Beyond Crises: A New Perspective on the Evolution of the Italian Banking Sector in the Long Run (1890-1973)

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“Yes, world history is indeed such an onion”

— Jared Diamond

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Foreword

As Jared Diamond (1997, p. 11) wrote:

> [World history is like] an onion, of which the modern world constitutes only the surface, and whose layers are to be peeled back in the search for historical understanding. Yes, world history is indeed such an onion! But that peeling back of the onion's layers is fascinating, challenging—and of overwhelming importance to us today, as we seek to grasp our past's lessons for our future.

A compelling and rather disarming metaphor that emphasizes the depth and complexity of history. It ought us to look beyond the surface, to explore the multifaceted and intertwined layers weaving the historical narrative—a challenging and yet rewarding process.

Indeed, if history is a stratification of facts—that unfolds differently in different epochs, in different loci, in different socio-economics contexts—then, the very *raison d'être* of this work is to translate Diamond's statement to the Italian financial history, and explore the how the events of the turbulent XX century shaped the banking sector and guided its evolution. In turn, as analyzing tree-rings helps us reconstruct past environmental conditions (dendrochronology), looking at the banking sector can offer a valuable perspective to interpret and reassess the abrupt and often contradictory changes of the *Age of Extremes*, as baptized by Hobsbawm (1994).

Navigating the blurred boundary between historical inquiry and methodological innovation, this work presents four contributions that leverage balance sheet data on the Italian banking sector contained in the *Archivio Storico del Credito in Italia* (ASCI) database to quantitatively reassess traditional narratives of Italian banking. By adopting an overlooked bank-level perspective, it aims to complement—and at times challenge—a long-standing historiographical position that has largely relied on aggregate or institutionally segmented analyses, often anchored in a crisis-centric interpretation of banking history. Thus, the leitmotif of this work is to go *beyond crises*.

Chapter 1

Introduction: How and Why Going Beyond Crises Matters

"Exploratory data analysis is a detective work [...] a detective investigating a crime needs both tools and understanding. If he has no fingerprint powder he will fail to find fingerprints on most surfaces. If he does not understand where the criminal is likely to have put his fingers, he will not look in the right places. Equally, the analyst of data needs both tools and understanding [...] Exploratory analysis can never be the whole story, but nothing else can serve as the foundation stone."

— John W. Tukey (1977, p. 1)

It is with resigned acceptance and a hint of critical awareness that Bartoletto et al. (2018, p. 2), when studying the evolution of the Italian banking sector, state that in the literature "the narrative approach is dominant." Despite the increasing availability of historical data, limited granular evidence exists on the long-run evolution of the banking sector—the mix of strategic choices, institutional constraints, and selective pressures that shaped the process of adaptation to changing external conditions. In this work, we address this gap by extensively leveraging the information contained in the *Archivio Storico del Credito in Italia* (ASCI), the Bank of Italy's balance sheet database for Italian intermediaries between 1890 and 1973.[1]

The macro-financial historiography of the Italian banking sector has traditionally been anchored in the analysis of the bank-industry nexus (see, e.g., Confalonieri, 1974; Conti, 2007; Fanfani, 2005; Toniolo, 1978). This focus is largely a legacy of a Gerschenkronian interpretation of the Italian industrial revolution, which posited banks as the necessary substitute for missing market capital in the late-comer economy (Gerschenkron, 1962). While this thesis requires interpretative caution—as noted, among others, by Fenoaltea (2011)—it closely aligns with the pivotal role banks held in the Italian economy, mirroring the dualistic structure of

[1] Full access to ASCI is kindly provided by the Bank of Italy and used upon request. Interested scholars can request access to the data following the procedure presented at https://www.bancaditalia.it/statistiche/tematiche/stat-storiche/stat-storiche-microdati/index.html.

the country's capitalism (Barbiellini Amidei and Impenna, 1999; Ciocca and Biscaini Cotula, 1994; Giannetti and Vasta, 2006). On the one side lays a dense web of "light" firms (e.g., textiles), served by small and local intermediaries, mainly cooperative and savings banks; on the other stands the large conglomerates operating in "heavy" and capital-intensive industries (e.g., chemicals), catered to by the few large intermediaries operating on the German model of the universal bank (Carnevali, 2005).

This structural duality has translated into a deeply asymmetrical historical coverage, largely focused on the major mixed banks and their critical function as the engine of industrial development (Battilossi, 2009; Confalonieri, 1974, 1994; Conti, 2007; Fanfani, 2005; La Francesca, 2004). This asymmetry may be considered a natural consequence of narrative formation: the impairment of a systemically important institution resonates deeper among observers than widespread but quieter distress.[2] Consequently, primary sources are naturally biased toward major banks, characterized by more comprehensive and accessible coverage (see, e.g., Benini, 1893; Pantaleone, 1895; Sraffa, 1922; Segre, 1926; Mazzantini, 1928, 1946). As a result, historical narratives are exposed to a "big-bank bias", with anecdotal subjectivity often blurring the boundary between the notions of "banking crises" (systemic distress) and "crises of banks" (idiosyncratic failures). It follows that, while an undeniably rich literature exists on local credit institutions (see, e.g., Conti and La Francesca, 2000), their alleged stability largely confined them to the realms of local history, leaving the macro-financial narrative to be defined by the *alta banca* (high finance) and its supposedly fragile relationship with industrial capital (Di Martino, 2000).

In turn, the focus on the *alta banca* has profoundly shaped the periodization of Italian banking history. If major banks' failures are structurally higher-profile, then the historical timeline naturally aligns with their moments of distress—episodes in which managerial frictions, such as fraud or moral hazard, abruptly materialized—leading to a controversial conflation of these events with system-wide instability. Examples include the housing bubble of the 1880s and the Banca Romana scandal of 1893 (Confalonieri, 1974; De Mattia, 1990; Toniolo, 1988), the stock market speculation of 1907 (Bonelli, 1982), the collapse of the mixed-banking system in 1921 (Confalonieri, 1994; De' Stefani, 1960), and the over-banking leading to the Great Depression (Battilossi, 2009; Toniolo, 1995). Moreover, in this narrative, these episodes are interpreted as the inevitable collapse of a structurally flawed banking model, with a consequentially legitimate (if not desirable) regulatory intervention: the creation of the Bank of Italy (1893), the laws of 1926, and finally, the banking law of 1936, widely credited as the precondition for the post-war era of stability (Cotula, 1999; Gigliobianco and Giordano, 2010).

As quantitative history expanded, these historiographic accounts became foundational to modern comparative studies on financial instability (e.g., Kindleberger, 1978). In turn, the Italian case has been widely integrated into international analyses framing uniform chronologies of banking crises (i.e., Bordo et al., 2001; Reinhart and Rogoff, 2008; Jordà et al., 2017; Metrick and Schmelzing, 2021; Baron et al., 2021). However, while undeniably valuable for cross-country comparisons, this approach leaves key analytical challenges unresolved, partic-

[2] A great example is the interwar period, when the distress of the four major banks is widely covered (Barbiellini Amidei and Giordano, 2015; Battilossi, 2009; Toniolo, 1978, 1995), while a pervasive distress of the small and medium institutions is firstly quantified by Molteni (2023).

ularly when linked to the specific institutional and structural features of the Italian context. By transposing broad, event-based definitions modeled on the Anglo-American experience onto a system characterized by high fragmentation and state activism, the literature encounters two distinct frictions:

1. A discrepancy in the timing and classification of crisis episodes. Significant disagreement exists between established chronologies of Italian banking crises. While it may be considered a necessary consequence of identification strategies in which subjective judgments remain central (Sufi and Taylor, 2021), the potential bias in qualitative evidence is particularly problematic. The cause lies in the specific Italian institutional context, which makes standard quantitative indicators—such as panics, government interventions, or stock market downturns—unreliable. Historically, central authorities demonstrated an overriding commitment to maintaining public confidence and systemic stability. This priority, combined with an inefficient bankruptcy law, led to a practice of managing financial distress through quiet, "backdoor" interventions rather than allowing for open bank failures (Di Martino and Vasta, 2010; Molteni, 2023). Moreover, the thinness of the Italian stock market and the limited number of listed banks make equity prices reflect only a restricted subsample of intermediaries for most of Italian modern history, namely the major ones, reinforcing the "big-bank bias" presented above. As a result, indicators reliant on publicly observable turmoil often fail to capture the true extent of the system's latent fragility, potentially hiding the presence of "ghost crises" (see Molteni, 2023). It is important not to treat these discrepancies as mere technical concerns, as they reflect fundamental questions about the nature of banking crises in relatively backward financial systems and their unfolding across different institutional contexts (Rajan and Zingales, 2003). In turn, the dichotomous nature of crisis chronologies (crisis/non-crisis), combined with the rarity of such events, makes these disagreements particularly impactful, as they feed forward into the identification pipeline, with the risk of biasing empirical results.[3] To mitigate this risk, a continuous measure of financial stress—computed on a dataset representative of the entire banking population—would be a valuable complement to established chronologies, flagging both moments where increasing risk is not reflected in systemic distress and moments of distress without significant systemic instability. Still, transposing modern continuous metrics into a historical perspective remains challenging or largely unfeasible due to unavoidable data limitations (e.g., Duprey et al., 2017; Romer and Romer, 2015).

2. The "good" vs. "bad" credit boom dilemma. Since the seminal works of Minsky et al. (1960) and Kindleberger (1978), the link between credit growth and banking crises has been central to the debate. This relationship was popularized by the empirical regularity identified by Schularick and Taylor (2012) in a panel of advanced economies dating back to 1870, where the credit-to-GDP ratio (macro-leverage) emerged as the single best predictor of financial instability. Yet, as noted among others by Dell'Ariccia et al. (2020) and Gorton and Ordonez (2020), in a historical perspective, it is paramount to qualify credit growth—specifically, to distinguish between "good" and "bad" booms: the former indicating a healthy process of fi-

[3] Inaccuracies in historical records are absorbed into modern chronologies. In turn, modern chronologies are at the core of classification models, which use crisis dates as the main dependent variable. Thus, historical imprecision may bias the identification of predictors and the selection of the best early warning indicators.

nancial deepening, the latter signaling excessive risk accumulation. The extreme consequence of the dichotomy between good and bad booms is put forward by Bordo (2018), who argues that banking crises are inherently unique. He contends that while unified definitions proposed by comparative studies highlight a relevant credit-crisis link, they often underestimate historical heterogeneity. Crises are the result of the specific institutional, economic, and social contexts in which they occur; thus, any one-size-fits-all identification strategy is bound to oversimplification. While financial development is generally considered beneficial for backward economies, if institutions and the regulatory framework are outpaced by credit expansion, it may entail excessive risk-taking: a "bad boom" (Dell'Ariccia et al., 2016; Sahay et al., 2015; Rajan and Zingales, 2003). Distinguishing between these two regimes is paramount, and yet operationally challenging in historical perspective, where the discriminant factors typically proposed by the modern literature—such as granular asset prices (Greenwood et al., 2022), sector-specific productivity (Gorton and Ordonez, 2020), housing prices and mortgage credit (Dell'Ariccia et al., 2020; Jordà et al., 2015), or global liquidity flows (Alessi and Detken, 2009)—are seldom consistently observable. This data scarcity leaves the analyst with an aggregate picture of how much credit grew, but little insight into how it was allocated or the quality of the underlying assets.

In this work, we argue that solving these analytical conundrums requires a "new perspective": one that moves beyond the episodic view of banking crises to adopt a micro-based, structural approach. This perspective serves as the leitmotif—the unifying theme—of the contributions presented in the following chapters. By shifting the focus away from the event itself, we aim to analyze the structural features of the financial system surrounding it—profitability cycles, business model evolution, and the subtle shifts that may (or may not) ultimately culminate in systemic distress. In other words, from the perspective we put forward, crises are not treated as isolated discontinuities but as cumulative dynamics catalyzed by risk accumulation, prompting institutional responses and ultimately shaping the long-run evolution of the banking sector.

Italy serves as a prime testing ground for this approach. The country not only offers an exceptional source of bank-level data (ASCI) but also features a financial history in which credit booms, contrary to common narratives, often did not mark major turning points in the credit cycle (Bartoletto et al., 2018, 2019). This evidence makes it a fertile ground for exploring the latent drivers of financial instability and for complementing—or, at times, contrasting—the established narratives (the "macro picture") with a bank-level perspective (the "micro picture"), which has often been overlooked due to data limitations. Note that, while Italy is an ideal pilot study, this exercise is not isolated; indeed, parallel efforts to collect historical bank balance sheet data for advanced economies are currently being pursued (e.g., by Baron et al., 2023). Moreover, it is important to clarify that our work does not seek merely to rebut traditional banking crisis chronologies or their comparative value. Rather, we maintain that caution is paramount when transposing findings from comparative studies directly into country-specific analyses. Our work highlights the potential pitfalls and unresolved questions arising from such transpositions, arguing that without granular insights, a top-down approach can yield partial and misleading interpretations.

After this introduction, the remainder of this work is organized around the following key research questions:

1. Are bank profits a relevant barometer of financial stress when market signals are unreliable? How does a continuous indicator of financial stress relate to established chronologies of banking crises?

A bank's profitability is a function of its asset and liability management, as well as the systemic context in which it operates—such as competition, monetary policy, and the regulatory framework (Freixas and Rochet, 2008; Savona, 2024). From this, it represents, by construction, a synthetic barometer of a bank's activity within the broader economic and financial context. From this, when market signals (like equity prices) are unreliable—damped by "backdoor" state interventions or limited in representativeness—internal accounting data may be the most reliable proxy for stress in the banking sector. Building on this premise, in chapter 2, we apply our micro-based perspective to construct a continuous measure of financial instability derived from bank profits. This indicator shifts the analytical focus from the binary identification of banking crises to continuous monitoring of stress, thereby mitigating the limitations of narrative evidence—namely, subjectivity, look-back bias, and an over-reliance on major systemic events (Baron et al., 2021). By analyzing profitability both in its cross-sectional distribution and its long-run cyclical evolution, we design a composite metric to directly address the discrepancy in crisis classification, allowing for a critical reassessment of the "canonical" signals. Specifically, during the crisis of 1891/1893, the indicator registers limited systemic stress, supporting the view that the event was less a market collapse and more a political and "moral bankruptcy" (*bancarotta morale*, Pantaleone, 1895 cited in Conti, 2007, p. 121), characterized by a significant scandal but limited systemic tensions. Similarly, for 1907, our results challenge the systemic severity often attributed to the event (Bonelli, 1982), aligning instead with modern revisions that describe a crisis largely confined to the stock market and the few large speculators involved (Vercelli, 2022). We find a similar pattern for 1921, confirming the highly idiosyncratic nature of the distress suggested by Battilossi (2009), and supporting Conti (2007, p. 161)'s characterization of the event as the specific "crisis of the Banca Italiana di Sconto." We detect a significant distress following the deflationary policies of 1926-1927, a shock that particularly hit smaller banks well before the canonical dating of the Great Depression—aligning with Molteni (2023) and described by Conti (2007, p. 171) as a "virulent but silent" crisis.[4] Most interestingly, the indicator reveals a "ghost crisis"—a subtle yet steady accumulation of systemic risk—during the post-1963 period. This phase, largely overlooked by traditional event-based narratives (except for an indication in Baron et al., 2021), highlights the indicator's capacity to detect latent vulnerabilities and raises a compelling puzzle about the nature of the post-war "economic miracle." Ultimately, these findings underscore that a continuous, profit-based metric can effectively decouple the identification of financial stress from the narrative visibility of specific resonant failures.

2. If the profit rate is a barometer of the financial sector, can we effectively discern between "good" and "bad" credit booms by analyzing how the main drivers of bank profitability evolve?

[4]We build on robust evidence on the real impact of the deflationary policy of 1926-27 on the Italian economy (see, e.g., Ferri and Garofalo, 1994; Fratianni and Spinelli, 2001). Yet we take an alternative perspective, considering the banking sector not as a conduit that exacerbated the policy-induced contraction of the real economy, but rather by directly studying how the policy impacted the banking sector itself.

Building on the established link between financial stress and profitability, chapter 3 directly addresses the "good" vs "bad" credit boom dilemma. We propose a novel framework to differentiate between these regimes in historical contexts, offering a solution for periods where granular data on asset prices or borrower quality are unavailable. Our methodology relies on a DuPont decomposition of Return on Equity (ROE) into three core drivers—tailored to the specificity of historical intermediaries: intermediation efficiency (Net Profit Margin), intermediation effectiveness (Asset Utilization Intensity), and financial leverage. By treating leverage as exogenous to market dynamics, we classify the interplay between efficiency and effectiveness into distinct credit regimes. This process effectively creates a micro-based counterpart to the credit cycle, ranging from good credit booms (high utilization/high efficiency) to bad credit booms (high/low), up to disintermediation (low/low). This framework allows us to complement quantitative evidence on *how much* banks lent with a quantitative perspective on *how* they lent. Our analysis identifies "bad" booms in both the 1920s and the post-war period (1950s-1960s)—a compelling finding, given the antipodal regulatory environments and the aura of stability and growth of the post-war period. The former captures the reckless expansion of the mixed banks in the interwar period (Battilossi, 2009; Confalonieri, 1994), while the latter reflects the structural repression of the post-war period (Gigliobianco and Giordano, 2010): while the "economic miracle" drove volumes, the rigid regulatory framework forced intermediaries to operate at declining margins. This parallel suggests that both the laissez-faire of the 1920s and the financial repression of the 1950s and 1960s fostered suboptimal credit allocation, increasing the latent fragility of the intermediaries (Berger and DeYoung, 1997; Engle and Ruan, 2019). However, a crucial difference remains: while the 1920s boom collapsed in the Great Depression, the vulnerabilities of the post-war period were masked by the exceptionally strong economic cycle and the Bank of Italy's policy of stabilization "at any cost," preventing the underlying risks from ever substantiating into an open crisis.

3. Do crises act as structural break points in the evolution of the banking system, or is the evolution of the Italian banking system primarily driven by regulatory adaptation? How does the "business model" of Italian banking evolve over the long run? Does "banking instability" change its meaning? In other words, are all crises alike?

While previous chapters measured stress and lending quality, in chapter 4 we analyze the structural evolution of the banking sector itself. To do so, we introduce a novel framework—the SCoPE (Self-organized COmposite Profiling and Evaluation) system—which leverages neural networks to map the evolving landscape of bank business models over time. This approach allows us to dynamically track how balance sheet compositions and risk profiles adapt to major shocks with variable resolution—from systemic trends to bank-level dynamics—enhancing both cross-sectional and long-run comparability. The system presents three notable properties. First, it enables a comprehensive reassessment of historical crises by detecting their timing, impact, and propagation mechanisms through the lens of balance sheet composition. This aligns our analysis with recent evidence suggesting that bank failures are rarely random "panics" but are almost always rooted in a deterioration of bank fundamentals, allowing us to distinguish between idiosyncratic mismanagement and systemic fragility (Correia et al., 2025). Second, it examines the bidirectional relationship among banking structure, instability, and regulation, aiming to disentangle whether specific business models drive instability or, conversely, whether the structure is shaped by the regulatory response to crises. Third, as a corollary, it provides important validation of the previously developed profitability-based framework, confirming the robustness of our stress identification. Our findings reveal a distinct historical pattern. During the major downturns of the 1890s and the Great Depression, we detect a sharp increase in market segmentation, in which smaller banks bore a distinct burden of adjustment, contrasting the idea of the inherent stability of smaller institutions (Confalonieri, 1974; Cafaro, 1999). Moreover, analyzing the canonical crises of 1893, 1907, and 1921, the results confirm that these events did not trigger significant changes in the system's structure or risk, reinforcing the view that they were "crises of banks" rather than transformative systemic episodes. The most significant change in banking activity is represented by the Banking Law of 1936, which aligns with the prevailing view in the literature. Still, this was not a stable equilibrium: a subtle but fundamental structural change occurred after 1964. In particular, we observe a general shift in which bank portfolios progressively pivoted away from commercial lending toward securities. This structural shift offers a preliminary explanation for the economic mechanism behind the "bad boom" identified in the previous chapter: the rising risk was not driven by reckless lending, but by a regulatory crowding-out effect that slowly eroded the system's allocative function.

4. What structural mechanisms drove the latent instability of the "economic miracle"? Specifically, was there a "ghost crisis" in the 1960s, symptomatic of a deeper malfunction of the financial repression regulation?

Finally, in chapter 5, we synthesize the findings of the previous chapters to analyze the conundrum of the 1950s-1960s—a puzzle characterized by rising financial stress (chapter 2), a "bad boom" credit regime (chapter 3), and a progressive securitization of intermediaries' asset composition (chapter 4). This analysis challenges the conventional view that conflates the postwar period up to the 1970s with a monolithic "financial golden age," in which interventionist policy supposedly guaranteed stability at the expense of efficiency (Cotula, 1999; Ciocca, 2003; De Cecco, 1968; Strangio, 2017). We contribute to the historiography of the Golden Age with an empirical reassessment of the hypothesized high allocative efficiency of the banking system during the period (Battilossi et al., 2011), an analysis which represents a valuable case-study for the economic literature on the effect of financial repression on the banking sector (Monnet, 2018; Reinhart and Sbrancia, 2015). Crucially, the applicability of our conclusions outflows the historical specificity, representing a compelling parallelism with present countries facing the trilemma of short-term stabilization, long-term development, and state intervention. In particular, by tracking the granular evolution of bank business models, we document a profound structural transformation: a shift away from traditional commercial lending and toward a deeper integration with Special Credit Institutes (SCIs)—a process known as *doppia intermediazione* (double intermediation, Gelsomino, 1999). Consistent with Reinhart and Sbrancia (2015), this mechanism led to a persistent, state-driven accumulation of securities in bank portfolios, which eroded the risk/returns positioning of the intermediaries. Moreover, we find that this shift was not merely a passive institutional imposition, but rather a rational and active response to a set of controversial incentives (as noted, e.g., by Carnevali, 2005), catalyzed by weak balance sheet fundamentals and pressures from the term structure of interest rates.[5] We conclude that the stability of the 1960s was not a sign of health but a symptom of a system turning inward, relying on regulatory arbitrage and state guarantees to compensate for the erosion of traditional profitability. This redefines the 1963 episode not as a mere macroeconomic cyclical downturn, but as the moment when the contradictions of the post-1936 regulatory framework materialized, starting the "diabolic loop" that inextricably linked the banking system's health to that of the sovereign (Brunnermeier et al., 2016; Farhi and Tirole, 2018), compromising the Bank of Italy's independence, and setting the stage to the new waves of instability of the 1970s and 1980s.

Taken together, the findings outlined above allow us to articulate the main contributions of this thesis. We claim that, by shifting the observational lens from the distress of the *alta banca* to the micro-level evolution of the broader banking population, this work dialogues with traditional historiographic accounts with a peculiar quantitative rigor. Moreover, the "new perspective" we propose should not be taken as a mere methodological novelty, but rather as a relevant addition to three fundamental debates within financial history and economics.

First, we contribute to the literature on the identification and measurement of financial instability. The dominant consensus in international macro-finance—grounded in the seminal works of Bordo et al. (2001), Reinhart and Rogoff (2008) and Schularick and Taylor (2012)—relies on "event-based" definitions to frame uniform crisis chronologies suitable for cross-country comparison. This approach, while necessary for standardization, fundamentally assumes that systemic risk is always visible through market turmoil (e.g., bank runs) or open failures. Our findings challenge this assumption on two fronts, highlighting the risk of severe selection bias in narrative-based identification. By showing that the canonical crises of 1893, 1907, and 1921 were largely idiosyncratic failures, we demonstrate how standard chronologies may conflate the spread of actual systemic distress with the spread of crisis narratives (Shiller, 2019). In these cases, the perception of crisis—driven by the visibility of the actors—outweighed the actual propagation of stress. Conversely, by documenting a "ghost" rise in systemic stress after 1963, we demonstrate that fragility can accumulate silently in apparently stable macro-financial contexts. The "new perspective" proposed here adds the intensive margin to these debates, that is, the continuous measurement of stress intensity, as opposed to the binary occurrence of a crisis event. We demonstrate that in bank-based economies with high state intervention, financial stress does not necessarily manifest as a crash, but often as a continuous degradation of allocative efficiency that binary indicators fail to capture. This finding aligns with recent evidence suggesting that bank failures are primarily driven by deteriorating fundamentals rather than random runs (Correia et al., 2025), and, methodologically, it validates a novel application of profitability metrics as a substitute for equity prices. In contexts characterized by thin stock markets, we show that accounting data can serve as an objective, quasi-real-time, and quantitative proxy for distress, as advocated by Baron et al. (2021), effectively easing the measurement of risk amid the idiosyncrasies of thin markets. This framework offers a robust alternative not only for historical analyses but also for modern emerging economies, where thin trading and institutional opacity often render standard market signals unreliable.

[5] The evidence of weaker banks being more exposed to the pressures of financial repression aligns with modern theoretical findings of Crosignani (2021).

Second, we intervene in the debate regarding the structural (in)stability of the Italian banking system, challenging the dichotomy that often characterizes local banks as stabilizers and universal banks as vectors of instability (Polsi, 1996; Confalonieri, 1974; Cafaro, 1999). We align with Di Martino (2000) and Molteni (2023) in highlighting that, despite their local roots, small banks faced severe asymmetric information, lower economies of scale, and binding constraints that exposed them to risk. Quantitatively, we validate the hypothesis of Kashyap and Stein (2000) of higher credit elasticity among smaller intermediaries, effectively tracking these dynamics through our profitability metrics. As returns diminished—such as between 1894-1899 and during the Great Depression—we observe a concurrent shift away from a business model rooted in loans. The evidence from the cyclical downturn of 1963 is particularly compelling, offering a prime example where the sharp involution of the peripheral system amplified the shock that regulatory intervention subsequently crystallized. This confirms that small banks were not inherently stable, but acted as an implicit source of instability by contracting credit during downturns—a mechanism distinct from the resonant failures of major institutions.[6] Conversely, the limited spread of distress detected in 1907 and 1921 is not merely a refinement of crisis chronologies: it suggests that describing the collapse of the giants as a deterministic outcome of the "universal banking model" requires careful reconsideration. We claim that the instability of the period is largely explained by the realization of specific governance failures—e.g., moral hazard and conflicts of interest (as hinted, for the interwar period, by Battilossi, 2009)—catalyzed by a regulatory vacuum around mixed banking activity, rather than by an inherent toxicity of the business model itself.

Finally, we engage with the literature on the function and legacy of the 1936 banking law. While both historical and economic works often interpret post-war stability as the legacy of a successful top-down technocratic design that insulated the system from risk (see, e.g., Cotula, 1999; Guiso et al., 2004, 2006), our findings point to a reassessment rooted in the political economy of banking.[7] We argue that the 1936 regulatory framework effectively subordinated the logic of market efficiency to political imperatives, a dynamic consistent with the "game of bank bargains" described by Calomiris and Haber (2014).[8] The political influence over the allocation of financial resources progressively compromised bank profitability and distorted their business models.[9] As a result, our analysis suggests that the stability of the 1960s represents a structural transformation from credit to market risk rather than its elimination. The "golden age" emerges not as a period of inherent financial stability, but rather as a politically induced equilibrium that successfully suppressed the symptoms of instability (open failures) only by exacerbating their causes (capital misallocation and rigidities), fostering a latent accumulation of inefficiencies. Ultimately, while further analysis is needed to fully validate this intuition, we maintain that the regulatory regime did not fully resolve the trade-off between stability and growth: it merely altered the temporal manifestation of distress, trading the

[6] Consistent with the non-monetary transmission channels described by Bernanke (1983) and Mishkin (1991), and applied to Italy by Ferri and Garofalo (1994).

