial institutions is strongly linked to both overall AI adoption and early-stage experimentation. This suggests that supervisors operating within more efficient financial systems are better positioned to explore AI applications. However, this effect becomes less significant once AI is fully deployed, as organisational size emerges as a more relevant factor. Larger authorities are more capable of transitioning from experimentation to operational use, highlighting the importance of resource capacity in sustaining and scaling AI projects.

Table 4: The Effect of Cloud and Sourcing Models on AI Adoption

VARIABLES	Panel A: AI Models			Panel B: Cloud Models			Panel C: Sourcing Models		
	(1) AI	(2) AI early stage	(3) AI deployed	(4) AI	(5) AI early stage	(6) AI deployed	(7) AI	(8) AI early stage	(9) AI deployed
Suptech Unit	0.2562** (0.1141)	0.1820 (0.1122)	0.0741 (0.0550)	0.0844 (0.2005)	0.1318 (0.2308)	−0.0474 (0.0938)	0.0781 (0.2215)	−0.0508 (0.2065)	0.1289 (0.1006)
Size	0.0533 (0.0673)	−0.0243 (0.0666)	0.0776* (0.0418)	0.0816 (0.0945)	−0.0667 (0.1237)	0.1483* (0.0763)	0.1040 (0.0956)	−0.1652 (0.1147)	0.2692** (0.1067)
FID	0.5632 (0.3932)	0.5264 (0.4011)	0.0367 (0.1374)	0.5274 (0.4039)	0.5389 (0.5751)	−0.0115 (0.2697)	0.0480 (0.3897)	−0.4349 (0.5450)	0.4828 (0.3521)
FIA	−0.4212 (0.3529)	−0.3735 (0.3394)	−0.0477 (0.1543)	0.4091 (0.4850)	−0.0839 (0.5773)	0.4930 (0.2974)	−0.3404 (0.6605)	0.1029 (0.5606)	−0.4433 (0.4023)
FIE	1.5626** (0.6229)	1.0306* (0.5796)	0.5320 (0.3541)	2.4457** (0.9290)	1.4024 (1.2137)	1.0433* (0.5545)	1.4547 (1.2828)	−0.1806 (1.2320)	1.6353** (0.6809)
FMD	0.2433 (0.5215)	0.6226 (0.5071)	−0.3793 (0.2829)	−0.4894 (0.4696)	0.3642 (0.7484)	−0.8535* (0.4412)	0.0971 (0.7172)	1.6426** (0.7030)	−1.5455*** (0.4068)
FMA	−0.0333 (0.2917)	0.0539 (0.2921)	−0.0872 (0.0924)	−0.1865 (0.4249)	−0.0193 (0.5278)	−0.1672 (0.2214)	−0.2889 (0.4499)	−0.3087 (0.4389)	0.0198 (0.2508)
FME	−0.3237 (0.3999)	−0.7291 (0.4370)	0.4053 (0.2710)	−0.1094 (0.4036)	−0.6966 (0.5867)	0.5872** (0.2843)	−0.4083 (0.4469)	−0.6812 (0.5286)	0.2730 (0.3470)
Public Cloud				0.4685* (0.2527)	0.1741 (0.3008)	0.2944* (0.1446)			
Private Cloud				0.0601 (0.1728)	−0.0088 (0.1949)	0.0689 (0.1087)			
Hybrid Cloud				0.2998 (0.1942)	0.1767 (0.2614)	0.1231 (0.1447)			
Sourcing model: Hybrid							−0.1920 (0.1445)	−0.3303* (0.1733)	0.1383 (0.1284)
Sourcing model: External							−0.6184** (0.2348)	−0.7571*** (0.2359)	0.1387 (0.1473)
Org. models Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic dev. control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76	76	76	45	45	45	36	36	36
R2	0.420	0.361	0.320	0.607	0.380	0.587	0.534	0.606	0.600

Note: The table shows the results from the linear probability model from equation (5). The different specifications of models include: authority-specific characteristics that include: suptech unit, size, organisational models (IT-centred centralised hub, hub & spoke, other org. model), agency type (standalone banking supervisors, central banks and other supervisory authorities); The cloud type dummies specification: Public, Private and Hybrid; The sourcing model dummies variables: Hybrid External and In-house; The IMF indices: FID, FIA, FIE, FMD, FMA, FME; regional area dummies: EAP, ECA, LAC, MENA, NA, SA, and SSA; Economic development dummies: ADs and EMDEs. Robust standard errors are reported in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Columns (3) to (6) examine the role of cloud infrastructure, using authorities with no cloud adoption as the reference group. The findings suggest that adopting a public cloud is associated with a 46.85% higher probability of having AI suptech tools at any stage of maturity compared to having no cloud infrastructure. This result remains significant for the implementation phase, with 29.44% of a higher probability of adopting AI tools, compared to having no cloud infrastructure. Leveraging public cloud computing services can boost authorities' implementation of AI and machine learning models, which demand significant computational power and data storage that is often difficult for individual authorities to own and maintain.

The last three columns (7) to (9) explore the correlation between the authority's sourcing model and its AI adoption. We consider the purely internal (in-house) approach (not reported) as the baseline for comparison. The results show a strong negative correlation between authorities relying exclusively on the external sourcing model and AI adoption. Specifically, an external-only approach is associated with a 61.8 per cent lower probability of any AI adoption and a 75.1 per cent lower probability of being in the AI exploration stage, compared to authorities that develop their solutions in-house. This finding likely reflects the challenges financial authorities face with external vendors, such as limited transparency and the "black box" nature of proprietary AI tools, which can hinder adoption relative to trusted and customised in-house solutions.

7 Conclusions

Financial supervision mitigates asymmetric information and moral hazard by producing and processing information on financial institutions (Pigou, 1932; Akerlof, 1970; Jensen & Meckling, 1976; Stiglitz & Weiss, 1981; Llewellyn, 1999). As financial markets become increasingly digital and data-intensive, the technological capacity of supervisory authorities becomes a central component of the regulatory production function. This paper provides the first systematic cross-country evidence on the determinants of suptech adoption. Using the 2024 State of SupTech dataset, covering 112 authorities and 97 use cases across 13 supervisory domains, we examine both the likelihood of adoption and the intensity of deployment. To account for the distributional characteristics of suptech activity, we employ hurdle models that distinguish between initiation and scale. Our results identify three core drivers. First, while authority size and a single supervisory mandate are associated with the initiation of more advanced projects, the strongest predictor of deployment intensity is the presence of a dedicated suptech unit. Organizational specialization appears crucial for translating strategic intent into operational capacity. Second, we document pronounced complementarities across strategic domains. Authorities that adopt integrated strategies spanning digital transformation, data governance, and suptech deploy substantially more tools, approximately 20 additional applications on average, than those pursuing isolated

initiatives. This integrated approach is also associated with fewer reported implementation and design challenges, suggesting that strategic alignment reduces operational frictions. Third, enabling infrastructure plays a key role: public cloud adoption is closely linked to AI-based implementation, while in-house development capabilities support early-stage experimentation.

These findings indicate that suptech is not a discrete IT investment but part of a broader organizational transformation. Effective modernization requires aligning strategy, organizational design, and technological infrastructure rather than relying on isolated technological upgrades. Our analysis contributes to the emerging stream of literature on suptech within the broader field of financial supervision (Eisenbach et al., 2022; Degryse et al., 2025; Brynjolfsson & Kazinnik, 2025) by identifying the institutional mechanisms that underpin supervisory modernization. More broadly, heterogeneity in suptech adoption implies cross-country variation in supervisory monitoring capacity with import implication for financial stability and cross-border supervision. As seminal evidence on the global state of SupTech, this paper sets the stage for future research that examines how supervisory technological capacity influences enforcement outcomes and the risk-taking behavior of financial institutions (Goldstein, 2025).

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Appendix

Table A1: Aggregated Supervisory Areas

Aggregated Categories	Supervisory Areas
Financial stability oversight and prudential supervision	Prudential supervision of banks and non-bank deposit-taking institutions Insurance supervision Capital markets, securities and investment instruments oversight Payments oversight
Licensing and compliance	Licensing Compliance assistance Anti-money laundering & combating the financing of terrorism and proliferation financing
Supervision and oversight of relatively new risks	Climate and environmental risks supervision Cyber risk supervision Digital assets and cryptocurrencies oversight
Consumer protection & conduct supervision	Competition monitoring Consumer protection and market conduct supervision Financial inclusion and gender monitoring

Table A2: List of challenges codified in the survey

Type of challenges	Challenges
Design	Increases time to production Creating an environment where all perspectives can be expressed and heard Aligning agency culture to support design thinking efforts Attracting or retaining quality talent Lack of internal product design skills and knowledge required to facilitate Limited ability for knowledge or data sharing across teams Resource-intensive (e.g., high costs, significant time investment)
Implementation	Collaboration challenges (e.g., issues in stakeholder coordination) Legal or regulatory barriers Quality of solutions (e.g., not meeting needs, poor functionality) Flexibility of solutions (e.g., lack of customisation options) Cost-related issues (e.g., over-budget, ongoing maintenance costs) Vendor understanding of needs (e.g., vendors not fully understanding agency requirements) Vendor lock-in (e.g., dependency on a single vendor for updates and support) Procurement process Black box (solutions are understood in terms of inputs and outputs, but the internal workings are not understandable)