[7] For a discussion on the technocratic nature of the 1936 Banking Law, see Calabria and Molteni (2026).

[8] Indeed, the interplay between banking and political connection represents a strand of financial history of growing interest. See, among others, Altamura (2021); Battilossi et al. (2022); Calabria and Molteni (2026); Jorge-Sotelo (2025); Torreggiani and Cardoso (2024)

[9] A dynamic already visible in the fascist period, as noted by Faccio and McConnell (2025).

visible distress typical of the liberal period for a subtle erosion of the function of financial intermediation that contributed to the structural instability of the 1970s.

Chapter 2

Bank Profitability and Financial Instability: A Barometer of Financial Stress for Historical Analyses

"Historians view each event as unique. In contrast economists search for the patterns in the data, and the systematic relationships between an event and its antecedents. History is particular; economics is general."

— Charles Kindleberger (1978, p. 38)

How can we accurately measure financial stress in historical contexts where standard market-based indicators are unreliable and narrative accounts may be distorted? While recent scholarship has effectively leveraged bank equity declines to identify distress (Baron et al., 2021), we argue that such market-based signals constitute a "first best" solution only in deep, liquid financial markets. In many historical periods (as well as present emerging economies)—characterized by thin trading and opaque institutions—reliance on stock prices introduces a potentially severe selection bias, as the market reflects only a small, often unrepresentative elite of the banking population.

This highlights a binding constraint for financial historians. Without a reliable quantitative anchor, scholars are forced to rely on narrative accounts, which suffer from three inherent frictions (see, e.g., Baron et al., 2021): *discreteness*, as binary indicators fail to capture the intensity of stress; *subjectivity*, as they risk conflating the spread of a crisis narrative with the spread of actual systemic distress (Shiller, 2019); and *look-back bias*, as they tend to flag crises based on manifested consequences (e.g., bank runs) while missing quieter rises of stress.

To ease these frictions, this chapter motivates, constructs, and validates the use of bank profitability as a continuous barometer of financial stress. In doing so, we shift the focus from the binary identification of banking crises to the continuous monitoring of stress. Aligning with the "fundamental-based" perspective in which bank failures are primarily driven by deteriorating balance sheets rather than unpredictable panics (Correia et al., 2025), we argue that accounting profits serve as the most robust proxy for systemic health when market depth is lacking. If profits are, by definition, a synthesis of a bank's fundamentals and the economic environment in which it operates (Freixas and Rochet, 2008; Savona, 2024), it follows that, by analyzing the Return on Equity (ROE), across both its cross-sectional distribution and temporal volatility, we can capture the "intensive margin" of stress. This approach allows us to detect the gradual accumulation of fragility across the broad banking population (including the unlisted majority), effectively decoupling the identification of risk from potential idiosyncrasies of the stock exchange.

Crucially, the novel approach here proposed is highly generalizable, thus representing a valuable tool to make the most of the recent expansion of global historical bank balance sheet data (pursued, e.g., by Baron et al., 2023). Yet, Italy serves as the ideal testing ground for this methodology as it exemplifies the "non-market" context where standard tools falter. Here, equity-based chronologies are constrained by the historical shallowness of the stock exchange, affecting Baron et al. (2021); narrative chronologies are particularly exposed to the opacity of political bank rescues and by the inefficient bankruptcy law (Di Martino and Vasta, 2010; Molteni, 2023), affecting Bordo et al. (2001); Reinhart and Rogoff (2008); Metrick and Schmelzing (2021); and, as shown by Rajan and Zingales (2003), credit-based measures prove ambiguous in an economy undergoing financial deepening, affecting Jordà et al. (2017). In such a context, our profitability-based barometer provides a relevant instrument to bypass these limitations and construct an alternative timeline of instability, to reassess, complement, and contrast (at times) the "canonical" signals.

By applying this novel composite metric to the Archivio Storico del Credito in Italia (ASCI) dataset (1890-1973), our results intervene directly in two fundamental debates. First, we relate to the long-standing methodological debate on crisis identification. Our continuous index aligns with the shift toward objective, quantitative detection (Baron et al., 2021), as well as to the "fundamental-based" interpretation of banking crises of Correia et al. (2025), offering a reproducible blueprint to measure stress in "thin-markets" that avoids the pitfalls of binary classification.[1] Second, in our specific application, we offer a novel quantitative and bank-based perspective to the historical debate on the structural stability of the Italian banking system. We critically confront the traditional crisis narratives (e.g. Bonelli, 1982; De' Stefani, 1960; De Mattia, 1990) which, by accepting the dichotomy between an inherently risky universal banking sector and a stable periphery of cooperative banks, may have historically blurred the boundary between idiosyncratic governance failures and systemic fragility.[2] Our results both align and diverge from conventional chronologies: we downgrade the systemic severity of the distress of 1893, 1907, and 1921 (reinterpreting them as largely idiosyncratic events), while simultaneously uncovering a "ghost crisis" in 1963—a period of silent but profound systemic fragility that standard narratives have systematically overlooked.

After this introduction, the rest of the chapter is structured as follows: Section 2.1 provides a panoramic view of the five most influential crisis chronologies—Bordo et al. (2001), Reinhart and Rogoff (2008), Jordà et al. (2017), Baron et al. (2021), and Metrick and Schmelzing

[1] Note that the methodology here proposed is not inherently limited to either historical or financial settings. It can very well be adapted to present-day data and non-financial entities.

[2] As suggested by Battilossi (2009) for the distress of the major banks in the interwar period.

(2021)—detailing their distinct methodological foundations. Then, it presents a historical narrative of the episodes of financial turmoil identified by these chronologies for Italy between 1890 and 1973, complementing the crisis description with notable regulatory checkmarks. Finally, it offers a critical assessment of the limitations of these standard frameworks when applied to the unique institutional, political, and economic context of Italy. Section 2.2 presents the Archivio Storico del Credito in Italia, the main source for this analysis. It describes the balance sheet data composition, its coverage, and representativeness. Then, it describes the construction of the working sample and the preprocessing operations. Section 2.3 presents the construction of the continuous barometer of financial stress. First, it discusses the validity of the ROE as a proxy of financial stress, relating it to standard measures such as the credit-to-GDP ratio. Then, it offers a detailed overview of the methodological framework. Section 2.4 presents the stress signals identified and critically confronts their validity with the historical narratives, detecting episodes of potential fragility previously overlooked while offering a novel perspective to qualify known crises. Lastly, section 2.5 concludes.

2.1 Chronologies and History: An Overview of Italian Banking Crises

Financial crises are a persistent and defining feature of economic history. Since the birth of modern economics, identifying the build-up of risk has remained a central challenge for both policy and historical analysis (Thornton, 1802; Bagehot, 1873). As shown by Figure 2.1, since the 19th century, the recurrence of these episodes is often documented as an inherent feature of the business cycle, a sequence of "manias, panics, and crashes" (Kindleberger, 1978) fostered by the powerful belief that "this time is different" (Reinhart and Rogoff, 2008): the illusion that, in the current boom, fundamental economic laws have been suspended.[3]

The global financial crisis of 2008 can be interpreted as an example of the "this time is different" syndrome, one that catalyzed a profound shift in macroeconomic thought, driving a renewed attention to the long-run dynamics of money, credit, and, crucially, financial instability (Frydman and Xu, 2023). Scholars and policymakers, confronted with the limitations of models that had largely ignored the financial sector, turned to economic history to gather evidence and lessons (see, among others, Baron and Xiong, 2017; Gourinchas and Obstfeld, 2012; Jordà et al., 2011, 2013). This revival of interest has driven a significant academic effort to construct comprehensive and systematic chronologies of banking crises, aiming to identify common early warning signals, patterns, macroeconomic consequences, and effective policy responses (Baron et al., 2021; Jordà et al., 2017; Laeven and Valencia, 2008, 2013, 2020; Metrick and Schmelzing, 2021; Nguyen et al., 2022; Reinhart and Rogoff, 2008). New long-run databases, built upon historical narratives and enhanced by newly available quantitative data, provide the foundations for modern empirical macro-finance.[4]

[3]Yet, "the pervasive view that this time is different is precisely why it usually isn't different, and catastrophe eventually strikes again" (Reinhart and Rogoff, 2008, p. 33).

[4]A most notable example is the *Macrohistory database*, compiled by Jordà, Schularick, and Taylor and a source for numerous publications.

Figure 2.1: The Overstone cycle of trade (1859)

The figure represents the Overstone cycle of trade, a representation of the cyclical nature of crises, characterized by a boom that eventually will lead to an irrational exuberance, panics, and crashes. The image is created by J. Johnston in 1859 and offers an effective synthesis of Kindleberger's main points.

The dominant method for cataloging historical instability remains that of "counting crises"—dichotomous classifications (crisis/non-crisis) grounded in event-driven nature of historical narratives (Sufi and Taylor, 2021).[5] Modern attempts at continuous indicators exist, but their implementation is severely constrained by data availability and variable institutional settings in the long run (Duprey et al., 2017; Romer and Romer, 2015). On the other hand, binary chronologies, while undoubtedly useful for broad comparisons, present three intertwined frictions that can distort the crisis timeline:

1. Discreteness and intensity. Financial crises are not uniform; they can vary from the distress of a single major bank to a widespread panic with systemic contagion. A binary indicator, however, is by construction unsuitable to capture the intensity of financial distress or the gradual nature of its build-up. Most importantly, it cannot detect periods of elevated but sub-crisis-level stress, which may not trigger a panic yet still have significant negative effects on the real economy—such as credit contractions or investment declines—or it may misclassify localized events, without systemic spillovers.

2. Narrative subjectivity. The identification of historical financial crises is often shaped by the power of narratives. As Shiller (2019) argues, economic stories can "go viral," introducing a significant layer of subjectivity into the classification of past events. This narrative effect

[5]The tendency of the historical analysis to focus on singular events rather than continuous processes is defended by Kindleberger (1978, p. 38): "Historians view each event as unique. In contrast economists search for the patterns in the data, and the systematic relationships between an event and its antecedents. History is particular; economics is general."

creates two mutually related challenges. First, caution is required to discern a true systemic crisis from one driven by informative contagion, where the spread of a crisis narrative can be conflated with the spread of actual distress. Second, it can introduce a significant "big-bank bias." The events surrounding major, politically-connected banks are more likely to resonate with the public, be documented in contemporary sources, be preserved in archives, and eventually be recorded as systemic distress, even if the broader system remains resilient. Conversely, widespread distress among smaller, peripheral banks often fails to generate a cohesive narrative, leading to their exclusion from official chronologies.

3. Hindsight and survival bias Finally, the ex-post investigation of crisis events is vulnerable to a look-back or hindsight bias (Baron et al., 2021). Knowing that a crisis ultimately occurred, we may perceive it as more predictable than it was. In turn, this retrospective approach may introduce a "narrative survivorship bias", where only the most dramatic events—such as those that culminated in widespread panics and failures—make a lasting enough impact to be recorded by modern accounts. This adds to the narrative subjectivity in making so that quieter episodes of widespread distress—e.g., for secret interventions—may be systematically missed. As proven by Molteni (2023), this may create "ghost crises" and underestimate the frequency of financial fragility.

Crucially, these three limitations—discreteness, subjectivity, and hindsight bias—are linked and self-reinforcing.[6]

The effort to systematically catalogue financial crises into a uniform framework has produced five main chronologies of Italian banking crises, each with a distinctive conceptual foundation: Bordo, Eichengreen, Klingebiel, Martinez-Peria, and Rose (2001), Reinhart and Rogoff (2008), Jordà, Schularick, and Taylor (2017), Baron, Verner, and Xiong (2021), and Metrick and Schmelzing (2021). These works do not represent a simple linear progression of data availability but distinct methodological choices linked to a deeper debate about the nature of a banking crisis (Sufi and Taylor, 2021). When applied to Italy for the period 1890-1973, these chronologies produce a timeline of financial instability which is summarized in Table 2.1.

In the following lines, we will offer an overview of the five chronologies, detailing their distinct methodological foundations. We will present a historical narrative of the episodes of banking crisis identified by these chronologies for Italy between 1890 and 1973. Finally, we will offer a critical assessment of the limitations of these uniform frameworks when applied to the unique institutional, political, and economic context of Italy.

[6] An example of the self-reinforcing nature of the three limitations may go as follows: a banking distress occurs. In its aftermath, hindsight makes the outcome seem inevitable and easily explainable. This sense of inevitability fuels the creation of a simple, powerful narrative that often focuses on a singular trigger or event. This compelling story, in turn, demands a clear "start date" for the crisis, reinforcing a discrete, binary view of a complex and continuous process. Historical chronologies are then built upon these narrative-defined events, codifying the simplification and obscuring the long, gradual build-up of risk that preceded the singular event.

Table 2.1: A comparative view of Italian banking crises chronologies

Chronology	1891	1893	1907	1914	1921	1925	1930	1931	1935
Bordo et al. (2001)	✓	✓	✓	–	✓	–	✓	✓	✓
Reinhart and Rogoff (2008)	✓	–	✓	✓	✓	–	✓	–	✓
Jordà et al. (2017)	–	✓	✓	–	✓	–	✓	–	✓
Baron et al. (2021)	✓	–	✓	✓	✓	–	✓	–	–
Metrick and Schmelzing (2021)	✓	✓	✓	✓	✓	✓	✓	–	✓

The table offers a comparative view of the five main chronologies of banking crises for Italy in the period 1890-1973. While episodes like 1907, 1921, and 1930 are unanimously signaled, disagreement exists between the other events.

2.1.1 Banking Crisis Chronologies: Methodological Choices

1. Bordo, Eichengreen, Klingebiel, Martinez-Peria, and Rose (BEKM, 2001)

This study was among the first to systematically analyze crisis frequency and severity over a long historical span, covering 120 years. Their methodology is primarily narrative, strongly building on Kindleberger (1978), defining a banking crisis as a period of "financial distress resulting in the erosion of most of aggregate banking system capital" (p. 55). Thus, the core criterion is the significant depletion of the banking system's capital, directly linking a micro-determinant of risk to the macro-context. For Italy, this approach identifies crises beginning in 1891, 1893, 1907, 1921, 1930, 1931, and 1935.

2. Reinhart and Rogoff (RR, 2008)

In their renowned work, *This Time Is Different*, Reinhart and Rogoff compiled a comprehensive database of banking crises over eight centuries, building on the preceding works of Kindleberger (1978) and Bordo et al. (2001). Their definition of a systemic banking crisis is event-based and relies on two primary signals: "(1) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; and (2) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions), that marks the start of a string of similar outcomes for other financial institutions" (p. 81). Thus, the main focus of the approach is on episodes of acute and observable systemic distress. Applying this definition to Italy, they flag crisis years in 1891, 1907, 1914, 1921, 1930, and 1935.

3. Jordà, Schularick, and Taylor (JST, 2017)

Building on preceding chronologies (primarily BEKM and RR), Jordà, Schularick, and Taylor defines a banking crisis as an event "characterized by major bank failures, banking panics, substantial losses in the banking sector, significant recapitalization, and/or significant government intervention." (Jordà et al., 2021, p. 1). Having its seminal form in the work of Schularick and Taylor (2012), the chronology is then updated as a part of the *Macrohistory database*. The authors hold a particular focus on Kindleberger's idea of crises as the outcome of the cyclical process of manias, panics, and crashes, with a narrative built around the pro-cyclical nature of credit. Their central finding is that a rapid growth in bank lending relative to GDP is the best single predictor of a subsequent crisis. Their chronology for Italy identifies crises in 1893, 1907, 1921, 1930, and 1935.

4. Baron, Verner, and Xiong (BVX, 2021)

Baron, Verner, and Xiong's recent work complements the preceding focus on panics with episodes of bank capital crunches, arguing that large equity declines are at the core of a banking crisis, and they tend to anticipate creditors' run. Sourcing contemporary newspapers, they construct a new dataset of bank equity returns for 46 countries since 1870 and define a crisis as a year with a decline in the national bank equity index greater than 30%. This market-based indicator offers a quantitative and real-time indicator of risk that mitigates the bias of dichotomous chronologies (see above). The signals from the stock market are then supplemented with narrative evidence—while cross-checking preceding chronologies with country-specific literature—to classify episodes as either "panic" or "non-panic" crises. Their methodology identifies crises in Italy in 1891, 1907, 1914, 1921, and 1930.

5. Metrick and Schmelzing (MS, 2021)

The chronology offers the most extensive historical coverage, going as back as the 13th century. The authors identify crises based on the policy response they elicit, under the assumption that "the existence of an intervention may be a sign that there was indeed a banking crisis that was overlooked by the past literature" (p. 2). Thus, building on country-specific literature, the authors construct a database of 1,886 government interventions across 138 countries, categorizing them into 20 types such as lending, guarantees, and capital injections. A crisis is identified by the presence of such interventions, regardless of whether a public panic occurred. This approach captures both "canonical" crises identified by the preceding literature and "candidate" crises where interventions may have preempted a wider collapse.[7] For Italy, this method flags crises in 1891, 1893, 1907, 1914, 1921, 1925, 1930, and 1935.

2.1.2 A Contested Timeline

Comparing the five chronologies reveals a clear methodological schism. On the one hand, BEKM, RR, and JST identify crises retrospectively based on their manifested consequences, a method described as "I know it when I see it" (Sufi and Taylor, 2021, p. 6). On the other hand, BVX and MS prioritize signal extraction. Note that, as a result, each group is measuring a subtly different phenomenon—historical outcomes versus market perceptions and policy actions. This fundamental difference explains why their application to a single country's history can yield divergent results. In this section, we provide the historical context necessary to understand the crisis timeline and to appreciate why Italy's unique institutional setting is a perfect case study for these tensions.

[7] To avoid false positives, a historical validation of the candidate crises is paramount. Yet, the authors state that "the main purpose of our database is to identify the interventions themselves, and we leave to later work any conclusive statements about the inclusion of our candidate crises in comprehensive crises lists" (Metrick and Schmelzing, 2021, p. 7).

The Crisis of the 1890s and the Birth of the Bank of Italy

Following unification in 1861, Italy's financial system remained fragmented and underdeveloped. A key feature was the existence of six different banks authorized to issue currency, a legacy of the pre-unification states.[8] The political willingness to enforce a regulation on the issuing bank was lacking (De Mattia, 1990; Gigliobianco and Giordano, 2010; Polsi, 1996).

This weak regulatory framework set the stage for a massive speculative boom in the 1880s, centered on the construction and real estate sector in the new capital, Rome. Fueled by an influx of foreign capital after Italy joined the gold standard in 1881, the boom was sustained by the issuing banks' involvement in the speculation. The bubble burst in 1887, leaving banks with vast portfolios of illiquid assets. Many banks ended up in severe distress. Some of them failed, most of them were bailed out with capital from the issuing banks. The operations involved printing banknotes well beyond the legal limits, possible thanks to the tacit government's approval (Fratianni and Spinelli, 2001).

The situation culminated in the infamous Banca Romana scandal of 1893, signaled by the chronologies (Negri, 1989; Pani, 2017; Toniolo, 2018). A parliamentary inquiry revealed that the bank had concealed massive losses, engaged in widespread corruption involving politicians and journalists, and illegally printed duplicate banknotes to cover its liabilities. The scandal was not merely a financial failure but a profound crisis of political legitimacy for the young Italian state—a "moral bankruptcy" (*bancarotta morale*) described by Pantaleone 1895). The fallout was severe. Weighed down by non-performing loans, Banca Romana was liquidated in 1894. The crisis spread, triggering the collapse of two major institutions connected to Banca Romana, the Banca Generale and the Credito Mobiliare.

This collapse forced a major regulatory reform: the Banking Law of 1893. This landmark legislation merged three of the issuing banks to create a new, dominant institution: the Bank of Italy. Alongside the surviving Banco di Napoli and Banco di Sicilia, the new Bank of Italy was granted the privilege of note issuance, marking Italy's first major step toward creating a modern central bank.[9]

The 1907 Crisis: An Example of Lender of Last Resort

At the dawn of the 20th century, Italy's newborn industrialization was largely financed by abundant foreign capital thanks to the favorable global economy (Fratianni and Spinelli, 2001). This rapid growth inflated the demand for long-term industrial credit, a role that was filled by newly created joint-stock banks modeled on the German "universal (mixed) banks". As a key feature, these banks held significant equity stakes in their industrial clients, creating a deep and risky entanglement.

After warning signs of market volatility in 1905 and 1906, a sharp downturn hit in 1907. The

[8] As of 1870, when the annexation of Rome concluded the unification process, the newborn kingdom of Italy inherited Banca Nazionale nel Regno from the Kingdom of Sardinia-Piedmont, Banco Nazionale di Toscana and Banca Toscana di Credito form the Gran-duchy of Tuscany, Banca Romana from the Papal States, and Banco di Napoli and Banco di Sicilia from the Kingdom of the Two Sicily.

[9] The 1893 law also separated government and banking roles and established state supervision over money creation. The Bank of Italy itself would remain publicly traded until 1936.

fall in stock prices spiraled, exacerbated when three of the four main institutions—Banca Commerciale Italiana (COMIT), Credito Italiano (CREDIT), and Banco di Roma (BR)—began liquidating their holdings to stop the losses. In a desperate counter-maneuver, Società Bancaria Italiana (SBI) alone tried to sustain the prices to protect the value of its assets. The effort failed, pushing the bank to the brink of collapse: This event is signaled by the chronologies (Bonelli, 1982; Vercelli, 2022).

To avoid contagion effects, the Bank of Italy, under the leadership of Bonaldo Stringher, organized a consortium to support the too-big-to-fail SBI and provided liquidity to the system, successfully preventing the stock market crash from spilling over into a systemic banking collapse (Gigliobianco and Giordano, 2010). This episode was a crucial test for the newly established central bank, solidifying its role as the lender of last resort and enhancing its authority and reputation within the national financial system.

Winds of War: the Moratorium of 1914

The outbreak of World War I in July 1914 triggered a global financial turmoil. Italy, which was initially neutral, was not immune to the panic (Toniolo, 1989). To prevent a run on the banking system, the government declared a moratorium on bank payments, effectively allowing banks to temporarily suspend the convertibility of deposits. This regulatory action is taken as a reference to mark the banking crisis, largely because it involved a major government intervention that suspended normal market functions.[10]

The post-war and the crisis of mixed banking: the collapse of Banca Italiana di Sconto (1921)

Italy's participation in World War I fueled the expansion of heavy industries and the universal banks that financed them (Toniolo, 1989). The post-war transition to a peacetime economy led to a severe crisis of war-inflated giants, like the Ansaldo steel and shipbuilding conglomerate. This industrial crisis immediately spilled to Banca Italiana di Sconto (BIS), one of the four largest banks, which was heavily exposed to Ansaldo (Gigliobianco and Giordano, 2010; Toniolo, 1995).[11]

Similarly to 1907, the Bank of Italy formed a consortium of banks to sustain the liquidity of the BIS, but the colossus was too-big-to-save. In 1922, the BIS was forced into liquidation, with a bailout operation managed by the Bank of Italy and the government to protect depositors and prevent systemic contagion. Panic spread to the ailing Banco di Roma, which experienced a run on its deposits but was successfully rescued by special subsidies from the new Mussolini government (Falco, 2003; Toniolo, 1995). The crisis of the BIS in 1921 is signaled by the chronologies and represents a profound failure of the unregulated universal banking model in Italy (Confalonieri, 1994).

[10] The episode raises a critical question on the definition of what is a banking crisis: does a preventative policy response to an exogenous geopolitical shock constitute a banking crisis in the same sense as one stemming from endogenous financial fragility, such as the 1893 collapse? Answering this question goes beyond the scope of this review.

[11] This relationship raises a profound conflict of interest since the shareholders of the BIS and the Ansaldo largely overlap. Due to the post-war real economic slowdown, monetary tightening, and the end of military contracts, Ansaldo's business was ailing. The increasing losses are covered by loans from the BIS, with the consequent erosion of its capital and liquidity. In 1921, the BIS experienced a run on its deposits (Sraffa, 1922).

The Interwar Years: Stabilization, Deflation, and Depression

The years between 1922 and 1925 were a period of intense economic growth in Italy, with joint-stock banks heavily financing the industrial boom (Gigliobianco and Giordano, 2010; Molteni, 2023; Toniolo, 1995). This created a situation where the soundness of the entire banking sector became dangerously intertwined with industrial performance. As credit demand from profitable firms became saturated, banks increasingly diverted funds towards speculation (Segre, 1926; Mazzantini, 1928, 1946).

This trend was exacerbated by the loose regulation, which led to the proliferation of banks of dubious quality. As the governor of the Bank of Italy noted: "The complete lack of any banking regulation allowed the establishment of a multitude of banks [...] with the specific aim of collecting deposits that often ended up in dreadful speculations" (Stringher, Relazione Annuale agli Azionisti of Bank of Italy, 1927, translation from Italian by Molteni and Pellegrino, 2021, p. 22).

It was in this overheated context that the first comprehensive banking law was passed in 1926. The legislation granted the Bank of Italy a monopoly on note issuance and formal powers to supervise the entire banking system. It also introduced a depositor safeguard mechanism, required government authorization for the establishment and merger of banks, and set capital requirements proportional to a bank's activities (Molteni and Pellegrino, 2021). While the law was a direct response to the rampant speculation—and the memory of the mixed banking failure of 1921—its initial enforcement was cautious. In particular, the largest banks were too big, too complex, and too deeply intertwined with the industrial sector to be supervised effectively (Fratianni and Spinelli, 2001).

In 1925, Italy's real economic growth stalled. Stricter government regulations aimed at curbing speculation halted stock market growth, while the real economy weakened due to domestic inflation and capital flight abroad.[12] In response, the government attempted to prop up the market by injecting £500 million into the banking sector to purchase blue-chip shares. This maneuver was unsuccessful: Its main consequence being to further deepen the already unhealthy financial ties between banks and the industrial sector. While this was a significant state intervention, and thus reported by Metrick and Schmelzing (2021), it can hardly be considered a banking crisis, justifying its absence in other chronologies.

Facing prolonged pressure on the Lira's exchange rate, the Fascist regime made monetary stabilization a key objective. In 1926, Mussolini famously announced "Quota 90," a policy aimed at revaluing the currency to the level of 90 per British Pound, seen as a matter of national prestige (Cotula and Spaventa, 1993; Fratianni and Spinelli, 2001). Achieving this target, however, required severe deflationary measures that placed both the industrial and banking sectors under extreme stress.

Publicly, the regime adopted a hard line. It declared that it would not support ailing banks, arguing that acting as a lender of last resort was incompatible with its tight money policy (Toniolo, 1995). Instead, the official strategy was to force the merger or liquidation of smaller,

[12] Capitals were fleeing out of Italy, as Great Britain increased interest rates to return to pre-WWI gold convertibility (Cotula and Spaventa, 1993).

poorly-managed banks. Behind this facade, however, the government and the Bank of Italy intervened heavily through covert, "backdoor" actions to stabilize the financial system. These secret operations successfully created an illusion of stability, concealing a widespread financial distress that was deliberately hidden from the public (Molteni, 2023, 2024).[13]

Thus, the onset of the Great Depression in 1930 hit the already fragile Italian economy. To avert a total collapse, the regime undertook significant, albeit largely secret, state interventions.[14] In 1933, the Institute for Industrial Reconstruction (IRI) was created, a state-owned holding company that took over the industrial shares of the failing banks, effectively nationalizing large portions of both the banking and industrial sectors (Toniolo, 1995).

Despite secret operations, the profound impact of the crisis is reflected in the structural transformation of the Italian financial sector that followed, culminating in the banking law of 1936.

The Law marked the end of Italy's free banking era, restructuring the system by defining banking as an activity of public interest (Art. 1). The law's reforms were comprehensive (Gigliobianco and Giordano, 2010). First, it transformed the Bank of Italy from a simple bank of issue into a modern central bank, granting it full authority over the money supply, bank supervision, and the role of lender of last resort. Second, competition was curtailed to ensure stability. Interest rates on deposits and loans were centrally fixed by a banking cartel, and the government retained the power to force bank mergers or liquidations. Third, the law's most significant reform was the strict separation between long-term credit and commercial banking. To prevent dangerous conflicts of interest and maturity mismatch, "universal banking" was prohibited. Long-term industrial lending was restricted to Special Credit Institutes (SCI), financed by long-term liabilities and with a direct involvement of the government.[15] Commercial banks, funded by short-term deposits, were required to invest only in safe assets.

Overall, the law's focus was macroprudential—controlling the market's structure and activities directly—rather than microprudential (e.g., setting capital adequacy ratios). Its principles will be remarkably durable. The core rationale of separating commercial and investment banking survived the fall of Fascism, the Second World War, and the birth of the Italian Republic until its replacement in 1992.

While the Great Depression left a weak financial system, the nature of the crisis of 1935, as signaled by the main chronologies, remains unclear. Bernanke and James (1990) reports a run on deposits following the international sanction imposed on Italy for the invasion of Ethiopia, a signal picked up by BEKM and RR. Still, while stress was present, particularly

[13] For instance, limitations on deposit withdrawal are imposed to prevent bank runs. In 1928, Banca Agricola Italiana was rescued by the Bank of Italy but ultimately liquidated in 1930. In 1929, under government pressure, the Bank of Italy provided liquidity to a consortium of ailing Catholics banks.

[14] The remaining large universal banks—COMIT, CREDIT, and Banco di Roma—had to be rescued with liquidity injections. In 1931, £330 million was lent to CREDIT, and £1 billion to COMIT. 47% of small and medium banks are secretly bailed out (Molteni, 2023).

[15] In particular, SCIs couldn't collect retail deposits. Their main funding comes from the issuing of long-term bonds and long-term mortgage-backed bonds (*cartelle fondiarie*) and short-term interbank current accounts.

among saving banks, there is no clear evidence to support either a significant run on bank deposits or a banking crisis (Molteni, 2021).

To sum up, this brief historical review reveals a path-dependent, co-evolutionary process between crises and regulation. The nature of financial instability in Italy changed over time, with an institutional framework constantly adapting to the lessons of the previous crisis. The 1893 crisis, born of a fragmented system of currency issuance, was met with the creation of the Bank of Italy. The instability of the early twentieth century, driven by the excesses of unregulated universal banking, was met with the introduction of formal supervision in 1926. The systemic collapse of the mixed-banking model during the Great Depression was met with the total separation of banking and industry in 1936. Each crisis was a unique product of the regulatory regime that preceded it. This is why Italian historical descriptions are strongly institutionally-focused, yielding crucial insights into the interplay between regulation and financial stability, and of how this unfolded with the changing political scene (Galanti et al., 2012; Gigliobianco and Giordano, 2010; Molteni and Pellegrino, 2021; Toniolo, 2018).

2.1.3 The Limitations of Existing Frameworks in the Italian Context

The historical narrative reveals a financial system with specific characteristics that challenge the assumption embedded in established chronologies. The application of a universal definition to the particular Italian context may exacerbate the frictions presented above. Five interconnected factors explain why:

1. Extensive state ownership. Extensive state ownership of the banking sector fundamentally alters crisis dynamics. Following the massive state bailouts of the 1930s, the government became “entrepreneur and banker” (Malanima and Zamagni, 2010, p.13). When the state is the primary owner of major banks, financial distress often manifests through fiscal rather than credit channels (Andrews, 2005).[16] Problems that might trigger a bank failure in other systems instead appear as budgetary pressures or contingent liabilities, rendering them invisible to chronologies that rely on public bank failures as their primary indicator.

2. Government backdoor interventions. To preemptively deal with banking crises—in particular to restart worthy but illiquid institutions —Italy had administrative tools that allow authorities to manage distress before it escalates: pre-bankruptcy official agreements (*concordato*) and receivership-like solutions (*amministrazione controllata*). Still, these procedures were often too complex and ineffective, motivating the recourse to alternative measures, as the informal bailouts seen above (Di Martino and Vasta, 2010).[17] This preemptive approach prevents the emergence of the clear distress signals that standard crisis methodologies are designed to detect. While backdoor interventions for the major banks are now well documented—such as the bailout of COMIT and CREDIT in 1931—those for smaller and medium banks remain

[16] For an example of the impact of fiscal dynamics on the banking sector, see chapter 5.

[17] For instance, the ex-governor of Bank of Italy Einaudi in 1960 clearly stated that the central bank’s role in a banking crisis is to preserve stability: “avoiding noises, the guilty are forced to sacrifice what remains to them, credit is preserved, and depositors are unaware of the danger they faced” (cited in Ciocca, 2003, p. 4, translated by the author).

"ghost" crises, as proven by Molteni (2023).

3. Regional and institutional heterogeneity. Third, the persistent economic divide between the industrial North and the less-developed South is a core feature of the Italian economy. This regional heterogeneity has profound impacts on the structure of the banking system that adapted to meet local financial development needs, a process often fostered by political incentives (Albareto and Trapanese, 1999; Guiso et al., 2004, 2006; Polsi, 1996).[18] As a result, the credit cycle may not be coordinated regionally, and banking crises are strongly localized, e.g., the crisis of 1893 is rooted in Roman banks, the crisis of 1907 in those banks involved in stock market speculation. Thus, it is particularly valuable to have a tool to effectively track within-country variations in instability, to complement traditional chronologies that, by construction, code Italy as a whole as either in crisis or not in crisis, possibly obscuring significant regional heterogeneity.

4. Uneven financial development. Italy's late and uneven financial development means crisis indicators appropriate for one period may be irrelevant for another. Equity-based measures, while broadly applicable to the liberal period, are ill-suited for most of the 20th century, with a relatively thin and illiquid stock market (Aganin and Volpin, 2003). Relying on the stock prices of the few large, listed commercial banks would not only amplify the big-bank bias but also provide a highly unrepresentative signal of the health of the banking system as a whole. In turn, credit-based indicators may misclassify episodes of financial deepening and cannot grasp tensions during periods of financial repression, when allocation occurs with strong administrative incentives, as in the 1950s-1960s (Cotula, 1999)[19].

5. Intertwinement between banking and political crises. The intertwinement of banking and political crises in Italy produces hybrid episodes without a clean categorization. A key analytical error is conflating the crisis of a single bank with a systemic banking crisis, often driven by the public and political reaction at the time of the event. For instance, the 1893 Banca Romana affair is better understood as a political *scandal* than a financial *crisis*: It was a story of corruption and fraud that was perceived by the public as a massive political corruption scandal that eventually felled the Giolitti government (Pantaleone, 1895). While its roots were in the 1887 housing market collapse, its failure did not spark a wider, lasting panic throughout the banking system.

These peculiarities suggest that dominant banking crisis models—largely derived from the Anglo-American experience—while offering a valuable lens for the analysis, must be cautiously generalized to the Italian context. At the same time, while historical top-down institutional analyses of Italian banking crises provide an essential understanding of the regulatory context, their narrative focus can be powerfully augmented with quantitative data.

Therefore, to build upon the existing literature, we propose a complementary tool: a continu-

[18] The local bank network is the result of both pre-unification conditions and ongoing development. For instance, savings banks were first established in the Austrian Empire, and thus are particularly concentrated in the north-eastern regions. Cooperative banks are more concentrated in agrarian regions, while joint-stock banks in urban centers.

[19] See chapter 3 for evidence of "good" booms and chapter 5 for an in depth analysis of the administrative incentives in the credit allocation of the 1960s.

ous measure of financial stress. Acting as a compass, this indicator is not meant to replace the rich narrative of chronology but to orient it. By pointing towards periods of rising, unseen financial pressure, it allows the researchers to direct the analysis to the most critical periods.

2.2 The Archivio Storico del Credito in Italia

The main data source for this work is the *Archivio Storico del Credito in Italia* (hereby, ASCI), a collection of balance sheets periodically sent by the intermediaries to the Bank of Italy as a part of its supervisory activity.

2.2.1 Sources, Data, and Harmonization

The ASCI database is constructed by aggregating and harmonizing data from a wide range of archival sources, combined with extensive digitization efforts by the Bank of Italy (Natoli et al., 2016).[20] It builds upon the reconstruction work of Cotula et al. (1996)—a dataset of bank balance sheets for 1890-1936—updated, corrected, and extended up to 1973, drawing from the Bank of Italy's supervisory archives. The result is a comprehensive database covering the entire 1890-1973 period.[21]

The periodicity of the accounts is annual (December) for the data before 1937, semi-annual (June and December) for the data between 1937 and 1950, and quarterly (March, June, September, December) for the data between 1951 and 1973. For long-run consistency, in this work, we are focusing on yearly data, for a total of 41,385 bank-year observations, before any pre-processing and sample selection.

The harmonization process consists of mapping 24 distinct accounting standards to a common structure, suitable for the entire 1890-1973 period.[22] The harmonized structure organizes data into the three main sections: Assets, Liabilities, Off-balance sheet items—with the notable presence of the Profits and Costs—with a hierarchical levels of detail: "main items" (voci), "sub-items" (sottovoci), and "tertiary items" (sottovoci1).[23] An example is presented in Table 2.2.

Main asset items include, among others, Sight assets (cash and interbank balances), Portfolio bills (bills of exchange and short-term Treasury bonds), Advances and REPOs, Mortgages (including unsecured ones), Securities (investment in both public and private securities, excluding short-term government bonds), Current account assets (both to retail and other financial institutions), Other assets (including non-performing loans). On the liabilities side, major categories include Fiduciary deposits (fixed term deposits), Current account deposits

[20] For a thorough analysis of the archival sources see (Natoli et al., 2016, p. 14).

[21] The choice of 1973 as the cut-off reflects a 40-year confidentiality rule at the time of ASCI's compilation.

[22] The different accounting standards are a function of both the historical period and the juridical category of the institutions (See Natoli et al. (2016, Tab. 3, 4 and 5)).

[23] Tertiary items are available after 1936, with the more comprehensive and unified accounting standard following the *Modulo 81 di vigilanza*.

Table 2.2: ASCI's Sight Assets decomposition (voce 100)

Sub items	Description
100.1	*Cash*
100.1.1	Cash
100.1.2	Banknotes and coins
100.1.3	Coupon, drafts and other sight-claim securities at other institutions
100.1.4	Foreign cash
100.2	*Deposits at other institutions*
100.2.1	Sight deposits at Bank of Italy
100.2.2	Sight deposits at other institutions
100.2.3	Restricted deposits at the Treasury and other institutions
100.2.4	Deposits at other institutions

The table shows an example of the three layers of detail present in ASCI. The table examines the composition of the main item "Sight assets" (voce 100). The table reports the sub-items and the more granular tertiary items in which "Sight assets" are divided. Note that granularity comes at the cost of reliability and long-run consistency.

(both to retail and other financial institutions), Capital and reserves, and Other liabilities (bonds, rediscounted bills). The result is a dataset that captures all the major balance sheet dynamics consistently over eight decades and different institutional contexts, allowing for both cross-sectional and longitudinal analyses, and particularly helpful to track major credit phenomena and long-run trends in banking (see Figure 2.2).[24]

During the homogenization process, when historical sources reported only aggregate figures that needed splitting for comparability or completeness, sub-items were imputed based on patterns from similar banks and adjacent years. When balance sheet totals did not match, if it was not possible to correct the error with original sources, a small "balancing item" was added to account for the discrepancy. All adjustments are carefully documented in the database.

2.2.2 Coverage and Representativeness

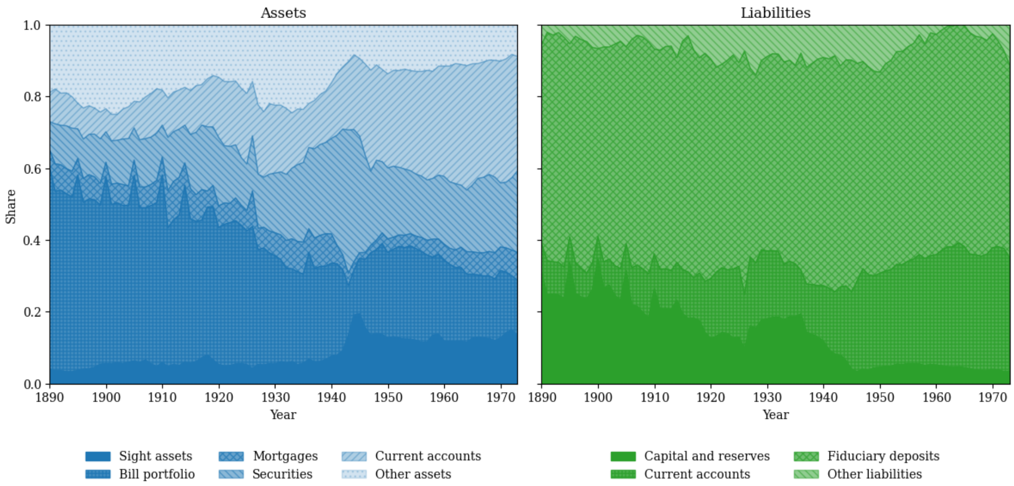
The ASCI database covers the main segments of the Italian banking sector, focusing on institutions that took deposits and made loans. The universe of banks covered by the ASCI database includes the following institutional categories operating between 1890 and 1973:[25]

— *Joint-stock banks (Società ordinarie di credito, SOC)*. Profit-oriented private commercial banks following the general law on joint stock companies until 1926. Until 1936, this category

[24] A caveat is due: as it always the case with balance-sheet data, we cannot fully rule out the possibility of manipulation or miss-classification, particularly in historical contexts with evolving accounting standards. To the best of our current knowledge, ASCI's declared profits represent the most reliable and widely accepted estimates available, and they have been consistently used in preceding studies (e.g. De Bonis et al., 2018; Molteni, 2023, 2024).

[25] Additional information in Natoli et al. (2016, p. 34)

Figure 2.2: ASCI Assets and Liabilities composition (share of the total), 1890-1973



The figure plots the average asset and liabilities composition as the share of the total assets and total liabilities, respectively.

includes major national banks, later classified as Banks of National Interest. Branches of foreign banks are included in this category.

— *Cooperative banks (Banche Popolari, BP).* Cooperative ownership banks, with the role of providing credit to the shareholders (but not limited to them) at advantageous rates. Shareholders voted with the rule of "one man, one vote."

— *Savings banks (Casse di Risparmio ordinarie, CRO).* Publicly oriented savings institutions, often under local foundations or municipal sponsorship, with the role of promoting the formation of savings and a suitable—i.e., not risky—allocation for them. Being non-profit oriented, returns were often allocated to capital formation or charity.

— *Banking houses (Ditte bancarie, DB).* Private banking firms (mainly family-owned) often involved in trading in both the stock and the foreign exchange market; they were only officially regulated and required to report after 1926.

— *Public Law Banks (Istituti di credito di diritto pubblico, IDP).* Created by law in 1926 to provide a legal status for former banks of issue. Similar in nature to private commercial banks, their charters were proposed by the government and required specific approval; top managers were appointed by the government.

— *Banks of National Interest (Banche di interesse nazionale, BIN).* Introduced by the 1936 Banking Act to denote the largest banks of systemic importance. Before 1936, these were a subset of joint-stock banks. Their charters had to be approved by the Ministry of Treasury, shares were registered, and top managers' appointments were subject to the approval of the supervisory authority.

— *First-class pledge banks (Monti di pietà di prima categoria, MDP).* Charitable credit institutions that made small loans against collateral (pawnbroking), included if they were "first class", a designation for the larger ones.

— *Central institutes (Istituti di credito di categoria, ICC):* central financial institutions serving as federations or clearing houses for other banks (for example, central institutes for cooperative banks or savings banks).

If a bank doesn't fit into any of the categories above, it is allocated to the residual category "Other banks". Notably excluded are the Special Credit Institutions (SCI), which under the 1936 law provided long-term credit to specific sectors (agriculture, industry, real estate) but did not operate as general banks, not collecting deposits from the public.

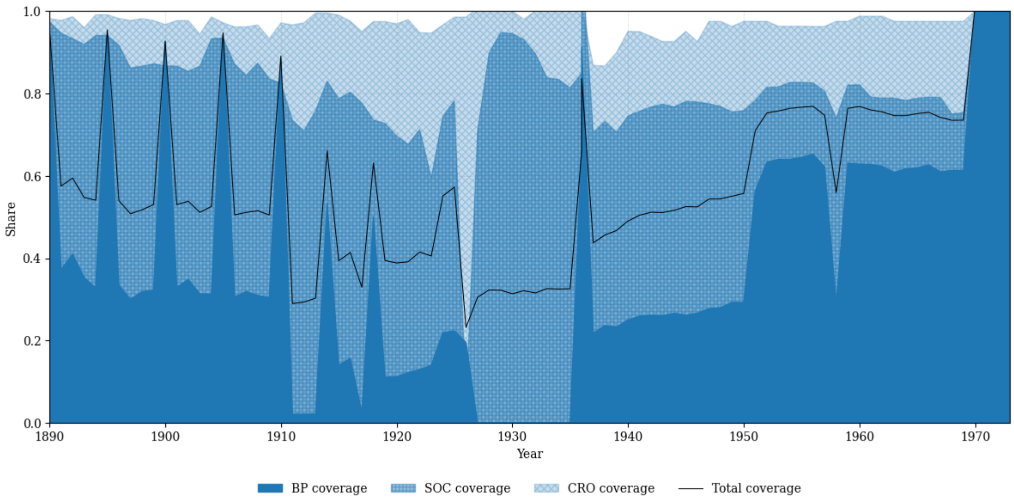
Within its target universe, ASCI's coverage is very high, but not a complete census in every year due to limitations related to historical data availability (see Figure 2.3). On average, 58% of the total population is present in the dataset, with a comprehensive coverage of the major institutions. Saving banks (CRO) present the best coverage with, on average, more than 97% of the total population present in ASCI (and a minimum coverage of 87%). Joint-stock banks are well represented, with an average coverage of 81% (with a notable gap in 1926 for a data lacuna).

The major driver of variability in the coverage is the number of cooperative banks, both for data limitations and for deliberate construction choices. Indeed, to control the amount of data to collect and digitalize, in the years between 1890 and 1910, ASCI reports the whole set of cooperative bank balance sheets only every five years (1890, 1895, 1900, 1905, 1910), while resorting to stratified sampling for the remaining. Consequently, in the benchmark years, the ASCI sample covers close to 100% of the banking population, dropping to around 50% in the remaining years, while retaining full representativeness. From 1911 through 1935, the coverage of cooperative banks becomes less systematic, falling to zero between 1927 and 1935, pulling down the overall percentage of banks covered in those years to around one-third of the total system. After the Second World War, the coverage shows a steady improvement: stabilizing at 75% of the total population from 1952 to 1970 (60% of the BP, 80% of the SOC, 100% of the CRO). Full coverage is present for the years 1970-1973. Lastly, major public banks (BIN and IDP) have a coverage of 100% throughout the sample, thus we omit those from Figure 2.3 for clarity.

A potential critique of the ASCI involves potential selection bias. Since missing banks are not statistically random but are typically the smallest institutions, one may argue that, in critical periods, the dataset may over-represents larger banks (see Table 2.3). While not being a probabilistic sample by a strict definition, we claim that this bias does not invalidate the analysis; at most, it may shift the focus to a broad and diversified sample of banks that constitute the vast majority of the financial aggregates, making the analysis very close to the true national totals.

A proof of this is found by weighting coverage by market share. Using total deposits as a proxy, Natoli et al. (2016, p. 50) find that the dataset is remarkably robust and comprehensive: It represents more than 95% of total deposits during the 1890-1910 and 1936-1973 periods. Coverage remains substantial at over 80% even through the more volatile years of 1911-1935. Thus, in the most critical period, the dataset still allows us to track the 30% of the whole

Figure 2.3: ASCI coverage (share of the respective populations)



The figure plots the coverage of the ASCI dataset. Blue areas represent the coverage of the major juridical categories—joint-stock (SOC), cooperative (BP), and savings banks (CRO)—with respect to their respective population. The black line represents the coverage of the database with respect to the total bank population. The bank population is retrieved from the reconstruction of Natoli et al. (2016, Tab. 2).

banking population that accounts for 80% of the total deposits, making it a powerful tool to analyze the overall sector. Nonetheless, caution is due when examining specific segments where this selection bias could have a more pronounced effect—such as cooperative or small rural banks in the 1920s. In our analyses, we apply the necessary due diligence to ensure the results are not significantly driven by this sampling method.

2.2.3 Working Sample Selection and Preprocessing

To construct the working sample for our analysis, we implemented basic data-cleaning and sample-selection procedures. First, we excluded all banking institutions for which profit data were missing. We further refined the sample by removing any banks that reported a zero value for essential balance sheet items, namely capital, total loans, or total deposits, as such entries likely represent data errors, inactive entities, or significant outliers. To preserve continuity and limit artificial volatility in the sample, we include all major categories of credit institutions—joint-stock banks, banking houses, savings banks, first-class pledge banks, public-law banks, and banks of national interest—while excluding cooperative banks. The exclusion reflects a well-documented practice in similar literature (e.g. De Bonis et al., 2018).[26] To mitigate spurious fluctuations driven by changes in archival procedures, our working sample for the years 1970-1973 retains only those banks that were already present in 1969. Finally, to address the potential influence of outliers and reduce the skewness of the

[26]Among the numerous robustness checks we tested the procedure with the inclusion of cooperative banks. Results are consistent.

Table 2.3: Total assets by category: descriptive stats (Billions of Italian Lira)

Category	Coverage	Count	Mean	Std	Min	25%	50%	75%	Max
BIN	1936-1973	111	3.65	3.76	0.42	1.23	1.90	4.58	19.50
BP	1890-1973	13511	0.02	0.10	0.00	0.00	0.00	0.01	3.49
CRO	1890-1973	10,952	0.05	0.22	0.00	0.00	0.00	0.02	7.00
DB	1926-1973	750	0.01	0.01	0.00	0.00	0.00	0.01	0.12
IDP	1926-1973	240	1.81	2.57	0.07	0.37	0.90	2.06	18.40
MDP	1899-1973	1,137	0.02	0.05	0.00	0.00	0.00	0.01	0.60
SOC	1890-1973	12,441	0.04	0.19	0.00	0.00	0.00	0.02	4.10

The table reports the descriptive statistics of the sample in terms of bank-year observations by category and asset size (GDP-deflated Italian Lira). The deflator is computed from Baffigi (2013).

data distributions, all the continuous variables used were winsorized at the 1% level.[27] This set of preprocessing operations returns a stable panel of 25,150 bank-year observations, suitable for longitudinal analyses.[28]

Figure 2.4 summarizes the evolution of the sample by legal category (left axis) and the total deposits-coverage ratio relative to ASCI aggregates (right axis). The cross-section is sizable before World War I (282-336 banks), expands during the 1920s credit boom (peaking at 426 in 1925), and then contracts sharply with the consolidation policies of the fascist period (-57% between 1926 and 1937, to a trough of 180 in 1938). The number of institutions stabilizes thereafter (190-230 through 1973). Despite changes in the count of reporting banks, total deposits coverage for our included categories remains comprehensive ($\geq$ 80%) over the full period, suggesting that system-level aggregates are well approximated by the sample's aggregates.

2.3 A Continuous Barometer of Financial Stress

Having established the added value of a new perspective on financial instability, this paper proposes a solution grounded in the microeconomic theory of banking. The central premise is that bank profitability, as proxied by the Return on Equity (ROE), serves as an ideal "synthetic barometer" of the health of the financial system.

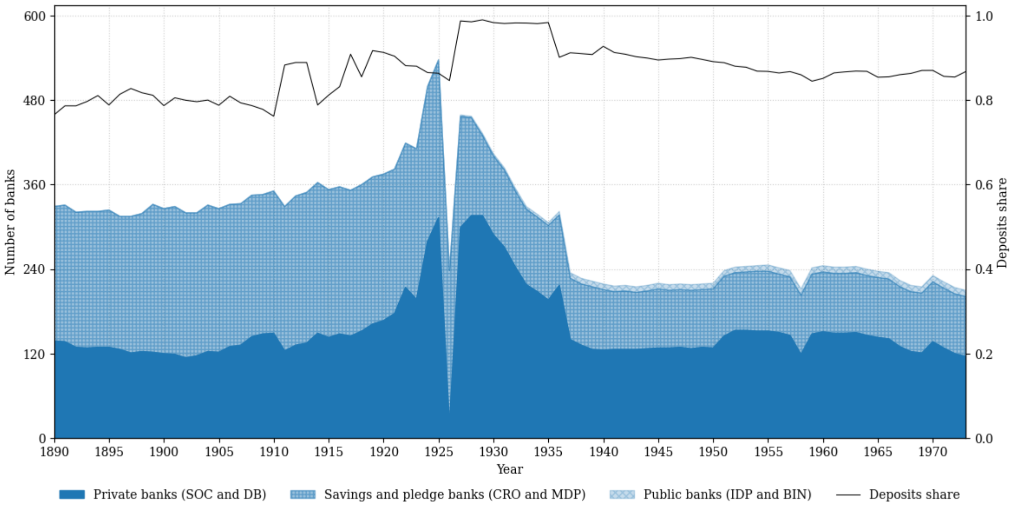
2.3.1 Profitability: Descriptive Insights

According to the foundational work of Freixas and Rochet (2008), a bank's profitability is a complex function, determined not only by its direct asset-and-liabilities management decisions but also by the systemic context in which it operates, including the intensity of

[27] This standard procedure involves capping the top 1% of observations at the 99th percentile value and, symmetrically, setting the bottom 1% of observations to the 1st percentile value.

[28] Before preprocessing, ASCI counts 26,397 bank-year observations for the categories of interest (no BP).