Table A3: Variables description

Variables	Description
SupTech life cycle	
PoC	A count variable that captures the number of suptech areas in which an authority has projects at the proof of concept stage.
WP	A count variable that captures the number of suptech areas where an authority has projects at the working prototype stage.
DP	A count variable that captures the number of suptech areas where an authority has projects at the deployed stage.
Challenges	
All	A count variable that captures the number of challenges faced by the financial authority during the design and implementation of a suptech project.
Design	A count variable that captures the number of challenges faced by the financial authority during the design stage of a suptech project.
Implementation	A count variable that captures the number of challenges faced by the financial authority during the implementation stage of a suptech project.
AI	
AI	A dummy variable that takes the value of one if the authority has any level of maturity in AI SupTech applications. Otherwise, it is zero.
AI deployed	A dummy variable that takes the value of one if the authority has fully deployed SupTech applications based on AI. Otherwise, it is zero.

Variables	Description
AI Early Stage	A dummy variable that takes the value of one if the authority's SupTech applications are based on AI pilot projects with limited deployment or are in the initial exploration and research phase. Otherwise, it is zero.
Cloud	
Cloud	A dummy variable that takes the value of one if the authority has adopted any cloud type: private, hybrid, or public. Otherwise, it is zero.
Public Cloud	A dummy variable that takes the value of one if the authority has adopted a public cloud solution. Otherwise, it is zero.
Hybrid Cloud	A dummy variable that takes the value of one if the authority has adopted a hybrid cloud solution. Otherwise, it is zero.
Private Cloud	A dummy variable that takes the value of one if the authority has adopted a private cloud solution. Otherwise, it is zero.
Agency characteristics	
Ln(size)	Natural logarithm of an estimation of the employee size of the supervisory authority.
Suptech Unit	A dummy variable that takes the value of one if the authority has a dedicated unit. Otherwise, it is zero.
Suptech Strategy	A dummy variable that takes the value of one if the authority has a Suptech Strategy. Otherwise, it is zero.
Digital Transformation Strategy	A dummy variable that takes the value of one if the authority has a Digital Transformation Strategy. Otherwise, it is zero.
Data Governance Strategy	A dummy variable that takes the value of one if the authority has a Data Governance Strategy. Otherwise, it is zero.

Variables	Description
IT-Centred	A dummy variable that takes the value of one if the authority organises suptech through an IT-Centred model. Otherwise, it is zero.
Centralised Hub	A dummy variable that takes the value of one if the authority organises suptech through a Central Hub model. Otherwise, it is zero.
Hub & Spoke	A dummy variable that takes the value of one if the authority organises suptech through a Hub-and-Spoke model. Otherwise, it is zero.
Other organisational models	A dummy variable that takes the value of one if the authority uses other organisational models. Otherwise, it is zero.
Other Supervisory Authority	A dummy variable that takes the value of one if the authority is not a Central Bank nor a Standalone Banking Supervisor. Otherwise, it is zero.
Central Bank	A dummy variable that takes the value of one if the authority is a Central Bank. Otherwise, it is zero.
Standalone Banking Supervisor	A dummy variable that takes the value of one if the authority is a Standalone Banking Supervisor or integrated financial supervisor. Otherwise, it is zero.
Development: In-house	A dummy variable that takes the value of one if the suptech tool is developed without external collaboration. Otherwise, it is zero.
Development: Hybrid	A dummy variable that takes the value of one if the suptech tool is developed collaboratively with external contributors. Otherwise, it is zero.
Development: External	A dummy variable that takes the value of one if external providers develop the SupTech tool. Otherwise, it is zero.
IMF indices	
Financial institutions depth	IMF Financial Development Index on financial institutions depth.
Financial institutions access	IMF Financial Development Index on financial institutions access.