Figure 2.4: Working sample numerosity and representativeness



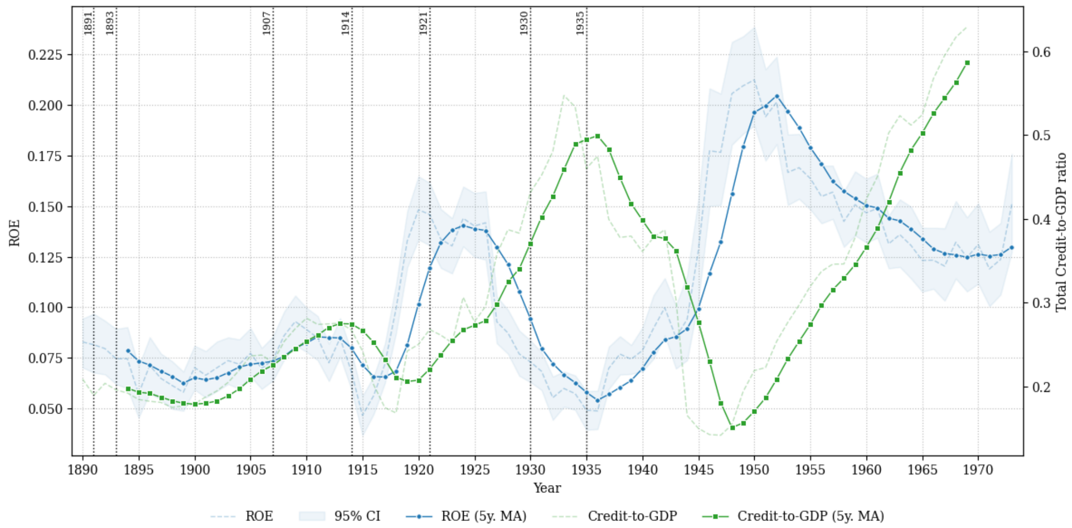
The figure plots the number of banks present in the working sample for each year (left axis), divided by macro-categories: private banks (SOC and DB), savings and pledge banks (CRO and MDP), and public institutions (BIN and IDP). The black line (right axis) reports the share of total deposits present in our working sample as the share of the total deposits in ASCI for each year.

competition, the stance of the monetary policy, and the prevailing regulatory framework. Profitability is therefore not a simple, isolated balance sheet metric but a composite indicator that implicitly weights and aggregates a vast array of information about risk management, market conditions, and institutional strategy: a synthesis of the bank's interaction with the wider macroeconomic environment (Buch, 2024; Savona, 2024).

In the literature, the link between profitability and risk is widely recognized, though the precise mechanism remains a subject of debate. On the one hand, higher profitability can increase a bank's "charter value" and encourage more prudent behavior (Acharya, 1996)—a view supported by recent evidence linking robust earnings to lower idiosyncratic risk (Xu et al., 2025). On the other hand, scholars warn that profitability can be linked to growing risk. Buch (2024) highlights that strategies boosting short-term returns often compromise long-term stability, while Martynova et al. (2020) and Meiselman et al. (2023) argue that the loosened capital constraints associated with high profits can fuel excessive risk-taking during credit booms. The timing of these signals is equally contested: while recent scholarship emphasizes that accounting metrics lag behind the real-time information captured by market prices (Begenau et al., 2026; Baron et al., 2025), there exists robust evidence from the supervisory literature that accounting profits are powerful predictors of distress (Chiaramonte et al., 2015; Cole and White, 2011; Poghosyan and Cihak, 2011).

Given this complexity, our choice of profitability as a barometer is dictated by the structural constraints of our historical setting. While we recognize that in deep, liquid markets, price-based indicators may offer superior forward-looking signals (Baron et al., 2021), relying on such measures would introduce a severe selection bias in our context, capturing only the (very few) largest banks while ignoring the vast web of unlisted institutions. Therefore, we

Figure 2.5: Return on Equity and the Credit-to-GDP ratio



The figure plots the 5-year moving average of the yearly average ROE (left axis) and of the Credit-to-GDP ratio (right axis). The dashed lines show the original (unsmoothed) series. The shaded area represents 95% confidence intervals based on the annual distribution across the sampled banks. Source: the ROE is an author's computation from ASCI, the credit-to-GDP ratio (1890-1969) is an author's computation based on De Bonis et al. (2012)'s total credit and Baffigi (2013) GDP estimates.

propose profitability as the necessary "second best." Despite the debates on its timeliness, it possesses two unique properties: *depth* and *breadth*. First, much like a stock price, accounting returns provide a comprehensive synthesis of a bank's fundamentals, serving as a reliable anchor for detecting the deterioration that precedes failure (Correia et al., 2025). Second, this metric applies to the *entire* banking population—including the unlisted majority—thereby decoupling the measurement of systemic stress from the limits of the market.

Figure 2.5 provides a first visual insight into the historical trend of bank profitability, and of its relationship with the credit-to-GDP ratio. The average ROE of Italian banks strongly correlates with major financial downturns. Profitability declined markedly during the banking crisis of the late 1890s, the turmoil of World War I, and the Great Depression, reflecting how these events triggered severe contractions in both credit supply and demand. In the post-World War I period, we observe a pronounced run-up in ROE, which peaked in 1924, mirrored by a significant expansion in the credit-to-GDP ratio.[29] No visible impact from the banking crises of 1907 and 1921—suggesting a lack of systemic contagion.[30] After peaking in 1952, the average ROE began a prolonged and steady decline that coexists with a sustained expansion in the credit-to-GDP ratio through the 1950s and 1960s. This hints at structural factors—such as interest rate ceilings and the "bank cartel"—explicitly designed to sustain

[29]The drivers of this expansion in the ROE are both economic trends—rapid industrial and stock market growth—and accounting artifacts— wartime inflation, which eroded the relative value of bank equity compared to the total assets (Gigliobianco and Giordano, 2010; Molteni and Pellegrino, 2021; Toniolo, 1995).

[30]For a thorough analysis of these events see subsection 4.3.2, in which we thoroughly analyze them to disentangle the nexus between "banking crises" and "crises of banks".

economic growth by artificially squeezing bank margins, effectively fueling the economic miracle at the expense of bank profitability.

Beyond individual observations, the most compelling evidence is the clear structural break in the relationship between bank profitability and the broader credit cycle. The correlation between the 5-year moving average of the ROE and the credit-to-GDP ratio is strongly positive up to 1927 (0.60), with profitability and credit expansion moving in tandem. After 1927, however, this relationship abruptly inverts, with the correlation approaching -0.59. We can hardly interpret such an abrupt decoupling of profitability and credit expansion as a mere statistical artifact: it must reflect a fundamental regime change in Italian banking. Indeed, as we will thoroughly analyze in chapter 5, the transformation is rooted in the institutional overhaul of the interwar period, which redefined banking from a "commercial activity" to a "function of public interest."[31] This new legislation, which prioritized stability over profitability, fundamentally alters the interpretation of traditional systemic risk indicators, adding to the historical evidence above. If a growing credit is the result of the successful implementation of a state objective—that is, guaranteeing a continuous channel of credit to the real economy—then, we must accept that the indicator becomes less a proxy for the internal dynamics (and fragility) of the banking sector and more an artifact of potentially state-sponsored stability. This reinforces the critical question we have introduced in the previous lines: if historical specificity makes market signals as well as credit quantity an unreliable guide, then we must look beyond macro-level indicators, and looking at the internal dynamics of the bank sector might be a necessary complement.

2.3.2 Methodological Implementation

Building on this theoretical foundation, this chapter's central contribution is the construction and application of a new, continuous, and quantitative measure of financial instability derived directly from bank ROE. To provide a holistic representation of systemic risk, the indicator considers both the cross-sectional distribution of profits and their long-run cyclical evolution.

The first dimension of the indicator examines the distribution of the ROE across all banks at a single point in time t, moving beyond simple sector-wide averages. Indeed, a high average level of profitability for the banking sector can easily mask underlying fragility. For example, a widening dispersion in profits, a growing bimodality in the distribution (top-worst performers segmentation), or the emergence of a "fat tail" of highly unprofitable institutions can signal deepening stress and a fragmentation of the system, even as the aggregate measure goes upward. Our barometer is designed to capture these distributional shifts, building a composite index of financial stress based on five "moments" of profitability, such that:

[31] From 1882, banking operations were accounted among the "commercial activities" (Commercial Code of 1882, Title II, Art. 3, comma 10). In 1936, the banking activity was recognized as a "function of public interest" (Banking law of 1936, Art.1). In 1956, the governor of the Bank of Italy Donato Menichella in a speech to the Italian Bankers Association clearly stated that "banking is a service [...] not a rich profession" (retrieved and translated from Albareto and Trapanese, 1999, p. 130).

$$\text{Barometer}_t = f(\underset{(-)}{\text{Median}_t},\ \underset{(+)}{\text{Std.Dev.}_t},\ \underset{(-)}{\text{Skewness}_t},\ \underset{(+)}{\text{Kurtosis}_t},\ \underset{(+)}{\%\ \text{Losses}_t}). \tag{2.1}$$

1. Median Profitability. It is used as a robust measure of the central performance of the banking sector. A declining median provides a clear signal that the profitability of the core of the banking system is deteriorating.

2. Standard Deviation. It measures the dispersion of profits across banks. An increase in the standard deviation points to a growing fragmentation within the banking system. It indicates that the performance gap between the strongest and weakest institutions is widening, a form of systemic fragility that can be masked by a stable average.

3. Skewness. It captures the asymmetry of the profitability distribution. A negative skew is a warning signal, as it reveals that a higher-than-normal number of banks are experiencing exceptionally poor performance.

4. Kurtosis. It measures the "fat tails" of the distribution, or the frequency of the extreme outcomes. Its increase is a two-sided signal of rising instability. A fat left tail (negative outcomes) indicates a heightened probability of severe, systemic losses. A fat right tail (positive outcomes) is an equally important, yet more subtle, indicator of systemic risk. A growing number of banks reporting exceptionally high profits can be a symptom of economic overheating or the engagement in unsustainable activities—i.e., during an asset bubble—and it may signal under-priced risk.

5. Share of banks reporting losses. To complement the kurtosis and provide a direct measure of the width of sectoral distress. A rising share is an intuitive signal of widespread financial weakness.

Table 2.4: ROE, selected moments: descriptive statistics

	Count	Mean	Std	Min	25%	50%	75%	Max
ROE	25,150	0.1004	0.1271	-0.2985	0.0415	0.0784	0.1292	0.7243
Median	84	0.0865	0.0292	0.0478	0.0636	0.0751	0.1067	0.1535
Std.Dev.	84	0.1188	0.0305	0.0596	0.1001	0.1123	0.1354	0.1991
Skewness	84	1.4743	1.1078	-1.8374	1.1422	1.7761	2.2408	3.9076
Kurtosis	84	9.2365	5.1564	0.9732	5.1499	8.3657	12.2438	32.0327
% Negative	84	0.0535	0.0415	0.0000	0.0125	0.0509	0.0834	0.1398

The table reports the descriptive statistics of the ROE and of the five moments on which the barometer is built.

To synthesize the information from the five moments into a single time series, we construct a composite Bank Stress Index (BSI) through a three-step process.

Normalization

First, to match the scale of the different indicators and to measure their intensity relative to historical norms, each of the five components is normalized. For each indicator, we compute its annual z-score against a dynamic benchmark that absorbs the structural evolution in the banking system. This benchmark is represented by a stiff trend component extracted from the time series of each indicator using a Hodrick-Prescott (HP) filter (λ=400). Thus, the z-score for each indicator x_i in a given year t is a stationary measure of its deviation from the underlying trend, expressed in units of mean absolute deviation (MAD):[32]

$$z_{it} = \frac{x_{it} - trend_{it}}{MAD_i}. \tag{2.2}$$

Aggregation

Next, the five normalized z-scores are aggregated into the final BSI using a weighted average. The weights are determined by the inverse of the variance of each component's z-score series. This common technique neutralizes differences in volatility across the indicators, ensuring that each component contributes equally to the variance of the final index, preventing more volatile series from dominating the signal.

To ensure that a higher value for any given component consistently reflects higher financial stress, we align their directionality. Since a higher median profitability and a less negative (or more positive) skewness are signs of stability, their respective z-scores enter the aggregation with a negative sign. The other three indicators—standard deviation, kurtosis, and the share of banks reporting losses—enter with a positive sign, as an increase in any of them directly signals rising fragility. Thus,

$$BSI_t = \frac{1}{5}\sum_{j=1}^{5} w_j z_{jt}, \quad \text{with} \quad w_j = \frac{1}{\sigma_j}. \tag{2.3}$$

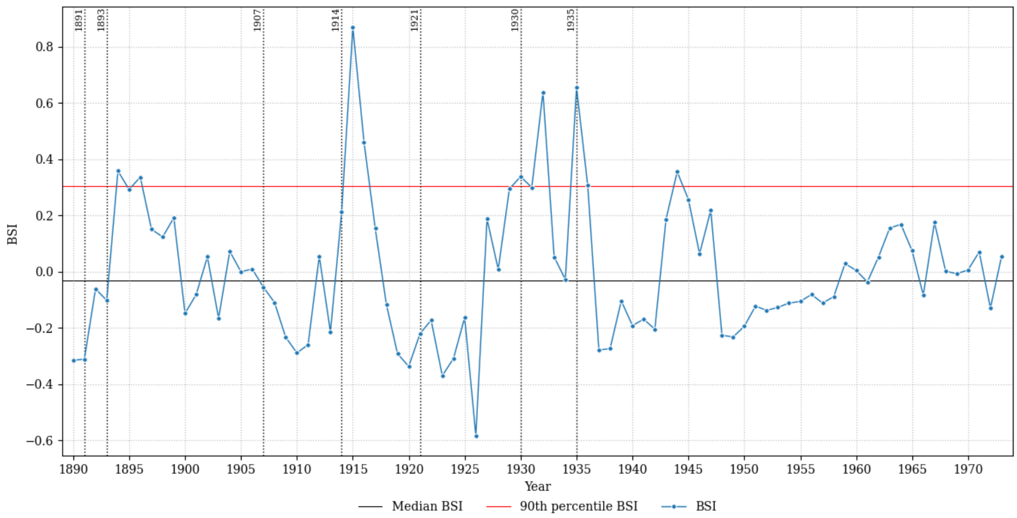
The resulting time series is the Bank Stress Index (see Figure 2.6). It is designed to be directly proportional to the level of fragility in the banking system; thus, a higher score indicates a greater deviation from normal conditions across multiple dimensions of profitability, signaling a higher level of systemic stress and an increased probability of financial instability.

Scaling

The last step is to effectively translate the BSI into a "likelihood of distress" measure that intuitively maps to traditional chronologies of banking crises. However, standard econometric methods to estimate crisis probabilities via maximum likelihood, such as a logit model, are not feasible in our context. Our sample has both a limited number of observations (N=84) and a limited number of crisis events (Crisis=7), a classic "rare events" problem that effectively precludes robust statistical estimation and necessitates a different approach. To circumvent this issue, we shift the perspective from an *estimation* problem to a *calibration* one, with a heuristic procedure to map the BSI onto a 0-1 probability scale. While the process required

[32] Benchmarking the value of a feature against its HP-filtered trend is, by construction, equivalent to taking the HP-filtered cyclical component. Here, we choose to explicitly write the difference to remain close to the traditional z-score definitions. The Mean Absolute Deviation (MAD) is defined as the median of the gaps between the feature and its median, taken in absolute value, such that: $MAD_i = \text{median}(|x_{it} - \bar{x}_i|)$. It is a measure of deviation that is more robust to outliers compared to the standard deviation.

Figure 2.6: The Bank Stress Index (BSI)



The figure plots the composite Bank Stress Index (BSI), which shows the latent stress in the financial system as proxied by the profitability's distribution and dynamics.

explicit assumptions on four key parameters, we claim that this was preferable to unstable econometric estimations.

First, we define two benchmark scores from our BSI distribution to represent distinct states of the financial system. A "high-stress" state is defined by the score at the 90$^{\text{th}}$ percentile of the BSI distribution ($S^c = \text{BSI}_{90^{th}}$), while a "normal-stress" state is represented by the median score ($S^n = \text{BSI}_{50^{th}}$).

Mapping these benchmark scores onto a probability scale requires an explicit a priori assumption. We assign the "high-stress" score a distress probability p^c of 0.8, reflecting a state of acute systemic vulnerability. Conversely, the "normal-stress" score is assigned a probability p^n of 0.02, representing a baseline level of risk in a stable environment. These represent conservative choices based on Engle and Ruan (2019), and are designed to provide clear anchors for what constitutes a high-risk versus a low-risk signal.

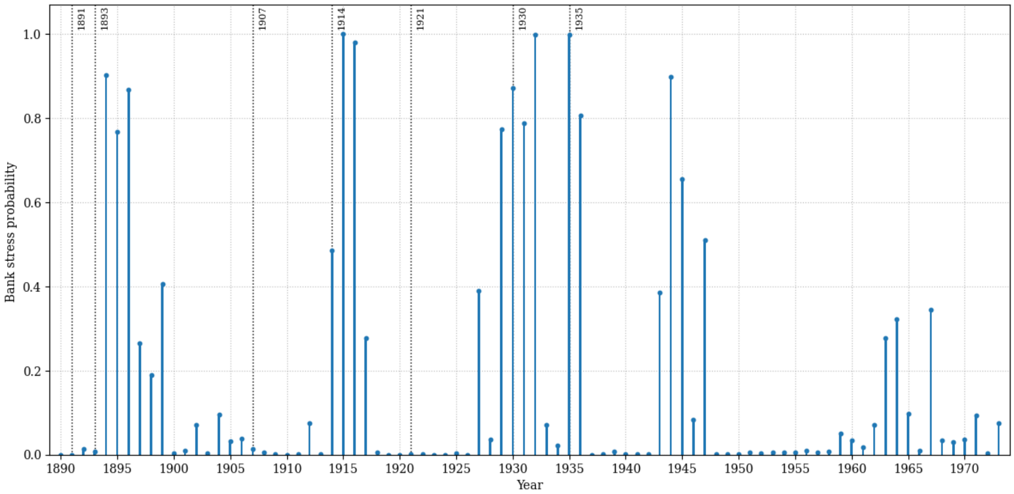
These two anchor points, (S^c, p^c) and (S^n, p^n), are then used to mathematically solve a standard logistic function for the two parameters, α and β:

$$p^k = \frac{1}{1 + e^{(-\alpha + \beta S^k)}}, \quad \text{for} \quad k \in \{c, n\} \tag{2.4}$$

which requires solving a two-equation system.

This procedure effectively calibrates the logistic curve to fit the benchmarks. With the parameters α and β determined, it is straightforward to transform the BSI values into a corresponding crisis probability. We apply this calibrated function to our entire annual time series of the BSI to generate the continuous indicator of banking stress probability represented in Figure 2.7. The results are remarkably robust to a plethora of alternative specifications, as proven in section A.2.

Figure 2.7: Bank stress probability



The figure shows the bank stress probability resulting from the calibrated logistic function.

To understand how risk exposure differs across the financial system, we segment our analysis by key bank characteristics. We apply our stress index to distinct subsamples grouped by total assets, legal category, and geographic region. The results are presented in Figure 2.8 and provide the foundation for the historical discussion in the next section.[33]

2.4 Results and Historical Validation

Our barometer of stress provides a new, continuous measure to assess the banking sector's fragility between 1890 and 1973. Its dynamics offer a novel perspective that both challenges and complements the established historical narrative of Italian banking, particularly by revealing periods of stress overlooked by traditional binary crisis chronologies and reassessing the systemic spillovers of the distress of major institutions.

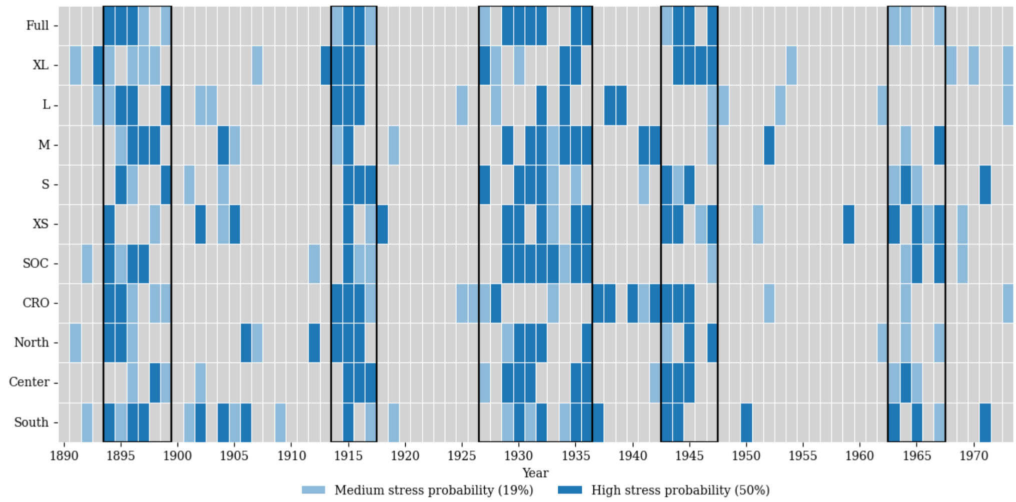
The Liberal Period (1890-1922), the 1890s Crisis, and the Big-Bank Bias

Contrary to established chronologies that mark 1891 and 1893 as major banking crises, the barometer shows minimal systemic stress during this period (see Figure 2.7 and 2.8). Minor stress is signaled in 1891, but this is confined to XL banks in the North (e.g., Credito Mobiliare). The pressure increases in 1893—from medium to high stress probability—but remains significant solely among XL banks (e.g., Banca di Torino, Banco di Roma, Banca Tiberina).[34] This validates the hypothesis of the 1893 event being better characterized as a crisis of a few large banks rather than a systemic banking crisis with broad spillovers. On the contrary, our indicator reveals a significant and prolonged spike in fragility between 1894 and 1899, a period overlooked in mainstream crisis narratives, and yet representative of a renown phase of

[33]For the complete series of bank stress see Figure A.1.

[34]Banca Romana, failing in 1893, is not present in ASCI.

Figure 2.8: The heterogeneous distribution of risk



The figure summarizes stress signals of the full sample (see Figure 2.7) and of selected subsamples. XL, L, M, S, XS represents total assets quintiles computed within each year (i.e. in year t a bank is classified as XL if its total assets fall within the top 20% of the year t total assets distribution). We considered only legal categories present throughout the sample, that is, joint-stock banks (SOC) and savings banks (CRO). North, Center, and South represent the macro-region of the HQ. Medium stress is defined as a probability of stress above the mean (19%). High stress is defined as a probability of stress 1.5 standard deviations above the mean (50%). The black frames serve as a visual reminder of the periods of significant risk in the full sample.

economic slowdown, social unrest and political crises: the *crisi di fine secolo*.[35] This stress is shared among the whole banking sector, affecting all bank types, sizes, and regions, hinting to a lower demand for credit and decreasing interest rates.[36]

At the dawn of the 20th century, a gradual recovery begins, with a positive economic phase and the start of the Italian industrialization process (Malanima and Zamagni, 2010). The banking system entered a period of substantial stability from 1900 to 1914, despite lingering tensions in the South between 1901 and 1906 and across small and medium banks. The crisis of the SBI 1907 is registered as a medium-level stress signal, strictly limited to XL banks in the North. Similarly, the crisis of the BIS in 1921-22 is absent in our indicator. Both episodes suggest that the impact was largely contained and did not generate systemic contagion, consistent with the specific goal of the Bank of Italy and the government to limit any spillover effects (Vercelli, 2022; Sraffa, 1922). This pattern substantiates the risk of a "big bank bias" in historical accounts.

The World Wars and the Great Depression

The indicator shows a sharp and unambiguous increase in systemic stress during World War

[35] The sharp economic downturn will impair, among others, the Banco di Sconto e Sete.

[36] The total credit over GDP decreased from 20% to 17% between 1893 and 1898, the bank interest rate on short-term operations decreased from 6.1% to 5.4% (De Bonis et al., 2012), the interest rate on short-term government bonds decreased from 3% to 2.6%, from 4.7% to 4.1% on long-term government bonds (Piselli and Vercelli, 2023).

I. While not usually classified as a banking crisis, the conflict represented a major economic displacement that put the entire banking sector under strain, with fragility spreading across all regions and bank types (Toniolo, 1989).

The Great Depression is correctly signaled as one of the major shocks of the analyzed period. Still, our measure shows the global shock did not hit a healthy system, but rather one already weakened by the deflationary policies aimed at controlling monetary stability, providing quantitative evidence for the domestic roots of the crisis. A gradual build-up of fragility begins between 1925 and 1929, hitting major banks (XL) as early as 1927, with a significant cluster of stress among the saving banks (CRO).[37] This weakness preceded a major phase of instability from 1929 to 1939, which our indicator shows unfolded in two distinct waves. The first wave, from 1929 to 1936, aligns with the global economic downturn and particularly hit the joint-stock banks (SOC) and medium and smaller institutions (consistent with Molteni 2023). Notably, the CRO, after forced consolidations and constrained in their investment strategies, proved sounder and are largely spared from this initial shock (Molteni, 2021). After a brief recovery in 1933, a second, sharp spike in risk emerged in 1934-36, hitting also the major institutions, and coinciding with the economic pressures of the Ethiopian War. This pattern confirms the claim of 1930 and 1935 being two instances of the same crisis, (Bartoletto et al., 2018). Moreover, our indicator shows a distinct second wave of instability hitting the CROs that, while resilient during the first wave, faced major stress in 1937-38.

Unsurprisingly, World War II emerges as another major stress source. Systemic risk surged during the final years of the conflict and the immediate post-war reconstruction (1943-47), reflecting a period of inflationary pressures and profound economic uncertainty.

The Overlooked Fragility of the 1960s

Following the post-war turmoil, the indicator shows a prolonged phase of substantial stability between 1948 and 1963, following Italy's "economic miracle." However, perhaps the most novel finding from our analysis is the identification of a significant and sustained increase in the banking sector fragility from 1963 to 1967, particularly concentrated among smaller banks, joint-stock banks, and in the Center-South of the country. This period, significantly overlooked in existing crisis literature, aligns with a major cyclical downturn and with a crash of the securities and stock market (Gelsomino, 2024, 1999; Fratianni and Spinelli, 2001).[38] In our barometer, this moment represents a previously unquantified episode of systemic stress and underscores the value of our continuous indicator in uncovering forgotten episodes of financial instability. Moreover, it raises a crucial question about the development of the banking sector in the 1960s, which we will address in chapter 5.

[37] The stability of the CROs was particularly eroded by the deflationary policies of the late 1920s and the compulsory conversion of short-term government bonds into long-term ones, which devalued their large public debt holdings. Moreover, the increase in interest rates to pursue monetary stability—from 5.1% in 1924 to 6.3% in 1927 (Piselli and Vercelli, 2023)—led to a strong devaluation in the asset portfolio built in the early 1920s (Molteni, 2021).

[38] This market downturn is signaled, among others, by Baron et al. (2021) despite not entering the crisis chronology.

2.5 Concluding Remarks

This chapter addressed a core challenge in financial history: the inadequacy of standard crisis indicators in contexts defined by shallow markets and opaque state interventionism. Using Italy as a testing ground—with its legacy of state ownership, administrative interventions, and a deep bank-politics nexus—we constructed a novel, continuous barometer of financial stress rooted in the microeconomic theory of profitability. By leveraging comprehensive balance sheet data (ASCI) for the period 1890-1973, our index moves beyond the "extensive margin" of binary failure counts to capture the "intensive margin" of systemic stress, revealing distress signals that traditional event-based chronologies previously missed.

The application of this index offers a revision of the established chronology of Italian banking. Our main findings show that: (i) Contrary to narratives focused on major institutional failures, the crises of 1893, 1907, and 1921 had limited systemic impact. For the crisis of 1891/1893, we support Pantaleone (1895)'s definition of the event as a "moral bankruptcy", that is, a socio-political scandal more than a systemic crisis. In 1907, we challenge the claim of a systemic spread of SBI's distress (Bonelli, 1982), aligning with modern reinterpretations of the crisis as circumscribed to the stock market and to the few speculators involved, with limited consequences on the real economy or on the rest of the banking sector (Vercelli, 2022). Lastly, we detect limited instability also in 1921, supporting Conti (2007, p. 161)'s definition of the event as the "crisis of the Banca Italiana di Sconto" and confronting the narratives of a systemic crisis (De' Stefani, 1960). Taken together, our findings suggest that official interventions successfully contained spillovers and point to a potential "big bank bias" in historical accounts. (ii) Our index uncovers a major, yet previously overlooked, period of stress between 1894 and 1899, coinciding with the sociopolitical unrest of the *crisi di fine secolo*, demonstrating that political instability can erode banking fundamentals even without visible runs (Baron et al., 2021; Correia et al., 2025). (iii) We detect significant banking stress emerging as early as 1927, well before the international shock. The crisis unfolded in three distinct waves—hitting small banks first (1929), major mixed banks second (1933), and savings banks last (1936)—challenging both the view of a monolithic collapse and highlighting a distinct spread of the crisis across the smaller banks beyond the renowned nationalization of the larger institutions. Our results align with recent evidence of Molteni (2023), by offering a continuous measure of stress among the smaller banks and ultimately validating Conti (2007, p. 171) definition of a "virulent but silent" crisis. (iv) We identify a profound and previously unquantified period of systemic stress from 1963 to 1967. The rise of stress, concentrated among smaller institutions in the Center-South of the country, directly challenges the interpretation of the 1960s as a monolithic "golden age" of stability (e.g. Cotula, 1999; Strangio, 2017), underscoring the unique value of our continuous measure.

In the following chapters, we will analyze these episodes from three complementary perspectives. In chapter 3, we will situate our stress measure within the broader credit cycle to distinguish between "good" and "bad" booms. Then, chapter 4 will dissect the micro-foundations of these profitability signals by using neural networks to track business model evolution. Lastly, chapter 5 will focus on the 1950s and 1960s to link the detected stress signals to the changing institutional landscape of the period, and the mechanism of financial repression.

Ultimately, the main purpose of our findings is not a mere refining of the Italian chronology of banking crises. Rather, we hope that they expose the fundamental methodological opportunity for comparative financial history and the necessity to go beyond (or at least, complement) binary crisis definitions. We demonstrate that where market signals are weak, accounting fundamentals could represent a "second best." As global efforts to digitize historical balance sheets accelerate, making bank-level data more accessible (Baron et al., 2023), this bottom-up, distribution-based approach offers a reproducible blueprint for moving beyond binary crisis templates, allowing scholars to quantify the true cost of financial instability across diverse institutional contexts, and enriching our understanding of financial fragility in historical perspective.

Chapter 3

Breaking the Cycle: Bank Profitability and the Anatomy of Italian Credit Regimes

"The destabilizing aspect of banking should not be surprising—after all, bankers are specialists in providing short-term financing to business, government, and households, and the banker sells his services by teaching customers how to use bank facilities. Bankers cannot make a living unless business, government, and households borrow; they are merchants of debt."

— Hyman Minsky (1986, p. 279)

Are credit booms systematically a good predictor of financial crises? This question represents a long-standing debate in both economics and financial history on the controversial relationship between credit expansion and systemic risk.

A substantial body of modern empirical research posits that rapid credit growth is the single best predictor of financial crises, suggesting that such crises are fundamentally "credit booms gone wrong" (Schularick and Taylor, 2012). Yet, this view is in tension with historical records showing that not all credit booms culminate in a bust, and conversely, not all financial crises are preceded by a significant expansion of credit (Gertler et al., 2020). In other words, *not all credit booms are created equal*. The Italian example is emblematic of this conundrum. As Bartoletto et al. (2018, p. 22) notes, "boom-bust dynamics represent an exception in the panorama of Italian banking crises," as most major crises were not a significant turning point in the credit cycle, as proxied by the credit-to-GDP ratio.[1]

This highlights the so-called "good" versus "bad" credit boom dilemma: the critical need to qualify periods of rapid credit growth rather than assuming they are all inherently risky (Alessi and Detken, 2009; Dell'Ariccia et al., 2016, 2020; Gorton and Ordonez, 2020; Greenwood et al., 2022). Yet, to effectively identify periods of dangerous financial fragility, one

[1]With the exception of the housing bubble burst of 1887.

must first be able to distinguish between benign and unsustainable booms. A common approach to this challenge is to analyze historical episodes. Researchers identify past credit booms and then retroactively classify them as "good" or "bad" based on their outcome. The reliance on historical data is necessary because financial crises are, by definition, rare events. However, this historical perspective presents two main challenges. On the one hand, crises are inherently specific, and ignoring the peculiarities of the context in which they unfold may lead to over-generalization, particularly when comparing countries and eras at different stages of financial development (Bordo, 2018; Rajan and Zingales, 2003). On the other hand, historical settings may lack the data to consistently distinguish between good and bad credit booms—such as, asset prices (Greenwood et al., 2022), productivity (Gorton and Ordonez, 2020), housing prices and mortgage credit (Dell'Ariccia et al., 2020; Jordà et al., 2015; Müller, 2022).

To explore this puzzle, the Italian case is exceptionally well-suited. The nation's notable reliance on bank financing for its industrial growth creates a historical setting where credit expansions often coincided with genuine economic development—that is, a strong demand for productive loans (Barbiellini Amidei and Impenna, 1999; Ciocca and Biscaini Cotula, 1994; Giannetti and Vasta, 2006). This context, combined with the availability of granular bank-level data from the ASCI archive, allows us to go beyond aggregate metrics: It provides the perfect opportunity to develop and test an alternative framework for why Italy's financial history often diverges from the conventional boom-bust narrative, making it an ideal laboratory for this study.

This chapter proposes such a framework, reassessing the debate by shifting the analytical focus from the aggregate quantity of credit (*how much* banks lend) to the underlying nature of credit intermediation (*how* banks lend). It does so by looking inside the "black box" of the banking sector itself (Bernanke and Gertler, 1995), leveraging the rich information embedded in bank profitability, a metric largely overlooked in the macro-financial literature. By adapting the DuPont analysis—a tool traditionally used to evaluate industrial firms—to the specificity of history and of the banking sector, this study develops two key proxies that capture the nature of bank lending: an "efficiency" proxy, the Net Profit Margin (NPM), which reflects the credit spread component of profitability, and an "effectiveness" proxy, the Asset Utilization Intensity (AUI), which measures how effective is the bank in generating gross income per unit of intermediated assets. Using these micro-founded proxies, this paper employs a Markov Switching model to endogenously identify distinct "credit regimes," or credit types, that characterized the Italian banking sector between 1890 and 1973.

Our results speak to three key debates. First, we contribute to the qualification of credit booms in historical perspective. Aligning with Bartoletto et al. (2018), we document that three of the five major banking crises traditionally recorded—1893, 1907, and 1921—were not preceded by a "bad boom," as defined by a regime of low and/or volatile NPM, and high-AUI credit expansion. This suggests that these crises originated from idiosyncratic factors, proven relevant by Battilossi (2009), other than an accumulation of systemic fragility resulting from an inherently risky banking model (Confalonieri, 1974, 1994; Fanfani, 2005; Toniolo, 1978). On the contrary, the interwar crisis is rooted in a "bad boom" beginning as early as 1924, highlighting how the supposed financial deepening of the period quickly deteriorated and fostered an accumulation of risk (Molteni, 2024; Segre, 1926).[2] Most interestingly, the post-war "economic miracle" (1950s-1960s) is classified as a "bad boom" regime, sharing quantitative characteristics with the 1920s growth. Second, by disaggregating these trends, we intervene in the debate on the structural efficiency of small and local banks. We challenge the view that in the liberal period these intermediaries were inherently stable actors (see, e.g. Polsi, 1996). Aligning with Stimpert and Laux (2011), we show that smaller institutions were the least efficient, suggesting a non-negligible impact of economies of scale. We observe a sharp reversal in the post-war era, where the economic policy explicitly shifted bargaining power in favor of smaller institutions. This highlights the decisive role of politics in reshaping the competitive landscape, consistent with the "game of bank bargains" of Calomiris and Haber (2014). Thus, third, we contribute to the political economy of banking.

Overall, our evidence suggests that a completely free market and a completely financially repressed market can lead to the same sub-optimal outcome: an intermediation characterized by an intense utilization of bank assets but with decreasing and unstable efficiency. Then, we argue that the outcome of a credit regime is conditional upon the prevailing institutional and regulatory framework and the external macro-financial context. If the bad boom of the 1920s culminated in the Great Depression, banks of the post-war period benefited from the stable international environment and the strong commitment of the Bank of Italy to preserve stability (Menichella, 1956; Monnet, 2018). Despite further investigation being needed, we argue that, beyond the stability and growth narrative, banks showed typical signs of weakness and risk—high leverage and low profit margin (Berger and DeYoung, 1997; Engle and Ruan, 2019). They were very exposed to the insurgence of a negative shock that never came, thanks to "an exceptionally favorable economic environment" (Gelsomino, 1999, p. 354).

After this introduction, section 3.1 offers a brief review of the literature on credit booms and on how they could impact financial stability, presenting the "good vs bad boom dilemma." Section 3.2 presents the data. Section 3.3 details the adapted DuPont framework for decomposing bank profitability and presents the Markov Switching model to move from profitability components to credit regimes, critically validating the signals in historical perspective. Section 3.4 analyzes how different types of institutions evolved compared to the broad credit regimes. Lastly, section 3.5 concludes.

3.1 A Perspective on Credit Cycles, Booms, and Financial Stability

The notion that credit cycles are intrinsically linked to financial instability is long-standing in economic literature. The historical-narrative tradition put forward by Kindleberger (1978) portrays financial history as a recurring pattern of speculative excess fueled by credit expansion, which inevitably leads to a crisis. Hyman Minsky further developed this thread, explicitly referring to a *financial instability hypothesis*, claiming that the economic system is

[2] We refer to the canonical crises of 1930 and 1935 as "interwar crisis" as, in chapter 2 we have shown how they can be interpreted as distinct waves of the same period of systemic distress.

inherently unstable (Minsky et al., 1960; Minsky, 1986, 1992). These perspectives emphasize the fragility of the financial system, driven by shifts in investor psychology and the procyclical nature of credit creation, as Bagehot (1873, p. 78) effectively summarizes: "All people are most credulous when they are most happy."[3]

In recent decades, a new wave of quantitative economics has sought to test these long-standing ideas with rigorous empirical methods.[4] This research has produced powerful evidence supporting the link between credit and financial instability. With novel cross-country evidence covering 14 advanced economies from 1870 to 2008, Schularick and Taylor (2012) finds that the growth of bank credit is a robust and significant predictor of financial crises, leading them to conclude that such crises are typically "credit booms gone bust".[5] Building on this work, Jordà et al. (2013) finds that "credit bites back", that is, credit booms are linked not only to the probability of a crisis but also to the severity of the subsequent economic downturn, motivating the paramount role of credit monitoring for macro-financial stability (Claessens et al., 2011; Dell'Ariccia et al., 2021, 2016).

While the link between aggregate credit growth and financial risk is well-established, the empirical evidence is complicated by the fact that many credit booms do not end in crisis (Gertler et al., 2020). This has spurred a rich literature attempting to differentiate between benign episodes of financial deepening ("good booms") and dangerous, unsustainable expansions ("bad booms"). Several distinct approaches have emerged. One strand of research argues that the sectoral allocation of credit is a key discriminant factor. The central idea is that "who borrows matters" (Müller, 2022). Credit extended to the non-tradable sector, particularly construction and real estate, is found to be a much stronger predictor of future financial crises and growth slowdowns than credit channeled to the tradable, productive sector (Dell'Ariccia et al., 2020; Greenwood et al., 2022; Jordà et al., 2015). Other studies link bad booms to periods of declining productivity and a worsening of capital allocation, where relaxed financial constraints allow capital to flow to riskier or less efficient projects (Gorton and Ordonez, 2020). Theoretical models, meanwhile, point to behavioral and structural factors, such as overly optimistic beliefs by financial intermediaries, strategic complementarities driven by cycles in collateral values, and implicit government guarantees that encourage excessive risk-taking during economic expansions (Berger and Udell, 2004; Bernanke and Gertler, 1989; Bernanke et al., 1999; Kiyotaki and Moore, 1997; Minsky, 1986, 1992).

This brief review shows how, despite the growing interest in credit cycles, the focus of the literature has largely remained on the quantity of credit supplied, the characteristics of the

[3] A vast literature examines how swings in credit supply amplify the business cycle, alternately fostering growth or deepening the crises. For a brief overview on how credit supply amplifies business cycles, see, among others, Aikman et al. (2015); Bernanke and Gertler (1995); Bernanke et al. (1999); Borio and Lowe (2002); Borio and Zhu (2008); Córdoba and Ripoll (2004); Drehmann et al. (2012); Iacoviello (2005).

[4] See, among others, Baron and Xiong (2017); Gourinchas and Obstfeld (2012); Jordà et al. (2011, 2013); Reinhart and Rogoff (2008); Schularick and Taylor (2012).

[5] In particular, the authors find that a one standard-deviation change in real loan growth increases the probability of a crisis by 2.8%, a non-negligible effect on an average crisis frequency of 4%. Policymakers have since incorporated credit-to-GDP trends into early warning indicators (see BIS and IMF reports on the financial cycle). They also document a crucial structural shift in the post-World War II era, where credit aggregates began to "decouple" from broad money, driven by increased financial leverage.

borrowers, or the macroeconomic environment. This approach is as reasonable as it is difficult to implement in a historical perspective, where limited data availability is a binding constraint. This paper argues that bank profitability, when properly decomposed, provides a direct window into the operational strategies, the risk appetite, and the soundness of the banking sector during a credit expansion (see also chapter 2). Thus, when comprehensive data on asset prices or credit allocation are lacking, this approach provides a micro-founded tool to assess the quality of a credit boom from the perspective of the lenders themselves.

3.2 Data and Sampling

This analysis is built upon the data of the *Archivio Storico del Credito in Italia* (ASCI), presented in section 2.2. Summary figures and preprocessing remain consistent with the ones above. After dropping any missing values in the input variables, the working sample covers 22,583 bank-year observations across 1,096 unique banks.[6]

3.3 A Micro-Founded Framework: Decomposing Bank Profitability

As a baseline assumption, in this work, we claim that a bank's profit rate provides a compelling lens on the nature of a credit boom, and thus, it retains a central role in characterizing the credit cycle. As the bottom-line measure of performance for a bank's shareholders, the Return on Equity (ROE) represents the outcome of its intermediation activity. It synthesizes a wide range of managerial decisions—integrating information from both the income statement (revenues, costs) and the balance sheet (asset composition, leverage)—and the systemic context in which the bank operates (Freixas and Rochet, 2008; Savona, 2024).[7] While a simple ROE figure can be informative, its true analytical power is unlocked through decomposition, which reveals the underlying drivers of performance. This approach draws inspiration from the DuPont decomposition commonly used in corporate finance, adapted to match banking metrics and data availability.[8]

[6]For all of the items derived from the ROE decomposition below, we have controlled for the risk of sample bias with the procedure described in section A.2. We do not detect any statistically significant difference between a closed sample of banks and the working sample at a 1% confidence level, suggesting that there's no significant selection bias concern.

[7]A thorough discussion on the ROE is presented in subsection 2.3.1.

[8]The DuPont decomposition (analysis) was introduced in the early 1920s by the chemical firm DuPont Co. as a tool to internally evaluate financial performance. The standard three-step identity for a non-financial breakdown the ROE into Net Profit Margin (a measure of operating efficiency), Asset Turnover (a measure of asset use efficiency), and Equity Multiplier (a measure of financial leverage). Though originally heuristic, the framework gained theoretical and empirical traction in corporate finance and accounting literature as an efficient and effective way to link accounting ratios with firm value creation (Nissim and Penman, 2001; Soliman, 2008). An adaptation is necessary to reflect the uniqueness of banks' balance sheets (Gruber et al., 2017; Gruber and Kavan, 2022; Koch and MacDonald, 2014).

3.3.1 The DuPont Decomposition of Bank Profitability

We adapt the DuPont identity to the banking sector, following a two-layer decomposition. In the first layer, we separate the return generated from a bank's operations from the effect of its capital structure. In the second layer, we break down a bank's returns into operational efficiency and scale effects.

Layer 1: Return on Assets (ROA) vs Financial Leverage

With simple algebraic permutation, we start by decomposing the ROE into Return on Assets (ROA) and Financial Leverage. For a bank i in year t, $\text{ROE}_{it} = \text{Returns}_{it}/\text{Equity}_{it}$, thus, multiplying and dividing by the amount of total assets and rearranging, we get that:

$$\underbrace{\frac{\text{Returns}_{it}}{\text{Equity}_{it}}}_{\text{ROE}} = \underbrace{\frac{\text{Returns}_{it}}{\text{Total Assets}_{it}}}_{\text{ROA}} \times \underbrace{\frac{\text{Total Assets}_{it}}{\text{Equity}_{it}}}_{\text{Leverage}}, \tag{3.1}$$

where the ROA measures the average return per unit of intermediated assets, while the Leverage ratio measures the risk exposure of a bank, with a higher ratio meaning that each unit of equity is backing more assets, amplifying profits and losses.

Following banking and financial accounting literature, ROA is largely driven by operational factors—that is, interest margins, non-performing loans, and cost efficiency—and thus has a high elasticity to business and credit fluctuations (Dietrich and Wanzenried, 2014). Leverage, on the contrary, is often constrained by regulation, the institutional framework, and asymmetric information; as a result, its dynamics reflect deeper structural shifts, rooted in regulatory changes on capital requirements or selective market pressures (e.g. expected costs of financial distress, transactions costs, signaling behavior, and agency problems; Berger et al., 1995). Thus, by examining ROA and Leverage separately, we can disentangle whether changes in the ROE stem from shifts in the average profitability of the intermediation or from changes in balance-sheet risk exposure.

Layer 2: Net Profit Margin (NPM) vs Assets Utilization Intensity (AUI)

We can further refine our understanding by decomposing the ROA itself into two components that capture different dimensions of bank performance, such that:

$$\underbrace{\frac{\text{Returns}_{it}}{\text{Total Assets}_{it}}}_{\text{ROA}} = \underbrace{\frac{\text{Returns}_{it}}{\text{Profits}_{it}}}_{\text{NPM}} \times \underbrace{\frac{\text{Profits}_{it}}{\text{Total Assets}_{it}}}_{\text{AUI}}, \tag{3.2}$$

where the Net Profit Margin_{it} (NPM) represents the share of each unit of revenue that the bank retains as net income per unit of gross income, reflecting the operational *efficiency* (e.g. cost minimization) of the intermediation.[9] A higher NPM is achieved with wider interest spreads and fee income—e.g., in periods when the bank has high pricing power—and/or low operating costs relative to profits. The NPM thus effectively synthesizes a bank's net interest

[9] Since, by definition, $\text{Returns}_{it} = \text{Profits}_{it} - \text{Costs}_{it}$.

margin and cost efficiency when those are historically unobservable. The Asset Utilization Intensity$_{it}$ (AUI) measures the *effectiveness* of the intermediation, that is, the ability of the bank to generate gross income per unit of intermediated assets.[10]

If we reasonably assume that loans earn higher yields than alternative asset classes (e.g., liquidity and securities)—an assumption validated by the estimates of De Bonis et al. (2012) for the Italian context—a higher AUI indicates that the bank is allocating a greater share of its assets toward lending activities, all else being equal.[11] It follows that a higher AUI not only reflects that a bank's asset allocation is yielding more income (or generally high interest rates on assets), but it also explicitly relates to the intensity (or volume) of lending relative to other asset classes (Koch and MacDonald, 2014).

Substituting Equation 3.2 into Equation 3.1, decomposes the ROE into

$$\underbrace{\frac{\text{Returns}_{it}}{\text{Equity}_{it}}}_{\text{ROE}} = \underbrace{\frac{\text{Returns}_{it}}{\text{Profits}_{it}}}_{\text{NPM}} \times \underbrace{\frac{\text{Profits}_{it}}{\text{Total Assets}_{it}}}_{\text{AUI}} \times \underbrace{\frac{\text{Total Assets}_{it}}{\text{Equity}_{it}}}_{\text{Leverage}} . \tag{3.3}$$

Thus, a bank's ROE is a function of the operating efficiency of the intermediation, its effectiveness in generating income from the held assets, and its risk exposure.[12] The central claim of this work is that the contribution of these three factors varies over time and, being a function of the regulatory and competitive context in which the bank operates, it carries important historical information. Figure 3.1 plots the historical trend for the key indicators of the ROE decomposition, and represents a preliminary validation of this hypothesis.

Consistent with the theory-based expectations, the NPM and the AUI absorb most of the cyclical fluctuation in the ROE, whereas the Leverage shows a smoother behavior. In particular, NPM and AUI exhibit a pro-cyclical behavior during major economic contractions—as in the 1890s, the two World Wars, and the Great Depression—with a decline of both metrics.[13] On the contrary, economic expansions are characterized by a clear trade-off, exhibiting either volume-driven growth (rising AUI, as in 1920-1926 and 1947-1952) or spread-driven

[10] This measure is also commonly referred to as Asset Utilization Ratio. We followed Koch and MacDonald (2014), which adopts the nomenclature for financial intermediaries.

[11] This assumption helps to significantly streamline the interpretative framework but is not foundational to the analysis. It is possible to relax it by simply taking the AUI as a measure of the gross yield of the intermediation as opposed to the net yield presented in the ROA.

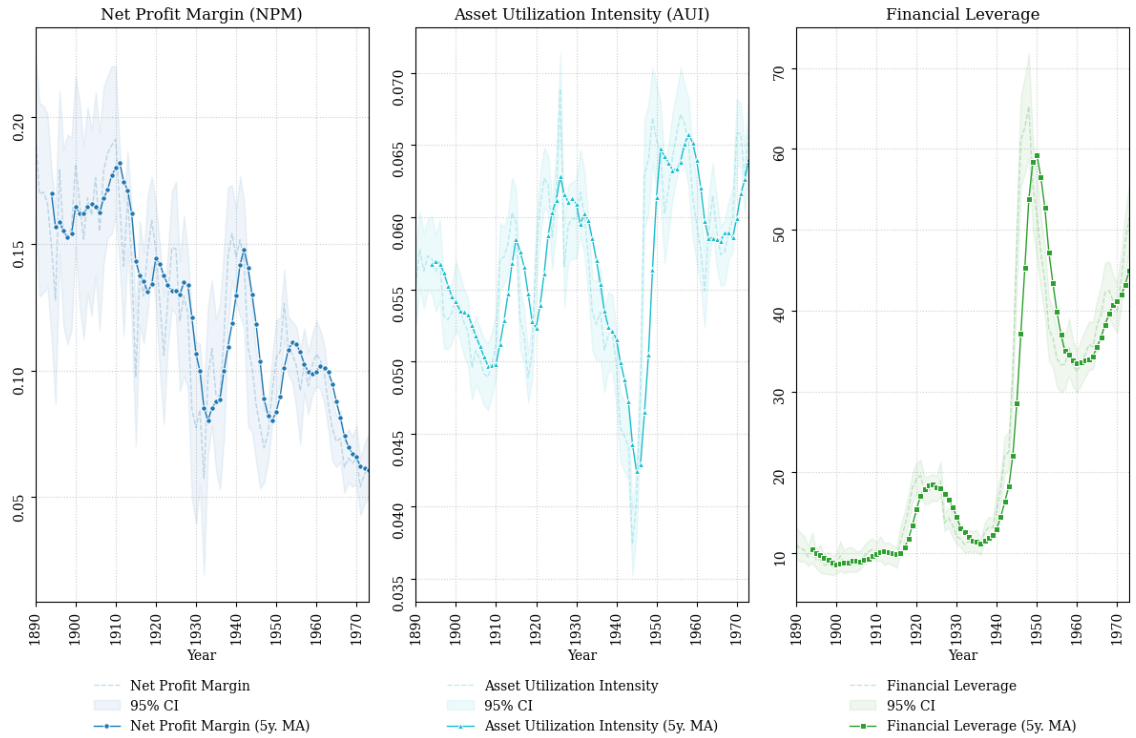
[12] A third layer of decomposition can further split the Asset Utilization into specific asset categories—for instance, isolating the marginal contribution of loans—effectively separating the price of credit (loan yield) and the quantity of credit (loan share of assets) such as

$$\underbrace{\frac{\text{Profits}_{it}}{\text{Total Assets}_{it}}}_{\text{AUI}} = \underbrace{\frac{\text{Profits}_{it}}{\text{Loans}_{it}}}_{\text{Loan Yield}} \times \underbrace{\frac{\text{Loans}_{it}}{\text{Total Assets}_{it}}}_{\text{Loan Share}} .$$

Still, it must be noted that each additional layer of decomposition provides diminishing returns, increasing the redundancy and the noise of the information. Thus, in this analysis, we do not pursue that third layer, focusing on the broader Margin and Utilization. The road remains open for further research.

[13] This pattern well aligns with theoretical models of the credit cycles, highlighting the interplay between the banking behavior and macroeconomic fluctuations (Bernanke et al., 1999; Kiyotaki and Moore, 1997)

Figure 3.1: ROE components: historical trend



The figure shows the historical trends of the key ratios of the ROE decomposition (Layer 1 and 2). Solid lines represent the 5-year moving average of the indicators, and the dashed lines show the original (unsmoothed) series. The shaded area represents 95% confidence intervals based on the annual distribution across the sampled banks.

profitability (rising NPM, as in 1900-1910 and 1936-1942).[14] Simultaneous growth is rare, and it clusters around reconstruction phases or economic booms (e.g., 1909-1911, 1919-1920, 1949-1952), aligning with the central role of the banking sector in providing the needed capital to meet investment demand (Ciocca and Biscaini Cotula, 1994; Rajan and Zingales, 2003). Leverage shows a smoother trend, with sharp increases during the World Wars—pointing to inflation eroding equity shares (Molteni and Pellegrino, 2021). The most clear feature is a structural break after World War II, where average bank leverage stabilized at a significantly higher level than in any preceding era. This shift was a direct consequence of the new regulatory regime under the 1936 banking law that prioritized stability and state control over strict capital requirements. It allowed banks to expand their balance sheets to fuel the booming real economy without the need to raise proportional amounts of equity (Gigliobianco and Giordano, 2010; Toniolo, 1995). This new, higher baseline for leverage fundamentally changed the risk and return profile of the banking system.

[14] Following De Bonis et al. (2018); Natoli et al. (2016), episodes of elevated margins correlate with periods of increasing concentration in the banking sector, either for banking consolidation or reduced competition.