Variables	Description
Financial institutions efficiency	IMF Financial Development Index on financial institutions efficiency.
Financial markets depth	IMF Financial Development Index on financial markets depth.
Financial markets access	IMF Financial Development Index on financial markets access.
Financial markets efficiency	IMF Financial Development Index on financial markets efficiency.
IMF income classification	
Advanced Economies	A dummy variable that takes the value of one if the country is an advanced economy. Otherwise, it is zero.
Emerging & Developing Economies	A dummy variable that takes the value of one if the country is in emerging and developing economies. Otherwise, it is zero.
World Bank regions	
EAP	A dummy variable that takes the value of one if the country is in East Asia Pacific. Otherwise, it is zero.
ECA	A dummy variable that takes the value of one if the country is in Europe and Central Asia. Otherwise, it is zero.
LAC	A dummy variable that takes the value of one if the country is in Latin America and the Caribbean. Otherwise, it is zero.
MENA	A dummy variable that takes the value of one if the country is in Middle East and North Africa. Otherwise, it is zero.
NA	A dummy variable that takes the value of one if the country is in North America. Otherwise, it is zero.
SA	A dummy variable that takes the value of one if the country is in South Asia. Otherwise, it is zero.

Variables	Description
SSA	A dummy variable that takes the value of one if the country is in Sub-Saharan Africa. Otherwise, it is zero.

Table A4: List of use cases by supervisory area

1. Financial stability oversight and prudential supervision
1.1 Prudential Supervision of Banks and Non-Bank Deposit Taking Institutions
Data handling (managing regulatory data)
Automated validation of the integrity and quality of periodic information
Analysis of interdepartmental data
Cross-entity analytics
Dynamic diagnostic & early warning systems
Monitoring of sectorial credit behavior
Monitoring of variations of credit categories across banks
Detection of investment patterns
Review of creditworthiness of borrowers
Risk-based supervision tools
Automated analysis of CCPs and infrastructures
Onsite examination
Stress testing
Scenario analysis
Peer group identification and classification
Fit and proper assessment
Other
1.2 Insurance Supervision

Continued on next page

Table A4 – *Continued from previous page*

Data handling
Automated compliance auditing
Filing and review of ORSAs
Automated validation of incoming data
Stress testing
Registration/authorization of stakeholders
Fit and proper assessment
Filing/approval of offerings
Risk assessment of licensees
Onsite examination
Other

1.3 Capital Market, Securities, and Investment Instruments Supervision

Extract insights from financial advice documents
Data handling
Identify poor market disclosure
Identify insider trading
Identify market manipulation
Onsite inspection
Prioritization of risks
Other

1.4 Payments Oversight

Real-time volumes and values analysis
Monitor network performance
RTGS stress testing
Other

2. Licensing and compliance

2.1 Licensing

Continued on next page

Table A4 – *Continued from previous page*

Automated guidance for applications
Automated processing of applications
Other

2.2 Compliance Assistance

Automated aggregate tables
Automated compliance auditing
Automated guidance
Machine-readable regulations
Real-time transaction monitoring
Other

2.3 Anti-Money Laundering, CFT and PF Supervision

Examination and investigation support
Data analytics on misconduct
Data on derisking
Examination of policies and training
KYC and entity matching
Metadata on AML/CFT/PF reports
Onsite examination
Suspicious activity detection
DNFBP supervision
Other

3. Supervision and oversight of relatively new risks

3.1 Climate and Environmental Risks Supervision

Collection and analysis of sustainable finance data
Disclosure assessment
Monitoring green market dynamics
Stress testing and scenario analysis
Portfolio analysis
Other

Continued on next page

Table A4 – *Continued from previous page*

3.2 Cyber Risk Supervision

Vulnerability and penetration testing
Audit trail analysis
Compliance monitoring (CISO, policies, MFA)
Onsite inspection
Other

3.3 Digital Assets and Cryptocurrencies Oversight

Automated compliance auditing
Automated validation of incoming data
Cross-jurisdictional intelligence sharing
Data handling
VASP supervision cooperation
On-chain analysis
Registration and licensing of VASPs
Other

4. Consumer protection & conduct supervision

4.1 Competition Monitoring

Monitor competition dynamics
Monitor rates and fees
Other

4.2 Consumer Protection and Market Conduct Supervision

Continued on next page

Table A4 – *Continued from previous page*

Alternative dispute resolution
Complaints data analysis
Consumer fraud detection
Credit bureau checks
Algorithmic bias detection
Misconduct risk indicators
Complaints handling support
Predatory pricing identification
Misleading disclosure checks
Onsite examination
Real-time complaints monitoring
Sentiment analysis (web/social media)
Terms & conditions validation
Other

4.3 Financial Inclusion and Gender Monitoring

Consumer satisfaction analysis
Simplified CDD analysis
Geographical trend mapping
Real-time monitoring of inclusion targets
Sex-disaggregated data analysis
Financial literacy and education
Gender disaggregated data analysis
Other