3.3.2 From Profitability to Credit Regimes

From the evidence above, it is reasonable to interpret the leverage as largely exogenous to cyclical conditions—that is, more influenced by regulation, bank practices, and information efficiency. This assumption allows us to classify profitability dynamics into "credit regimes" based on the interplay between the NPM and the AUI. The result is a powerful lens to analyze the nature of a credit boom, allowing for a distinction between *how* (credit regime, micro-perspective) and *how much* (credit cycle, macro-perspective) the banking sector is lending, thus going beyond the focus on the aggregate volume of credit. Our logical framework assesses credit regimes by analyzing both the level (magnitude) and variance (stability) of the AUI and NPM series in a two-stage procedure.

Stage 1: Identify a Boom Analyzing the Asset Utilization Intensity (AUI)

The first stage focuses on the activity level of the banking sector, that is, the intermediation intensity proxied by the AUI. As seen above, the AUI captures the effectiveness with which the banking sector is allocating its assets to generate returns and, when loans pay higher interest than alternative asset classes, it directly maps to the volume of credit. It follows that a "boom" can be intuitively identified as a period of high levels of AUI, pointing to an intense and effective credit intermediation. Complementarily, periods where AUI is persistently low point to limited credit intermediation, the result of either market frictions or economic stagnation. Furthermore, the temporal variance of the AUI differentiates between an unstable expansion (high variance) and a persistent boom (low variance).

Stage 2: Qualify a Boom Analyzing the Net Profit Margin (NPM)

Having identified a boom, the goal of the second stage is to assess its quality by analyzing the Net Profit Margin (NPM)—that is, to distinguish between sustainable expansions ("good booms") and those masking growing risk ("bad booms"). We define a "good boom" as a period of intense credit activity that is both profitable (exhibiting elevated NPM) and stable (exhibiting low NPM variance). This effectively represents a phase of financial development, where credit expansion is supported by solid returns. A "bad boom", in contrast, is a credit expansion characterized by latent fragility, even if credit volumes are high. This fragility can manifest either as depressed net profitability (low NPM) or high instability (high NPM variance).

Empirical Identification with a Markov Switching Model

To rigorously implement the logical framework above, we apply a two-state Markov Switching (MS) model that endogenously determines the threshold between "high" and "low" states for both the NPM and the AUI components based on their level and variance. This methodology, introduced by Hamilton (1989), offers a data-driven approach to model cyclical series that transition between a finite number of unobserved "regimes" or "states", and to probabilistically estimate regime transitions without imposing arbitrary breakpoints.

The model assumes that the observed variable y_t follows a regime-dependent process where

$$y_t = \mu_{S_t} + \varepsilon_{S_t} \quad \text{with} \quad \varepsilon_{S_t} \sim N(0, \sigma^2_{S_t}), \tag{3.4}$$

Table 3.1: Markov Switching Model parameters

	Low regime		*High regime*		*Transition prob.*		*Exp. duration*	
y_t	μ_0	σ_0^2	μ_1	σ_1^2	P_{LL}	P_{HL}	*Low*	*High*
NPM	-0.5134*** (0.045)	0.0571*** (0.016)	0.4085** (0.177)	1.3736*** (0.286)	0.9648*** (0.029)	0.0156 (0.017)	28.4	64.1
AUI	-0.7486*** (0.095)	0.3604*** (0.078)	0.9661*** (0.078)	0.1689*** (0.045)	0.9666*** (0.025)	0.0403 (0.031)	29.9	24.8

*The table reports the estimated parameters for a two-states Markov Switching model with regime-dependent mean μ_{S_t} and variance $\sigma^2_{S_t}$ for the trend component of NPM and AUI. Transition probabilities are complementary thus, $P_{LH} = 1 - P_{LL}$ and $P_{HH} = 1 - P_{HL}$. Expected durations are computed as the expected value of a geometric series based on the transition probabilities $\mathbb{E}_t[D_{S_t=i}] = 1/(1-P_{ii})$. ***, **, * denote significance at 1%, 5%, and 10% level respectively.*

where $S_t \in \{0,1\}$ denotes the latent regime at time t. Each regime is characterized by a distinct mean μ_{S_t} and variance $\sigma^2_{S_t}$, allowing the model to capture both level shifts (e.g., persistently high vs. low spreads) and volatility changes (quiet vs. turbulent phases) in the data-generating process. The latent state evolves according to a first-order Markov chain with transition probabilities $P_{ij} = \mathbb{P}\{S_t = j \mid S_{t-1} = i\}$, allowing us to estimate both the timing of regime changes and the persistence of each phase.[15]

To identify persistent structural changes in the banking system, we apply the Markov Switching model to the HP-filtered trend components of NPM and AUI.[16] It is important to clarify that this approach is designed to capture shifts in medium-term dynamics, not short-term events. A regime switch occurs only when the underlying data-generating process experiences a persistent structural change. Therefore, a banking crisis may represent an extreme realization *within* an existing regime without triggering a transition. Conversely, the model will detect the impact of regulatory or competitive changes that permanently alter the system's structure, even if they do not manifest as an acute crisis.

3.3.3 Results and Historical Qualification

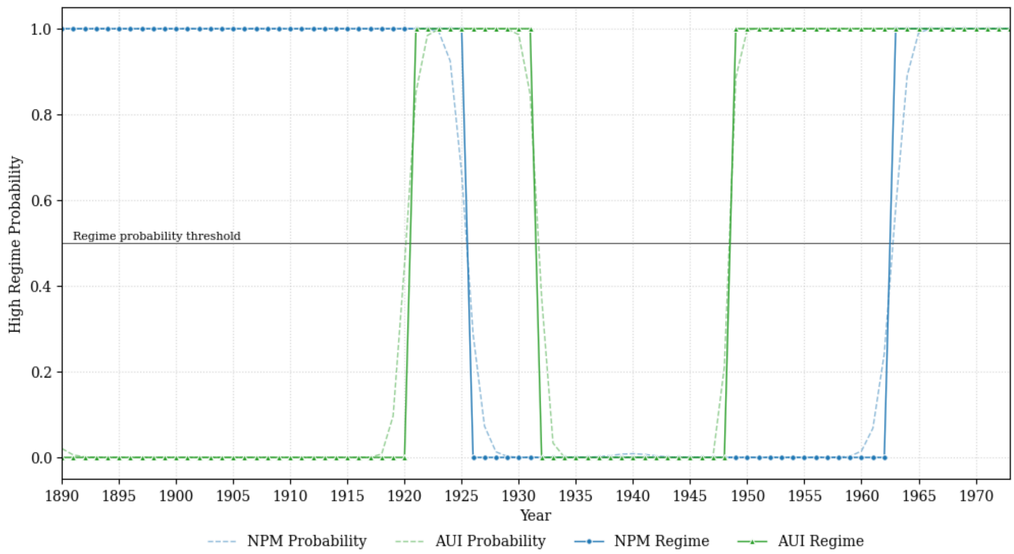
Markov Switching Model: Empirical Results

Table 3.1 reports the estimated parameters for the standardized NPM and AUI trend series. As expected, we find clear evidence of a regime-dependent structure. For both NPM and AUI, the first regime, which we refer to as *Low regime* (S_t=0), is characterized by a statistically significant negative drift, -0.5134 and -0.7486, respectively, indicating a series that is decreasing in levels. On the contrary, the second regime, that we refer to as *High regime* (S_t=1),

[15] If in *t-1* the series is in regime *1*, the probability of remaining in regime *1* in *t* is P_{11}. If P_{11} is high, the series is highly persistent, and the expected duration of the phase is $1/(1-P_{11})$—that is, the expected value of a geometric series.

[16] We use λ=100, a standard HP-filter parameter for annual data (Ravn and Uhlig, 2002). Robustness checks for different values of λ are presented in Appendix B.

Figure 3.2: Markov Switching High regime: probabilities and classification



The figure plots the Kim smoothed probabilities for the High regime (expansion) as dashed lines and the regime classification as solid lines. The regime is classified based on a threshold of 0.5 on the regime probabilities.

shows a significantly positive drift, 0.4085 and 0.9661, respectively, tracing level growth. Interestingly, the two series exhibit opposite volatility patterns. The High regime for the AUI shows a lower variance, 0.1689, compared to 0.3604, making it a clear indicator of a sustained boom period. In contrast, the High regime for the NPM is significantly more volatile (1.3736 vs. 0.0571), highlighting a fundamental trade-off between profitability and stability that motivates a careful interpretation of this state to qualify a credit boom.

The estimated transition probabilities show a significant persistence in the regimes—i.e., once in NPM is in the Low (High) regime, there's a probability of 94.68% (1-0.0156=98.44%) to remain in the same regime the next year, that is, an expected duration of the Low (High) regime of 28.4 (64.1) years. These figures are broadly consistent with the findings of Bartoletto et al. (2019) that report a medium-term credit cycle duration between 20 and 40 years for the same historical context.

Figure 3.2 provides a visualization of Kim's smoothed probability of the High regime for both series over the analyzed time sample.[17] For a strict classification of the regimes, a threshold of 50% probability is used to differentiate between High and Low states.[18] Consistent with the persistence highlighted above, the figures exhibit remarkably stable regime probabilities: a strong signal of the model's ability to identify switches linked to meaningful structural changes rather than short-term oscillation, and an important preliminary validation. Ta-

[17] For a year t, the *smoothed* probability of being in regime i is computed using all the available information in the series, both in the past (from 0 to t-1) and the future (from t+1 to T). This provides a more accurate estimate of the regimes, with less noise and uncertainty. The results are robust to the use of *filtered* probabilities, which use only past information.

[18] That is, if at time t the smoothed probability of being in a High state is above 0.5, then year t is classified in a High state. Conversely, if the probability is below 0.5, year t is classified in a Low state.

Table 3.2: Descriptive statistics of the credit regimes

			NPM (%)		AUI (%)		
Start	End	Years	Mean (μ)	Var. (σ^2)	Mean (μ)	Var. (σ^2)	Classification
1890	1920	31	16.24%	1.10%	5.43%	0.20%	Selective credit
1921	1925	5	12.81%	0.46%	5.98%	0.09%	Good boom
1926	1931	6	10.58%	0.72%	6.01%	0.09%	Bad boom (μ and σ^2)
1932	1948	17	10.94%	0.85%	5.19%	0.34%	Disintermediation
1949	1962	14	10.03%	0.36%	6.22%	0.16%	Bad boom (μ)
1963	1973	11	6.80%	1.06%	6.12%	0.19%	Bad boom (μ and σ^2)

The table reports the descriptive statistics of the credit regimes identified by the Markov-Switching model, using a probability of 0.5 as the threshold to classify a year in a High regime. Mean (μ) and variance (σ^2) are computed on the trend series within the same phase. Boom classification is based on the qualitative framework introduced in subsection 3.3.2.

ble 3.2 reports the descriptive statistics of each phase identified by the intersection of the AUI and NPM states. Those are 1890-1920, 1921-1925, 1925-1931, 1932-1948, 1949-1962, 1963-1973, with a remarkable alignment with known historical patterns.

Historical Qualification of the Identified Regimes

The Liberal period (1890-1920) is defined by a persistent equilibrium, characterized by wide spreads (16.24% on average) but limited credit intensity (5.43% on average). This classifies the NPM in a High regime, and AUI in a Low regime: we term this configuration a peculiar case of "Selective credit", which greatly aligns with the specificity of the historical context. Indeed, in a financial sector operating under *laissez-faire*, banks face severe information asymmetries and no formal lender-of-last-resort that, in turn, leads to an under-use of capital (Amrein, 2025).[19] Thus, the cautious lending stance appears as the rational response to an unstable institutional framework. In turn, the diffusion of the German mixed-bank model is the endogenous solution to market frictions, allowing banks to leverage relationship lending to finance the early industrialization in the absence of a developed capital market, easing supply-side constraints (Bartoletto et al., 2019; D'Auria et al., 1999).[20] Despite relatively higher variance in the series (1.10% for NPM and 0.20% for AUI), this Selective credit regime proved remarkably stable, lasting 31 years even through the downturn of World War I. The framework confirms that the canonical crises of 1893, 1907, 1914, and 1921 were not "credit boom gone wrong" that followed an accumulation of risk and a deterioration of the banking

[19]The focus of the institutional and regulatory framework—the Banking Law of 1893 and the creation of Bank of Italy in the same year—remained on the banks of issue and on the process of money creation (Fratianni and Spinelli, 2001; Gigliobianco and Giordano, 2010). The first example of the Bank of Italy acting as a lender-of-last-resort is in 1907 with the bailout of Società Bancaria Italiana (Bonelli, 1982; Vercelli, 2022). A more codified role of the Bank of Italy's supervision and a mechanism of depositors' safeguard would be introduced only with the Banking Laws of 1926 and 1936 (Galanti et al., 2012; Gigliobianco and Giordano, 2010; Molteni and Pellegrino, 2021; Toniolo, 1995). For a more detailed description, see subsection 2.1.2.

[20]This has often been described as an empirical realization of Gerschenkron (1962) hypothesis on the development of relatively backward economies (De Bonis et al., 2013; Polsi, 1996; Toniolo, 2022).

activity.[21] This evidence aligns with historical accounts that point to idiosyncratic causes of the crises, such as fraud and stock market speculation (see subsection 2.1.2). This highlights our framework's ability to capture structural features of banking, which are not necessarily swayed by macroeconomic fluctuations.

The first post-war period (1921-1932) corresponds to a major expansion of the AUI, lasting up to 1931. However, our analysis of the credit regimes reveals a critical shift in the nature of the boom in 1925. The period 1921-1925 is marked by a switch to the High regime for the AUI, with an average value that grew from 5.43% to 5.98%. Although the average NPM declined from 16.24% to 12.81%, the MS model firmly classifies it in its High state, while its variance more than halved from 1.10% to just 0.46%.[22] Taken together, this combination of intense credit activity, high profitability, and stability provides a strong empirical support for what our framework defines as a "good boom."

In this period, banks enjoyed both widening profit margins and increasing credit demand from the industrial sector, fueled by the reconversion process from the war to peace time economy, "ambitious expansion projects," and inflationary bursts (Cotula and Spaventa 1993, p. 59; Fratianni and Spinelli 2001).[23]

By 1925, these dynamics had largely exhausted. A clear divergence emerges between credit activity and profitability: While AUI remained high and stable, the sharp decline in NPM to 10.58% and the simultaneous rise in its volatility (0.72% from 0.46%) signal a fundamental shift in the credit environment as represented by the transition into a low-margin regime. This regime switch provides strong evidence of the boom's deteriorating quality, which we classify as a "bad boom." This is historically consistent with (i) rising demand from capital-intensive industries (Carreras and Felice, 2012); (ii) expanding financial access;[24] (iii) increasing competition in the banking sector, which, in turn, bolsters deposit rates to attract small savers and match the branch expansion (Toniolo, 1995; De Bonis et al., 2012).[25]

While credit volumes remained robust, signs of "over-banking," emerged (Molteni, 2023, p. 22): limited prudential oversight allowed the proliferation of institutions of dubious quality that, as the credit demand of profitable firms saturated, increasingly diverted lending to-

[21] We do not comment on the crisis of 1891, since the eventual boom-bust pattern is likely out-of-sample, tracing to the housing bubble burst of 1887.

[22] Note that the lower variance can be partially the mechanical consequence of the shorter duration of this phase.

[23] Indeed, in 1919, the monetary base (M0) grew by 8%, and narrow money (M1 aggregate) by 11%. This led to an inflation rate of 31% and 18% in 1920 and 1921, with a real interest rate on medium-to-long-term loans of -26% and -13% respectively (Baffigi, 2013; De Bonis et al., 2012). The spread between deposit rates and medium-to-long-term loans between 1919 and 1923 increased from 1.96% to 2.51% (De Bonis et al., 2012). The lower elasticity of deposit rates (Drechsler et al., 2021), coupled with the sustained demand for credit, improved the profitability of banking. The effect of inflation on credit creation is well documented in economics literature, see e.g., Bernanke and Gertler (1995); Kiyotaki and Moore (1997).

[24] The total branches increased from 6,012 in 1920 to 11,444 in 1926 (Ciocca and Biscaini Cotula, 1994); the number of banks in ASCI rises from 489 in 1920 to 695 in 1925.

[25] The increasing competitive pressures generated a pro-cyclical behavior a lá Hotelling's "excessive sameness." In particular, De Bonis et al. (2018) and Natoli et al. (2016) point to an increasing competition between mixed-banks opening branches in small towns and local cooperative banks, amplifying natural economic fluctuations and reducing the overall credit quality.

ward speculative uses (Toniolo, 1995).[26] This transition from a "good boom" to a "bad boom" is a key finding. It acts as a powerful early-warning signal, preceding conventional crisis timelines by five years. It suggests that the Great Depression's impact in Italy was significantly amplified by endogenous financial fragility. The strong credit expansion of the preceding years was masking unhealthy competition and progressive credit quality deterioration.

The "bad boom" of the 1920s culminated in the crisis of 1930 and the Great Depression, ushering in a prolonged "Disintermediation" phase that persisted through the 1930s and World War II. Our framework captures this transition as a regime shift in Asset Utilization (AUI) beginning in 1930 and formalized in 1932. This new phase is characterized not only by a lower level of credit activity (a mean of 5.19%) but also by significantly higher instability, with a nearly quadrupled variance of 0.34%. Lasting until 1948, this regime of low credit intensity empirically reflects the structural collapse of the mixed-banking model and the distress of a large share of the banking sector, both the major banks and the smaller and medium ones (Molteni, 2023).

These events prompted massive state intervention, culminating in the Banking Law of 1936, which fundamentally reshaped the financial landscape by prioritizing stability over competition. As bank lending severely contracted in the 1930s, the state stepped in—via the bank rescue agency IRI and through tighter Bank of Italy control—to restructure and support the financial system. After the crisis, the banking law of 1936 codified these changes (Galanti et al., 2012; Gigliobianco and Giordano, 2010; Toniolo, 1995).

The post-war "economic miracle" produced a new credit boom, identified by an all-time high AUI level of 6.22%. However, this period of intense growth was also marked by declining bank profitability, with the NPM contracting to 10.03%. Consequently, our framework classifies this era as a "bad boom"—high intensity but low profitability credit expansion. Still, unlike the competition-driven "bad boom" of the 1920s, this was arguably a policy-induced one. The 1936 banking law, now fully implemented, created a tightly regulated environment where credit grew rapidly to fuel reconstruction, but bank margins were artificially compressed by interest rate controls and increasing competition.[27] As famously described by Bank of Italy Governor Donato Menichella, banks acted as quasi-"public service" institutions,

[26] As the governor of Bank of Italy Stringher states in 1927 looking at the preceding years' expansions: "The complete lack of any banking regulation allowed the establishment of a multitude of banks with little or trifling capitals and their mushrooming in small and large cities through improvised networks of branches, with the specific aim of collecting deposits that often ended up in dreadful speculations" (Stringher, Relazione Annuale agli Azionisti of Bank of Italy, 1927, translation from Italian by Molteni, 2023, p. 22). The very banking law of 1926 was introduced to tackle these imbalances.

[27] To divert the public preference toward banks' deposits, Bank of Italy imposed a reduction of the interest rate spread between deposits and loans, achieved by managing the cartel rates—that represented the benchmark of the whole sector—and by supporting the development of a capillary banking sector, characterized by the expansion of small and local banks, while denying further expansion of the major banks (Albareto and Trapanese, 1999; Ciocca, 2003). Between 1952 and 1954 the minimum interest rate on fiduciary deposits rose from 1.5% to 2.5% for 3-months deposits, from 2% to 3.25% for 6-months deposits, and from 2% to 4% for 12-months deposits; between 1949 and 1951 the interest rate of current account loans decreased from 8.77% to 7.50%, the rate on bills discounting decreased from 6.27% to 5.25% (Cotula, 1999, p. 940). Moreover, the Special Credit Institutions (Istituti di Credito Speciale) created by the Law of 1936 channeled subsidized long-term credit to the industry, further compressing commercial banks' margins by removing their most profitable lending.

expected to finance growth at modest returns (Albareto and Trapanese, 1999). Our empirical findings corroborate this characterization, yet they critically reframe the narrative of the "economic miracle." They show that while favorable regulations sustained a high-growth environment, this came at the cost of crystallizing inefficiencies and structural imbalances within the banking sector, possibly masking growing risk.

The last and most prominent transition detected by the MS model begins in 1959, formalized by 1963, revealing a new form of post-war credit boom. While the AUI remained high, indicating a continued expansion, to trigger the regime switch is a strong contraction in the NPM, reaching its lowest average level (6.80%) and a surge in its variance to 1.06%, three times higher than the preceding period. In our framework, the combination of low profitability and high instability unequivocally is classified as a "bad boom", which would persist till the end of the sample, and is remarkably consistent with the increase in systemic stress detected in chapter 2.

The observed decline in profitability and rise in instability contradict the traditional narrative of a post-war "golden age" for Italian banking, and yet they are consistent with the institutional changes of the period. With the end of the Menichella governorship at the Bank of Italy, the tight credit restrictions of the 1950s were eased, the bank cartel was dismantled, the system was gradually opened to external competition, and, most importantly, the policy objective gradually pivoted from stability toward real economic growth, particularly responding to the stock market crash of 1962-63 and the economic slowdown (Cotula, 1999; Fratianni and Spinelli, 2001; Gelsomino, 1999, 2024).

Our findings challenge the idea of stable growth: they reveal a pattern in which the booms of both the 1950s and 1960s were, in fact, "bad booms," sharing key quantitative traits with the fragile expansion of the late 1920s. This finding suggests that vastly different market structures—from *laissez-faire* to financial repression—can paradoxically converge on the same suboptimal outcome. It raises the crucial question of why one "bad boom" collapsed into crisis while the other became a "happy island" of stability. To answer this question is beyond the scope and possibility of this chapter. Still, we may preliminarily argue that the outcome was conditional on the context: The 1950s and 1960s boom was sustained by a stable international environment and a robust institutional framework pivoting on the Bank of Italy's commitment to stability—safeguards absent in the 1920s. We will explore this puzzle in greater detail in chapter 5, where we analyze the evolution of bank business models in response to these institutional changes.

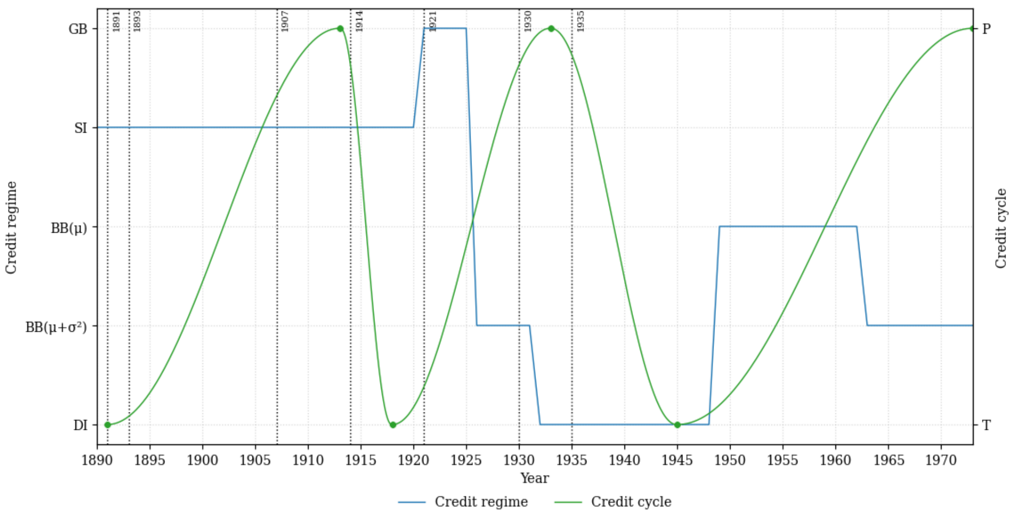
The Relationship Between Credit Regimes and the Credit Cycle

We can generalize our empirical findings by mapping the credit regimes into five distinct archetypes. These archetypes are defined by their distinct combination of AUI and NPM. Moving from the most fragile state to the most robust, we have detected:

1. Disintermediation (Low AUI, Low NPM): A severe impairment of the banking sector where both credit activity and profitability are impaired, typically reflecting a deep economic downturn.

2. Bad Boom – Unprofitable and Unstable (High AUI, Low NPM & High NPM Variance): The most

Figure 3.3: Credit regimes and the credit cycle



The left-axis plots the credit regimes resulting from the Markov Switching model, based on the Net Profit Margin (NPM) and Asset Utilization Intensity (AUI) trends. "GB" indicates a Good Boom, "SI" Selective Intermediation, "BB(μ)" an unprofitable Bad Boom, "BB(μ+σ^2)" a Bad Boom both unprofitable and unstable, "DI" a phase of Disintermediation. The right-axis plots the Peaks (P) and Troughs (T) of the credit cycle as proxied by the total loans of the banking sector (source: Bartoletto et al. 2019).

precarious type of expansion. High credit activity is undermined by both low profitability and high instability, signaling a significant build-up of systemic risk often driven by excessive, unregulated competition (see Berger and DeYoung, 1997; Das et al., 2018; Jiang et al., 2017).

3. Bad Boom – Unprofitable (High AUI, Low NPM & Low NPM Variance): A credit expansion characterized by high volume but low, albeit stable, profitability. This often reflects a financially repressed environment where regulatory policy artificially suppresses bank margins (see Monnet, 2018).

4. Selective Intermediation (Low AUI, High NPM): A period of cautious but profitable lending. Low credit activity is a sign of a rationed supply, typical of environments with high uncertainty, information asymmetry, or substantial agency costs (see Amrein, 2025).

5. Good Boom (High AUI, High NPM & Low NPM Variance): The ideal state of financial development, where a high volume of intermediation is supported by both solid and stable bank profits.

How do these micro-based credit regimes relate to the macro credit cycle? Figure 3.3 shows the credit regimes classification and dating based on the MS model compared to the credit cycle dating of Bartoletto et al. (2019, Tab. 2), allowing for a few compelling insights.[28]

During the Liberal period, the credit regimes exhibit a remarkable persistence, even through the cyclical downturn of World War I. This suggests how the underlying institutional structure—

[28] The peaks and troughs represent the medium-term credit cycles, computed on the sum of total bank loans as the reference indicator.

characterized by high uncertainty and information asymmetry—was the primary determinant of bank behavior, enforcing a cautious stance that was largely insensitive to short-term economic fluctuations.

The early warning signal of the 1920s is validated by the comparison with the credit cycle. Credit regimes effectively differentiate a subtle change within the credit cycle upturn.

Following the crisis of 1930, both the micro and macro perspectives align, capturing the profound and prolonged "Disintermediation" of the Great Depression and World War II. However, the two perspectives diverge again in the post-war era, revealing how the institutional framework fundamentally reshaped the nature of credit expansions compared to the post-World War I period. As a result, our findings offer strong empirical support for (i) the claim of Molteni (2023), which detects a substantial discrepancy in micro and macro credit dynamics in the Italian interwar period; (ii) the claim of Bartoletto et al. (2018, p. 22) that classic "boom-bust represent an exception in the panorama of Italian banking crises."

3.4 The Heterogeneous Transmission of Credit Regimes

Having identified the aggregate credit regimes for the Italian banking sector, we now turn to the bank-level data to explore the micro-foundations of these system-wide dynamics. Which types of institutions were the primary drivers of each regime, and how did their performance differ during these periods?

Table 3.3 provides a perspective into the heterogeneous "transmission" of the credit regimes, reporting the difference in the NPM and AUI averages between the broad bank population and selected subsamples to track key idiosyncratic traits of the institutions: total assets size, juridical category, and geographic region. The results highlight both persistent differences and major structural breaks in the Italian banking system over these 84 years, offering a compelling micro-foundation for the aggregated analysis presented above. Three mutually-related findings emerge (see also section 2.4).

1. A great reversal in the performance of banks based on their size. In the pre-war *laissez-faire* financial market, economies of scale were a key driver of efficiency (Stimpert and Laux, 2011). Major banks (XL and L) consistently outperformed the population, achieving between 5% and 8% higher NPM. This occurred despite a more conservative asset allocation—characterized by a systematically lower AUI—suggesting that high market power and operational efficiency allowed them to focus on prime lending to major industrial firms (Polsi, 1996). Conversely, smaller institutions were the least efficient, a vulnerability particularly compelling during the 1926-1931 credit regime. In this period, the smallest banks (XS) operated with an NPM 8% below average while their AUI remained 2% above: the combination indicates that smaller institutions were particularly exposed to the "bad credit boom," hinting at a higher concentration of risk (see Molteni, 2023).

After World War II, this dynamic reversed thanks to a new regulatory regime designed to stimulate competition (Albareto and Trapanese, 1999; De Cecco, 1968; Mastromatteo and Es-

Table 3.3: Heterogeneity of NPM and AUI across credit regimes (Difference-in-means with the full sample)

		1890-1920		1921-1925		1926-1931		1932-1948		1949-1962		1963-1973	
Bank Type		NPM	AUI	NPM	AUI	NPM	AUI	NPM	AUI	NPM	AUI	NPM	AUI
Full sample avgerage		0.157	0.054	0.138	0.062	0.102	0.061	0.105	0.052	0.103	0.063	0.072	0.059
Size (cat.)	XL	0.08***	-0.02***	0.05***	-0.01***		-0.01***		-0.01***	-0.06***	-0.00***	-0.03***	
	L	0.04***	-0.00***		-0.01***		-0.01***		-0.01***	-0.02***	-0.00**		
	M		0.00***										
	S		0.01***					0.04*		0.03***		0.02*	
	XS	-0.09***	0.01***		0.02***	-0.08*	0.02***		0.01***	0.06***	0.01***	0.02**	0.00***
Category	IDP	n.a.	n.a.						-0.01***	-0.08***	-0.01***	-0.05***	-0.01***
	BIN	n.a.	n.a.	n.a.				-0.05***	-0.02***	-0.08***	-0.02***	-0.04***	-0.02***
	DB	n.a.	n.a.	n.a.						0.04***		0.04***	
	SOC	0.11***	-0.00**		-0.00***		-0.01***	0.04***	-0.00***	0.05***	-0.01***	0.01**	-0.01***
	CRO	-0.09***					0.01***	-0.03***	0.00*	-0.06***	0.01***	-0.02***	0.01***
	MDP	-0.07***	0.01***		0.02***		0.02***	-0.08***	0.02***		0.02***		0.01***
Macroregion	North	0.06***	-0.01***		-0.01***		-0.01***	0.03***	-0.01***		-0.02***		-0.01***
	Center	-0.05***	0.01***				0.01***	-0.05***	0.01***	-0.03***	0.01***	-0.02***	0.01***
	South		0.01***		0.01***				0.01***	0.05***	0.01***	0.04***	

*The table reports the difference in the mean of the full sample and of selected subsamples for the six phases of the credit regime. The full sample average is computed on the NPM and the AUI of all the bank-year observations in each phase (non-filtered series). Subsamples are defined to track idiosyncratic characteristics of the banks: size, juridical category, and macro-region of the HQ. Size is a categorical variable that splits the annual sample into quintiles of the total assets (i.e., a bank in year t is XL if it falls in the top 20% of the total assets distribution in year t). Category includes all the categories in the sample. BIN and DB are introduced with the banking law of 1936, thus, they are n.a. for the first three credit phases. IDP are introduced with the banking law of 1926, thus are n.a. for the first two credit phases. ***, **, * indicate significance at a 1%, 5%, and 10% level respectively. P-values are Bonferroni-adjusted to correct for multiple comparisons. For clarity, coefficients not significant at the 10% level are not displayed.*

posito, 2023; Strangio, 2017). Artificially constrained, the major banks underperformed the average by 3% to 6% NPM. Meanwhile, the smallest banks (XS) were the winners, outperforming the average by up to 6%. This structural break shows how policy deliberately constrained larger institutions to foster the growth of small and medium local banks, highlighting how political bargains can effectively redistribute competitive advantages across different types of banks (Calomiris and Haber, 2014).[29] This trend began to shift after 1963. As financial repression gradually eased, major banks, while still underperforming, showed a marginally better relative positioning, hinting at how, while institutions can redistribute competitive advantages, market and economic forces remain binding (Calabria and Molteni, 2026; Faccio and McConnell, 2025).

2. An evolving North-South divide. The North was an efficiency leader in the pre-war period (+6%), while the Center and South lagged, despite operating on slightly higher AUI. The trends reversed in the post-war period, Southern banks outperformed in the NPM up to 5%—suggesting the geographic targeting of the new regulatory environment[30]—though this reversal was temporary; in the post-1963 period, these same banks were hit marginally harder by the decrease in profitability.

3. A fundamental divergence in the bank's objective function. Profit-oriented joint-stock banks (SOC) exhibit a positive NPM deviations and negative AUI deviations across all six historical phases, between 1% and 11%. In direct contrast, the social purpose of savings banks (CRO) and pledge banks (MDP) is clearly shown by the low-NPM (between -9% and -2%), high-AUI models (up to +2%) (see Natoli et al., 2016). Looking at BIN and IDP further confirms the previous findings: after 1948, they significantly and persistently underperformed on both efficiency (-5%/-8%) and effectiveness (-1%/-2%), hinting at a role closer to policy instruments rather than profit-maximizing entities.

3.5 Concluding Remarks

This chapter has reinterpreted historical credit booms by shifting the analytical lens from macro-level aggregates to the micro-level dynamics of bank profitability. We introduce a methodological framework that adapts the DuPont identity for the banking sector and employs a Markov Switching model to distinguish between different credit regimes. This micro-founded approach proves especially valuable in historical contexts where data on asset prices or loan allocation are scarce, providing a new tool to assess the "quality" of a credit cycle based on the efficiency and effectiveness of bank lending. Applying this framework to Italian financial history yields a significant set of findings for three key debates.

First, dialoguing with the macro-financial literature on credit booms, the analysis comple-

[29] "Menichella sacrificed competition and efficiency in the banking sector to ensure that competitive impulses emerged from the pluralism of banks and reached industrial firms" (Ciocca, 2003, p. 3). Cotula (1999, p. xiv) claim that this action was deemed necessary to protect the development of small and medium local banks, impossible under a strongly oligopolistic sector.

[30] The development of the South were a major policy objective, which motivated the creation of ad-hoc institution (e.g. the *Cassa per il Mezzogiorno* and the SVIMEZ).

ments the stress indicator discussed in chapter 2 with a perspective on how the banking activity interacted with the credit cycle around Italy's major banking crises. We confirm that the limited systemic stress detected during the early crises (1893, 1907, 1921) is explained by their origins in isolated factors—like fraud, stock market speculation, or industrial collapse—rather than systemic "credit booms gone bust" (Battilossi, 2009; Bartoletto et al., 2018). Conversely, we validate the Great Depression as a structural crisis rooted in a deterioration of banking efficiency that began as early as 1924, aligning with a growing literature on the interwar period's over-banking (Molteni, 2024). Most significantly, our framework sheds a new light on the "economic miracle", identifying a "bad boom" in the 1950s-1960s quantitatively similar to the 1920s. These results validate the post-1963 rise in instability signaled by the barometer in chapter 2. We argue that this post-war boom didn't burst into a crisis thanks to a radically different institutional and regulatory environment that successfully suppressed the symptoms of financial fragility.

Second, regarding the structural efficiency of local banks, we challenge the traditional view that small institutions were inherently stable anchors of the system (Polsi, 1996). By disaggregating our trends, we document that during the *laissez-faire* period, smaller banks were the least efficient intermediaries, suggesting that economies of scale acted as a binding constraint on their performance, aligning with the dominant economic literature (Stimpert and Laux, 2011).

Third, our analysis uncovers significant asymmetries in how credit regimes were transmitted, directly connected to the political economy of banking. We document a "great reversal" of performance in the post-war era with a gap between large and small banks favoring the latter: the economies of scale that benefited major banks under *laissez-faire* were completely eroded by the post-war regulation, designed to foster competition (Cotula, 1999; Mastromatteo and Esposito, 2023; Strangio, 2017). This suggests how the post-war banking landscape was fundamentally shaped by a political bargain that redistributed competitive advantages, consistent with the framework of Calomiris and Haber (2014). This policy shift also reversed the traditional North-South divide, with Southern banks outperforming their Northern counterparts in the post-war era. However, after 1963, as the system was broadly hit by decreasing profitability, these smaller and Southern banks were marginally more affected. This suggests that, while financial repression and interventionism can redistribute competitive advantages, they cannot indefinitely suppress basic market and economic forces (Calabria and Molteni, 2026; Faccio and McConnell, 2025).

The central lesson of this study is that *how* banks lend is at least as important as *how much* they lend. This distinction is crucial for historical analysis, as it challenges the assumption that rapid credit expansion is a uniform predictor of vulnerability (Schularick and Taylor, 2012). Our evidence suggests that the outcome of a credit boom is conditional on the institutional context: financial regulation, central bank mandates, and international markets act as containment mechanisms that determine whether a high-utilization credit regime precipitates an acute crash (as in the 1930s) or fosters a silent accumulation of risk (as in the 1960s).

Building on these findings, future research could apply this profitability-based framework to other nations to test its external validity. Further work could also classify credit regimes at the individual bank level or integrate more granular data on loan types and lending standards as they become available, offering an even deeper understanding of the complex relationship between banking, credit, and instability.

Chapter 4

Laws, Orders, and Crises: the Italian Banking Sector Through the Age of Extremes

An Application of the SCoPE System: How Neural Networks Allow for a Comprehensive Study of Banks' Business Models and Risk in the Long-Run.

"The eye... the window of the soul, is the principal means by which the central sense can most completely and abundantly appreciate the infinite works of nature."

— Leonardo da Vinci

"The greatest value of a picture is when it forces us to notice what we never expected to see."

— Tukey (1977, p. vi)

The previous chapters used bank performance, measured through the ROE and its components, to identify financial stress and analyze credit cycles. Yet, this outcome-oriented view naturally leads to a deeper question: what were the underlying drivers of this performance? Aligning with recent literature (see, e.g., Correia et al., 2025), to truly understand the mechanics of financial instability and the forces that have shaped the banking sector's long-run evolution, it is paramount to shift the focus from income statements (i.e., profitability) to a holistic analysis of balance sheets. We need to "micro-found" our understanding of banks' performance by systematically analyzing the asset-and-liability structures—i.e., the business models—that banks adopted to achieve their economic results.[1]

[1] In this work, we take the widely held position in the literature that defines the business model as the set of balance sheet characteristics of a bank, proxied by its assets and liabilities composition (see Ayadi et al., 2011, 2018; Farnè and Vouldis, 2017, 2021; Roengpitya et al., 2014, 2017; Savona, 2024).

This shift in perspective enables a reassessment of three key debates about the evolution of Italian banking.

First, we can empirically test traditional narratives regarding the nature and impact of historical crises. We revisit the comparison between the 1890s and the 1930s—events traditionally distinguished by their domestic drivers (real estate speculation vs. industrial entanglement) yet linked by the transmission of international shocks (Di Martino, 2022; Fratianni and Spinelli, 2001) and the inherent fragility of universal banking (Confalonieri, 1974, 1994; Toniolo, 1978). By tracing the evolution of business models, our framework allows us to determine whether these episodes shared the same structural patterns or unfolded in fundamentally different ways, thereby verifying whether the mixed-bank model was consistently defective or—as suggested in chapter 3—whether we must distinguish between the idiosyncratic governance failures of the 19th century and the systemic stress of the Great Depression. Moreover, by shifting our focus to the balance sheets, we can challenge the established view of the 1907 and 1921 panics as systemic ruptures, with a complementary perspective to those of the previous chapters (from aggregated to bank-level insights). Aligning with debates of the Italian historiographic literature on the interplay between crisis and regulation (Galanti et al., 2012; Gigliobianco and Giordano, 2010), we empirically verify whether these events prompted a regulatory overhaul that fundamentally changed banking activity or if—despite their financial severity—they were ultimately localized "crises of banks" that left the system's architecture surprisingly intact. Thus, while the indicators built on profitability presented above capture the acute symptoms of distress, the focus of this chapter is on its structural dynamics.

Second, concerning the drivers of distress, we evaluate the classic dichotomy between large, risk-taking universal banks and a periphery of supposedly stable, smaller institutions—i.e., savings and cooperative banks (Polsi, 1996). This allows us to verify if fragility was intrinsic to specific institutional types (e.g., larger universal banks)—confirming established narratives—or if it cut across legal categories and geographical regions in ways the traditional narrative has missed.

Third, our framework enables us to disentangle the primary catalysts of structural change, systematically evaluating whether the banking system's evolution was shaped more profoundly by market selection (crises) or by top-down design (regulation), such as the landmark 1936 Banking Act (Galanti et al., 2012; Gigliobianco and Giordano, 2010; Toniolo, 2018, 2022). Moreover, by offering a comprehensive reassessment of long-run dynamics, our analysis seeks to highlight general patterns in the process of distress and adaptation relevant for both historical analysis and modern policy. How does instability propagate? Does it trigger a dispersal of business models, where the crisis filters inefficient strategies (in a Schumpeterian creative destruction), or does the regulatory response lead to a concentration of business models in a generalized flight-to-safety?

Answering these questions amplifies the analytical challenge. The rich, multidimensional data of the Archivio Storico del Credito in Italia (ASCI) make for excellent information, but traditional analytical tools can be severely inefficient for a comprehensive and time-consistent analysis of bank strategies. Thus, in this chapter, we develop a novel framework to analyze rich datasets in a time-saving and yet deeply meaningful way, tailored for (but not limited to) a comprehensive perspective on bank balance sheets. This is what we call the *SCoPE* (Self-organized COmposite Profiling and Evaluation) system. The SCoPE system is designed specifically to connect macroeconomic events to micro-level balance sheet dynamics, providing a comprehensive, bottom-up view of the evolution of bank business models and their implications for stability. The system integrates two complementary elements.[2] The first, and the most novel methodological contribution of this chapter, is the *Map*: an unsupervised artificial neural network (Kohonen's Self-Organizing Map) trained to identify, classify, and visualize the evolution of bank business models over time, significantly enhancing comparability. This is then paired with the *Index*: a composite indicator of bank soundness.[3] By combining the Map (the drivers) and the Index (the outcome), we can forge a direct link between a bank's strategy and its soundness. This offers a truly holistic view of the sector's dynamics, allowing us to see not just if banks were in distress, but also why.

The SCoPE is fully unsupervised: it endogenously highlights intrinsic structures in complex, multidimensional data solely based on observed evidence, overcoming the need to fit predetermined outcomes.[4] This significantly enhances the flexibility of the system, making it a valuable framework to tackle different research questions.[5] And yet, the *raison d'être* of the System lies in its ability to process data into meaningful insights within a visual framework, thanks to what van Wijk (2005, p. 1) defines as "the unique capabilities of the human visual system to detect interesting features and patterns." Leveraging the comparative advantages of the human brain for visual perception, the core value of the SCoPE is thus to enhance analytical efficiency and effectiveness.

The rest of the paper navigates the blurred boundary between historical uniqueness and economic regularity: In section 4.1 we offer a brief presentation of the main data source for this analysis, the *Archivio Storico del Credito in Italia*; then, in section 4.2, we introduce the SCoPE System, describing the construction, training, and interpretation of the *Map* and the *Index*; then, in section 4.3 we will move from methodological to empirical considerations, with an application of the SCoPE System to analyze the balance sheets of Italian banks between 1890 and 1973, that intersects systemic observations with bank-specific dynamics; lastly, section 4.4 sums up key findings, explores future extensions, and concludes.

[2] Crucially for long-term perspectives, these two elements are designed to guarantee comparability between different historical periods and idiosyncratic characteristics.

[3] The *Index* represents a bank-level counterpart of the stress indicator presented in chapter 2.

[4] As a valuable byproduct of its design, the SCoPE can also classify distress at the bank level, a crucial application for the Italian context, where such supervisory data is largely unavailable for most of the period studied. Yet, this is not explored in this chapter and left for future research.

[5] Indeed, in this exercise we trained the System on the balance sheet data of Italian banks, but it can be easily adapted to other data—i.e., industrial firms' balance sheets, macroeconomic data for cross-country analysis, stock prices, and firms fundamentals. As is often the case, imagination is the only boundary.

4.1 Data description

The main data source for this analysis is the Archivio Storico del Credito in Italia (ASCI), as detailed in section 2.2. In this chapter, the sample is augmented by the inclusion of cooperative banks (banche popolari, BP) to ensure the broadest possible coverage of the Italian banking landscape. This is possible thanks to the robustness of the training process. First, the training of the neural network (SOM) is batch-based, meaning it learns the overall topological structure of the inputs from the entire dataset at once, rather than sequentially (year-on-year). Second, as will be thoroughly explained in the following section, the algorithm is designed to map the density of the input space; a sudden absence of a certain type of bank means that the density of the banks on the Map is representing the remaining institutions, but the Map structure is unaffected. Still, while the algorithm itself is robust, caution is due in the interpretation. I.e., any analysis of the dynamics around 1925-1926 must explicitly account for the change in sample composition. All interpretations in this work are made with this consideration in mind to prevent spurious conclusions.

Consistent with the previous chapters, we perform standard preprocessing operations on the balance sheet data. The only difference is the use of non-winsorized data, thanks to the inherent robustness of the SOM algorithm to outliers.[6] This is a significant advantage for our analysis: It allows us to explicitly consider extreme observations—which often include banks in financial distress.

The resulting training sample is composed of 39,142 annual balance sheets from 2,474 unique Italian banks from 1890 to 1973. The sample covers, on average, 97% of the total assets of the population, with a minimum of 89% in 1894.

4.2 The SCoPE System

The Self-organized Composite Profiling and Evaluation System (SCoPE) has four values at its core:

1. *Scalability*. The tool allows for analyses that span the whole spectrum of resolution and granularity. It offers a system-wide perspective, suitable for tracking long-run dynamics, the effect of institutional changes, or systemic crises. It allows for subdividing systemic considerations into specific peer groups—e.g., bank categories, region, size—to control for asymmetries and idiosyncratic trends. Lastly, it can go as deep as bank-specific dynamics to get a full understanding of how an institution's business model and risk changed in the long run or in periods of interest, and to compare it with its peers.

2. *Adaptability*. The variable resolution makes the SCoPE a valuable tool to help the analyst with multiple research questions, simply changing the perspective or the desired output. This can be easily done within the established framework, without the need to change the

[6] As will be explained later, the SOM's learning process ensures that an outlier influence is localized to specific and peripheral neurons, without distorting the overall structure of the Map.

underlying model, making for an easy and efficient swap.

3. *Integration:* the flexibility is further enhanced by the possibility to include additional data into the System without changing it. By projecting the needed information on the Map, the analyst can match specific research questions and enrich bank insights with other exogenous factors (i.e., macro-financial variables or social factors).

4. *Visualization:* the ability to transform complex data into graphical representations rounds up the core values. Effective visualization allows users to quickly recognize and interpret patterns and relationships, facilitating deeper data exploration and the analytical process.

Thus, these four core values make the SCoPE a powerful and reliable tool for detailed and comprehensive analyses that, while not replacing them, can effectively complement traditional methods, enhancing both the depth and width of the research questions.[7]

4.2.1 The *Map*

The central element of the SCoPE System is the *Map*, a visual synthesis designed to facilitate the exploration of latent structures within high-dimensional economic data, in our analysis of banks' balance sheets. The *Map* is built using Kohonen's Self-Organizing Map (SOM) algorithm, an unsupervised neural network particularly well-suited for uncovering nonlinear patterns and clustering structures in complex, multidimensional datasets (Kohonen, 1982, 1990, 1991).[8] Crucially, and unlike other dimensionality reduction or clustering algorithms, the SOM projects high-dimensional feature vectors onto a two-dimensional discrete grid preserving the topological relationships of the input space, that is, similar banks are closer in the Map. The result is powerful: both a dimensionality reduction technique and an *interpretable visual interface* for analyzing heterogeneous data—an essential feature in historical contexts, where a structural and comprehensive interpretation of the output is paramount.

The Map's Input Set

The input set for this exercise covers the business model, that is, the asset and liabilities composition of a bank, following the growing acknowledgment among both academic literature and the regulators that not all banks are created equal and that the structure and the evolution of the banking activity has notable implications on its risk profile (see, i.e., Ayadi et al., 2011, 2018; Farnè and Vouldis, 2017, 2021; Roengpitya et al., 2014, 2017; Savona, 2024).[9] In

[7] A necessary note: the SCoPE framework is built to provide *simple* but not necessarily *easy* insights.

[8] As it is often the case with neural networks, the SOM is a computational abstraction of biological models of the neural system. The goal of the algorithm is to create a space in which neighboring parts of the network respond similarly to certain input patterns. This follows the biological subdivision of our brain, in which the processing of sensitive impulses—visual, auditory, or other—occurs in distinct parts of the cortex, with similar neurons within.

[9] Some notable quotes from Farnè and Vouldis (2017, p. 4): Carney (2015), Governor of the Bank of England, "Our supervision is [...] tailored to different business models around the sector." Yellen (2012), Chair of the Board of Governors of the Federal Reserve System, "when it comes to bank regulation and supervision, one size does not fit all [...] rules, and supervisory approaches should be tailored to different types of institutions." Draghi (2016), President of the European Central Bank, "banks may have to do more to adjust their business models

particular, when it comes to the balance sheet composition of a bank, it is established that it proxies "the fundamental way in which the bank pursues its economic objectives [that] result from this strategy [...] in fact, is above all a model of financial intermediation" (Ayadi et al., 2018, p. 24). Thus, it offers an insightful perspective on the holistic process of intermediation undertaken by the institute and how it reacted to exogenous shocks (Nucera et al., 2018; Savona, 2022, 2024).[10]

In this analysis, the balance sheet composition of the institutes is measured as the *share* of total assets or liabilities to decouple the mechanical influence of size, enabling the SOM to identify similarities and differences in banks' asset-and-liabilities management. Still, it must be noted that this choice does not imply that size is analytically irrelevant or excluded from the analysis. On the contrary, size can be treated as a derived structural attribute, rather than an input feature, allowing for clearer identification of business model patterns and the investigation of scale-related regularities across the banking system.

The choice of the input features must confront an important trade-off: long-term comparability against the granularity of the information. Given the goal of this analysis, we take as a priority the former. In particular, on the asset side, we track: (i) *Liquidity*, measured as the share of sight assets held by a bank. Among sight assets, cash reserves and current account deposits at the central bank or other financial institutions are included. This dimension is related to the liquidity of a bank's fundamentals. (ii) *Loans*, indicating the reliance on credit intermediation, both to financial and non-financial customers. This dimension is related to the credit risk faced by a bank.[11] (iii) *Securities*, measuring the share of (mostly public) financial instruments held by the bank, and the consequent exposure to liquidity and market risk. (iv) *Other assets*, that notably includes non-performing loans.[12] This subdivision covers on the median, 97% of the total assets of a bank. On the liabilities side, we track: (i) *Equity*, indicating the share of capital and reserves, that is, the importance of internal funding. (ii) *Deposits*, indicating the reliance on the "traditional" form of financing, that is, the gathering of deposits among the public (financial and non-financial actors).[13] (iii) *Other liabilities*, including most notably bonds, advances, and REPOs. The liabilities composition covers, on the median, 98.3% of the total liabilities. Summary statistics are presented in Table 4.1.

A Metaphorical Introduction to the Self-Organization

A new library has just opened, and you're a librarian! You are faced with the daunting task of organizing an enormous collection of newly acquired books, which are your *input data*. Initially, these books pile up in your office, scattered and unsorted, each one with distinct themes, topics, and characteristics, their *features*. Your goal is to arrange these books in a way that's intuitive and logical, allowing visitors to easily navigate the collection and quickly find what they need.

to the lower growth/lower interest-rate environment".

[10] The ROE was a synthetic indicator of these factors; here, we explicitly consider the higher-dimensionality.

[11] Unfortunately, it is not possible to differentiate between retail loans and bank loans before 1951.

[12] Other items are *esattorie*, *debitori diversi*, and *azionisti a saldo azioni*.

[13] Similarly to loans, it is not possible to differentiate between retail deposits and deposits from other financial institutions before 1951.

Table 4.1: Balance sheet composition: descriptive stats (Shares)

Feature	Count	Mean	Std.	Min	25%	Median	75%	Max
Sight Assets	39,142	0.10	0.10	0.00	0.03	0.07	0.14	0.98
Loans	39,142	0.58	0.20	0.00	0.44	0.58	0.74	1.00
Securities	39,142	0.18	0.16	0.00	0.05	0.15	0.27	0.98
Other Assets	39,142	0.07	0.12	0.00	0.01	0.02	0.07	0.99
Equity	39,142	0.16	0.19	0.00	0.04	0.09	0.18	1.00
Deposits	39,142	0.75	0.22	0.00	0.71	0.84	0.90	1.00
Other Liabilities	39,142	0.06	0.11	0.00	0.01	0.03	0.07	0.98

The table reports the descriptive statistics of the balance sheet composition used as inputs for the analysis. The asset and liabilities composition is expressed as the share of total assets or liabilities.

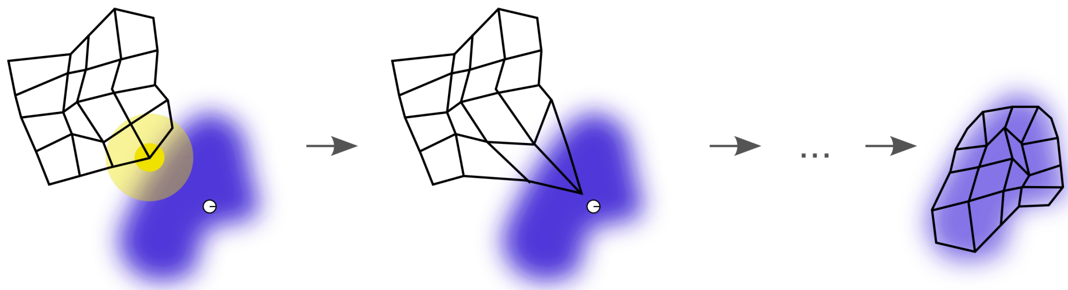
Grouping them based on how similar they are must be the most intuitive starting point. And yet, at first glance, your task seems overwhelming: a chaotic assortment of seemingly unrelated subjects, each book isolated in its distinctiveness. Your understanding of how these books relate to one another, or how they might group into meaningful categories, is minimal. We must start by making sense of this complexity and bringing order from apparent chaos. A deep breath, and you are ready to start. You look around at all the empty shelves arranged neatly into a grid: this is your *Self-Organizing Map (SOM)*. Initially, each shelf, or *neuron*, is the same: featureless and with no inherent category or specialization. Its identity will be gradually shaped based on the books it receives.

Now the conscious and deliberate work of arranging the collection begins. You pick up the first book and place it on a random shelf. Then, an iterative process takes place. You pick up each book, closely examining its contents and themes with the intent of finding the most suitable shelf, that is, the one whose current books most closely match the features of the books in your hands. Note that placing a book on a shelf doesn't simply occupy space: it subtly reshapes the identity of that shelf, making it slightly more similar to the book just added. Moreover, this subtle influence isn't confined to just one shelf. Neighboring shelves also adjust slightly, their identities shifting gently toward the themes of the new book. This creates a natural transition and meaningful connections between shelves.

Over time, as you systematically process hundreds of books, your previously uniform shelves begin to gain a clear identity: books on similar topics naturally group together, forming coherent categories or thematic *clusters*. Historical texts cluster with related historical subjects, economic journals find their neighbors, economic history works lay naturally between the two subjects, guiding visitors intuitively from one topic to another in a smooth transition.

This is the idea behind the notion of self-organization. What began as a scattered and confusing assortment of books gradually transforms into a neatly ordered library, with each shelf naturally attracting similar books. *Patterns* emerge organically, not through predetermined rules, but from the incremental and subtle influence that each book exerts on its surroundings, like a gravitational attraction. Ultimately, your library becomes a comprehensive and intuitively organized resource. Economists and historians, unfamiliar with the meticulous

Figure 4.1: A sketch of the SOM training process



The figure sketches the training process of the Self-Organizing Map (SOM) algorithm. The blue area represents the multidimensional structure of the input space, and the white grid is the structure of the two-dimensional map space. In the initialization step, the SOM nodes are arbitrarily positioned in the map space. During the competition step, we arbitrarily extract an observation from the input space (white point) and find the neuron closest to it (yellow point): the Best Matching Unit (BMU). Then, during the cooperation step, the BMU and the neighbor neurons (yellow shaded area) are updated to move closer to the extracted observation. After many iterations, the map space learns how to approximate the input distribution, like a flexible sheet that is gradually stretched to fit the blue cloud. Source: `https://en.wikipedia.org/wiki/Self-organizing_map`

process behind this arrangement, can now comfortably navigate the shelves. They can easily identify categories and discover connections between topics. Just as visitors rely on an intuitive library arrangement to efficiently find information, we apply the Self-Organizing Map algorithm to make sense of complex datasets. The metaphor aims at capturing the power of self-organization: transforming scattered data into meaningful, accessible insights.

The SOM Algorithm: Theory, Training, and Optimization

Let $\mathcal{X} = \{\mathbf{x}_1, ..., \mathbf{x}_N\} \in \mathbb{R}^d$ be the input space of the analysis, with N observations over d features.[14] The *Map* (SOM) consists of a set of neurons arranged in a two-dimensional rectangular lattice, the *map space*, $\Lambda \in \mathbb{Z}^2$. Each neuron $l \in \Lambda$ is associated with a d-dimensional weight vector (codebooks) $\mathbf{w}_l \in \mathbb{R}^d$.

Training the SOM involves updating these weight vectors over many iterations so that they learn to represent the input data, allowing them to discover patterns by organizing similar input vectors so that they activate neighboring neurons on the grid—that is, observations that are similar in the original d-dimensional feature space will be mapped to neurons that are close in the two-dimensional map. The learning process is unsupervised, that is, no output labels are required, and relies on two key principles: *competition*, neurons compete to get activated by each input, and *cooperation*, nearby neurons cooperate and learn together. In turn, competition ensures that different neurons specialize to represent distinct subsets of the input space, and cooperation ensures that neighboring neurons are tuned to similar patterns, thus leading to a consistent topology. In practice, the training involves the following steps, summarized in Figure 4.1:

[14] The *Map* is built following the original formulation of Kohonen's Self-Organizing Map algorithm. The following description is an elaboration based on the theoretical formulation present in Kohonen (1982, 1990, 1991, 1998, 2013).

1. Initialization. For each neuron $l \in \Lambda$ its codebook vector $\mathbf{w}_l$ is initialized with a random set of small values.[15]

2. Competition. At each training step, an observation $\mathbf{x}_i$ is sampled from the input space and fed to the network. The Euclidean distance between the vector and each neuron is computed, and the neuron $l_i^* \in \Lambda$ whose weight vector $\mathbf{w}_l$ minimizes

$$l_i^* = \arg\min_{l \in \Lambda} ||\mathbf{x}_i - \mathbf{w}_l||_2 = \arg\min_{l \in \Lambda} \sqrt{\sum_{j=1}^{d} (x_{ij} - w_{lj})^2} \tag{4.1}$$

is selected as the Best Matching Unit (BMU) of $\mathbf{x}_i$. This competitive step follows a *winner-takes-it-all strategy*: only the BMU (and its neighbors) responds to the input, while other neurons remain unchanged.

3. Cooperation. After finding the BMU, the algorithm defines a neighborhood of neurons around the BMU following the Gaussian function:

$$h_{ll_i^*}(t) = \exp\left(-\frac{||r_{l_i^*} - r_l||^2}{2\sigma^2(t)}\right) \tag{4.2}$$

where $||r_{l_i^*} - r_l||^2$ represents the vectorial distance between the neuron l and the BMU l_i^* on the Map while $\sigma(t)$ controls the width of the neighborhood, exponentially decaying in t.[16] Neurons within this neighborhood (including the BMU itself) are allowed to cooperate, that is, they will undergo an update of their codebooks $\mathbf{w}$, with the closest neurons receiving the strongest update.

4. Learning rule. The codebooks vectors $\mathbf{w}$ are updated iteratively to better represent the input $\mathbf{x}_i$. The adjustment process follows a non-parametric, recursive regression learning rule:

$$\mathbf{w}_l(t+1) = \mathbf{w}_l(t) + \alpha(t) \cdot h_{ll_i^*}(t) \cdot (\mathbf{x}_i - \mathbf{w}_l(t)) \tag{4.3}$$

with $0 < \alpha(t) < 1$ being the time-dependent learning rate, exponentially decaying in t, $h_{ll^*}(t)$ the neighborhood function centered around the BMU l^*, and $(\mathbf{x}_i - \mathbf{w}_l(t))$ defining the direction of adaptation.

The training process iterates over steps 2-4, with each iteration bringing the codebooks $\mathbf{w}_l$ closer to the input structure in a self-organization of the map space. As the neighborhood size $\sigma(t)$ and the learning rate $\alpha(t)$ shrink, the adjustments became negligible and the codebooks stabilize.[17] At this point, the algorithm has converged, and the training process stops. The result is a SOM where each neuron represents a particular cluster or pattern in the data.

To ensure an effective convergence to a meaningful and organized map, it is important to select a set of hyperparameters that leads to both a low quantization error, a measure of how

[15] An alternative is to initialize the codebooks via PCA loadings, to make the convergence process faster.

[16] The size of the neighborhood is initially large to encourage broad cooperation and create a faster organization of the map space. Then, $\sigma(t)$ will gradually decrease during training, to allow fine-tuning of the structure as the map stabilizes.

[17] Despite not having a formal cost function, it can be argued that SOM is implicitly optimizing the objective function representing the distance between each observation and its BMU, known as the *quantization error*.

well the map synthesizes the inputs (good fit), and a low topological error, a measure of the consistency of the mapped topology (good structure). In particular, the quantization error evaluates the Euclidean distance between each observation and each BMU (lower is better), such that

$$QE = \frac{1}{N} \sum_i ||\mathbf{x}_i - \mathbf{w}_{l_i^*}||_2 \in [0, \infty) \tag{4.4}$$

with QE=0 representing the case in which for every single observation x_i there exists a neuron on the map whose weight vector is identical to it.[18] On the other hand, the topological error counts for how many observations the BMU and the second-best matching are not neighbor neurons (lower is better), such that

$$TE = \frac{1}{N} \sum_i \mathbb{I}_{\{BMU \text{ not adjacent to } l_i^*|_{\Lambda \setminus BMU}\}} \in [0, 1], \tag{4.5}$$

where TE=0 indicating a perfect preservation of the topology of the inputs—that is, for every data point, the two most similar neurons in the data space are also neighbors on the map.

We employed a Bayesian optimization strategy with Gaussian Processes minimization to tune four key parameters: the map's size ($\Lambda_X \times \Lambda_Y$), the neighborhood radius (σ), and the learning rate (α).[19] The optimization objective was the minimization of a cost function defined as a weighted linear combination of the QE and the TE, such that:[20]

$$C(\cdot) = \lambda \cdot \tilde{QE}(\Lambda_X, \Lambda_Y, \alpha, \sigma) + (1 - \lambda) \cdot \tilde{TE}(\Lambda_X, \Lambda_Y, \alpha, \sigma). \tag{4.6}$$

where $\tilde{QE}$ and $\tilde{TE}$ represent the scaled QE and TE based on values obtained from a preliminary training run, to ensure a comparable magnitude and to prevent the metric with naturally larger values from dominating the cost function. The relative importance of the scaled errors was controlled by the weighting parameter, λ, which was systematically varied across a discrete set of values in [0,1]. For each λ value, we optimize the set of hyperparameters.[21] The final hyperparameter configuration was then selected by identifying the parameter set that yielded the lowest overall composite score across all tested values of λ, thus ensuring the optimization of the chosen map structure. The SOM that yields the best representation of the input data is with Λ_X=9, Λ_Y=8, α=0.1667, and σ=3.

Training Results: How to Interpret the Map

[18] This is possible only in the theoretical case in which the number of non-identical observations is lower or equal to the number of neurons.

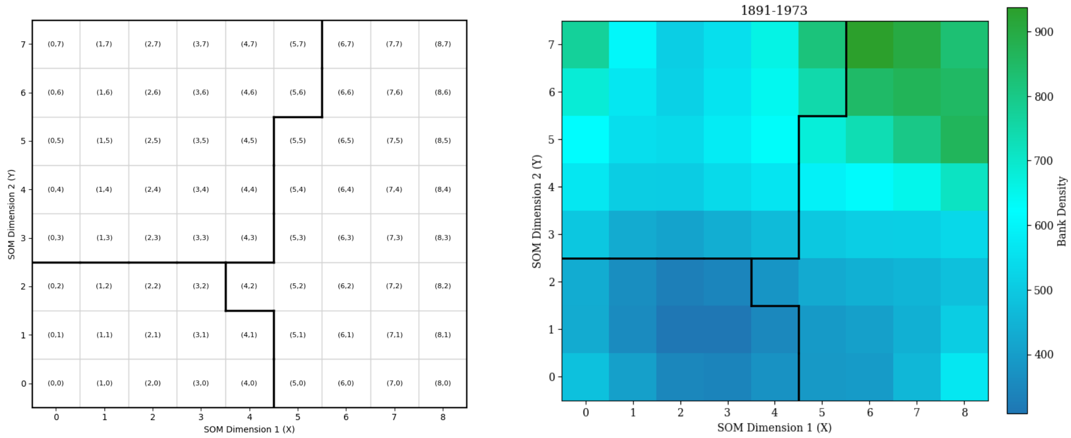
[19] The GP minimization can be summarized in the following steps: (i) The optimizer begins by training a predefined number of SOMs (20 in our case with 2,000 training iterations) with randomly selected hyperparameter sets within predefined bounds and calculates their cost function. (ii) It uses these initial results to build a probabilistic model of the relationship between hyperparameters and the final score. This model essentially creates an educated guess about what the score might be for untested parameter combinations, thus significantly reducing the number of combinations to test and improving the training efficiency. (iii) The optimizer then uses this model to intelligently select the next set of hyperparameters to test, probabilistically exploiting regions that are already known to produce good scores. (iv) This process is repeated for a fixed number of calls, with the model becoming more accurate after each iteration.

[20] We combine the two metrics since strictly optimizing one degrades the other.

[21] The tested hyperparameters are: Λ_X and Λ_Y in [8,20], α in [0.01,0.5], σ in [0.5,3].

After training, the SOM has effectively reduced the 39,142×7 input space into a 9×8 grid of neurons, each with a learned codebook vector of length 7 (the original number of features). Each neuron occupies a specific position on the grid, represented as an array of cells (see Figure 4.2a) associated with a pair of coordinates (X, Y). Crucially, these coordinates have no *a priori* meaning in terms of the original features. The neurons are abstract: their characterization endogenously emerges from the learning process (i.e., *self*-organization).[22] By mapping similar observations onto nearby neurons—while preserving the topology of the input space—each neuron effectively acts as a *bank prototype*, representing a distinct and unique group of banks sharing similar balance-sheet characteristics.

Figure 4.2: A first visualization of the Map



(a) The SOM grid (b) Bank-year density

Plot 4.2a shows the Map space created by the SOM algorithm: a 9×8 rectangular grid of neurons characterized by a (X, Y) pair of coordinates. The solid black line draws the boundaries between statistically similar clusters of neurons, that is, business models. Plot 4.2b shows the number of bank-year observations in each node.

To enhance the interpretability of the *Map*, we group neurons into clusters based on the set of codebook vectors.[23] This process effectively segments the *Map* into discrete and economically consistent regions, each one corresponding to a set of neurons with statistically similar balance-sheet profiles across the seven input features. Following the definition provided above, these clusters de facto draw the boundary between different business models (the solid black line in Figure 4.2a), providing a reference point for a following deeper economic interpretation.

After the training process, *the Map is fixed*, but we can project different information onto it by coloring each neuron according to a specific variable.[24] In Figure 4.2b, for example, we overlay

[22]Recalling the metaphor above, the neurons are the empty shelves, their meaning emerges endogenously by studying the shared characteristics of the banks located in each one.

[23]In particular, we utilize the *KMeans* algorithm to cluster neurons according to their codebook vectors. The number of clusters is endogenously selected as the one that elbows the within-cluster sum of squares (WCSS), resulting in 3 optimal clusters. The clustering is robust to other specifications for the objective function of the optimization process (e.g., Silhouette score).

[24]In other words, by training the Self-Organizing Map on the entire dataset, we create a stable topological

the number (density) of bank-year observations mapped to each neuron—that is, how many observations activate each neuron as their BMU.[25] Note that the colors solely represent the specific overlaid variable and have no intrinsic meaning outside the context. In the following figures, we will project other features (e.g., balance sheet composition), and the colors will then represent the relative intensity of those specific variables across the map. Thus, each figure must be interpreted relative to its specific color bar and projected feature. For instance, from Figure 4.2b we can note a significant concentration of bank-year observations in the North-East and North-West corners (the green areas). This naturally leads to the following step: what is the economic meaning of different areas of the Map?

To investigate this, a powerful visualization is used: the so-called *component planes* representation (see Figure 4.3). In the component planes, each cell of the grid corresponds to a neuron and is color-coded according to the value of a particular feature in that neuron's weight vector. Blue shades reflect a lower value of the feature and green shades a higher value.[26] Examining the component planes is paramount to economic interpretation: it allows us to see which features are driving the separation between different regions of the Map!

Take, for instance, the South-West cluster of the Map. It is populated by highly capitalized banks (see from the component Equity), complementarily linked with a low share of the deposits (see from the component Deposits). On the other hand, the Eastern and North-West clusters group those banks whose main source of financing is represented by deposits (see from component Deposits); the discriminant here comes from the asset side: North-West we have institutes with a loan-intensive asset allocation (see from component Loans), while the Eastern cluster covers more defensive asset allocations, namely a relatively higher share of liquidity on the North-East corner (see from component Sight) and of securities on the South-East corner (see from component Securities). Around the neuron (4,0) we find the stronger anomalies, grouping the banks with a significant share of other assets (among which the non-performing loans, see from component Other Assets), and other liabilities (among which advances and REPOs from the financial sector, see from component Other Liabilities). Table 4.2 summarizes these findings, characterizing the topology of the Map as distinct balance sheet structures. Still, what is of particular interest in the visualization is that we can interpret multi-dimensional patterns. In fact, preserving the topological structure of the data, the *Map* allows for the visualization of correlations and structural features of the banking activity. For instance, one may notice the strong positive correlation between "other assets" and "other liabilities", suggesting a substitution effect between deposits and REPOs, advances, and equity in those banks with a notable share of non-traditional activities, such as non-performing loans.

Having characterized the stable structure of the *Map*, it is important to note that the SOM effectively acts as a *trajectory space*, that is, *every movement on the Map is meaningful*. Since each neuron represents a specific combination of the input features *(bank prototypes)*, movements

space that allows for consistent temporal and cross-sectional comparison of bank positions.

[25] The color map is gaussian filtered ($\sigma = 1$) to produce a smoother gradient, enhancing the interpretability.

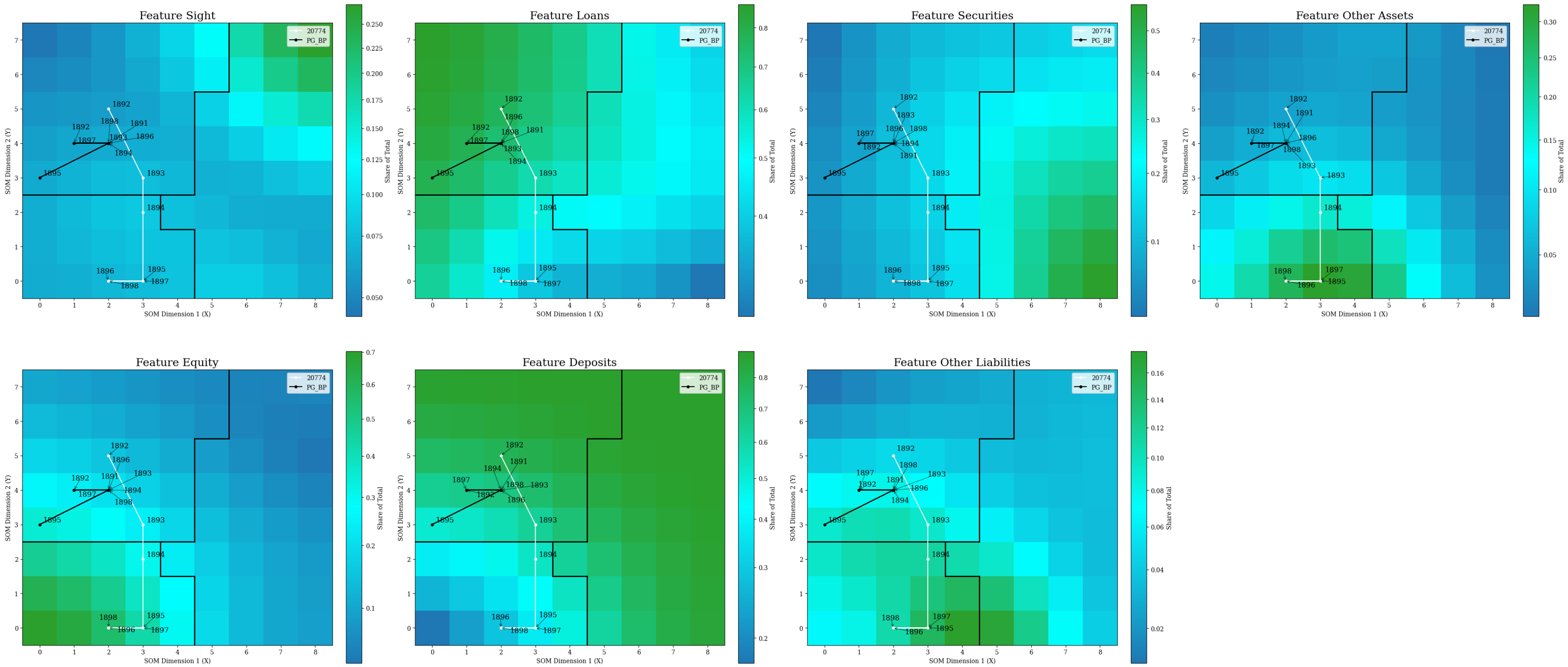
[26] Remember, the grid is *fixed*! The color gradient changes from one component plane to another, but the underlying SOM grid remains the same. That is, each neuron retains the same position across all planes, making spatial patterns comparable across variables.

Table 4.2: Map's topology and balance-sheet structures

Location	Main Assets	Main Liabilities
NW	Loans	Deposits
N	Loans + Liquidity	Deposits
NE	Liquidity	Deposits
E	Liquidity + Securities	Deposits
SE	Securities	Deposits
S	Other Assets	Other Liabilities
SW	Loans + Other Assets	Equity
W	Loans	Equity + Deposits
Center	Diversified	Diversified

This table summarizes the Map's topology, characterizing each region in relation to a distinct balance sheet structure.

Figure 4.3: SOM's component planes



The figure represents the component planes of the Map. Each subplot shows the values of the respective input features in the map space. Note: the color scale and meaning vary with the features, but the map's topology does not: each neuron has the same position across all component planes. The white line plots how the location of the Cooperative Bank of Brescia (ID 20774) changes between 1892 and 1898; the black line plots a peer group as the median position of all cooperative banks in the same time frame (PG_BP). The movement in the map space allows for easy identification of changes in the underlying balance sheet structure of the bank.

across the map reflect shifts in the bank's balance sheet composition. Thus, following a bank (or a group of banks) across different time periods allows us to easily visualize how its (their) balance sheet structure evolved. This dynamic perspective is paramount to the interpretation: they offer an intuitive and informative way to track institutional development, episodes of financial distress, or convergence toward particular balance-sheet structures in a framework that ensures *consistent comparisons* in the long run and across different types of banks. In Figure 4.3 you can find an example of this dynamic and comparative interpretation. On the component planes, we have mapped the cooperative bank of Brescia (ID 20774) movements as a white line and a benchmark which represents the median position of all cooperative banks (black line) in the same time frame. For example, note the higher dynamism of the cooperative bank of Brescia compared to its peers. The sharpest movements are recorded between 1893 and 1895, with a progressive substitution between deposits and other liabilities on the liabilities side, and between loans and other assets on the assets side. This movement hints at a process of disintermediation experienced by the bank and a plausible situation of distress.[27]

To summarize, in this section, we have presented the *Map*, a grid of neurons where each location corresponds to a distinct balance sheet structure. By examining the *Map*, we can have a visual representation of static and structural patterns (clusters), of how the observations are distributed around certain balance sheet structures, and of the dynamics of a bank or of specific peer groups. In section 4.3 we will test the *Map* against historical episodes, tracking how the banking system changed around crises and regulatory shifts. Still, how does the balance sheet structure relate to risk? To answer this question, we will present the second element of the SCoPE System: the *Index*.

4.2.2 The *Index*

The *Map* provides a rich and multi-dimensional representation of balance sheet structures, highlighting clusters, transitions, and underlying patterns. To complement this perspective, while bridging the gap between balance sheet dynamics and risk, we constructed a synthetic indicator of risk: the *Index*.[28] The *Index* is rooted in the CAMEL indicators that, while simple, have been proven to be significantly related to a bank's soundness by both academics and supervisors (see Chiaramonte et al., 2015; NCUA, 2021; Gaul and Jones, 2021; Lopez, 1999). The Index aims to capture latent risk along multiple dimensions of the banking activity: *C*apital adequacy, *A*sset quality, *M*anagement, *E*arnings, and *L*iquidity, encapsulating the information into a single, synthetic metric. This process rounds up the SCoPE System, allowing for an interpretation of the SOM's topology beyond structural terms, explicitly through the lenses of vulnerability. By projecting this index onto the Map (overlay), it is possible to evaluate whether specific balance sheet configurations—endogenously identified by the

[27] Indeed, it faced a deposit run in 1894 and underwent a liquidation procedure until 1898. The substitution between deposits and other liabilities or equity is a strong signal of a run, which we will explicitly consider in the construction of the *Index*.

[28] A perspective on the link between banks' balance sheet structure and risk in, among others, Ayadi et al. (2018).

Map—are systematically associated with higher or lower levels of potential risk.[29]

The Construction of the Index

The construction of the Index involved the following steps:

1. CAMEL construction. For each bank i in each year t, the indicators that track the multi-faceted dimensions of risk are defined as:

$$\mathrm{C}_{it} = \frac{\mathrm{Equity}_{it}}{\mathrm{Total\ Assets}_{it}}; \tag{4.7}$$

$$\mathrm{A}_{it} = \frac{\mathrm{Loans}_{it} - \mathrm{NPL}_{it}}{\mathrm{Loans}_{it}} \tag{4.8}$$

$$\mathrm{M}_{it} = \frac{\ln(\mathrm{Total\ Assets}_{it})}{\ln(\max(\mathrm{Total\ Assets}))}; \tag{4.9}$$

$$\mathrm{E}_{it} = \frac{\mathrm{Returns}_{it}}{\mathrm{Total\ Assets}_{it}}; \tag{4.10}$$

$$\mathrm{L}_{it} = \frac{\mathrm{Sight\ Assets}_{it}}{\mathrm{Total\ Assets}_{it}}. \tag{4.11}$$

Thus, the C dimensions represents the capital ratio of the banks; the A represents the share of non-deteriorated loans among bank's assets;[30] the M dimensions is a measure of the relative size of the bank;[31] the E reports the profitability of the bank over total assets (ROA). Lastly, the L is the share of liquid assets held by the institute.

2. Benchmarking. The performance of each bank i in year t along the k-th CAMEL dimensions is computed as its deviation from a long-run benchmark (z-score). In turn, benchmarks are defined as the 15-year rolling stats of the average value of each CAMEL in each year, winsorized at 1% to control for outliers:[32]

$$\text{z-score}_{itk} = \frac{\mathrm{k}_{it} - \mu(15)_{kt}}{\sigma(15)_{kt}}. \tag{4.12}$$

This approach allows us to isolate a bank's relative performance within each historical context, while ensuring long-run comparability. Lastly, to allow for an intuitive interpretation, we min-max scaled the z-scores in [1, 100], with a 1% cutoff to mitigate the effect of outliers

[29]We acknowledge that the present analysis is correlational, establishing an association between map position and risk. However, the map's output can represent a new variable for subsequent causal inference, utilizing the (X, Y) coordinates as synthetic indicators. Future work could leverage the panel nature of the data by employing established quasi-experimental methods. For example, one could use matching techniques to compare the subsequent performance (i.e., profitability, distress) of similar banks that migrate to different map regions. This would allow for a formal investigation of the causal effects of specific, endogenously identified bank strategies on future outcomes. Yet, these analyses are left for future thinking.

[30]We consider the share of "healthy" loans against the more common share of Non-Performing Loans to create consistent ranking with the logic of "the-higher-the-better".

[31]The normalization allows for an M bounded in [0,1], thus comparable in scale with the other indexes.

[32]The rolling window is defined to capture long-run changes while being unaffected by short-run events.

Table 4.3: The *Index*: descriptive statistics

	Count	Mean	Std	Min	25%	50%	75%	Max
Index (pre-refinements)	39,303	55.6	19.8	1.0	47.1	57.9	67.6	100.0
Index (post-refinements)	39,303	53.5	21.3	1.0	44.7	56.9	67.1	100.0

The table reports descriptive statistics of the Index, computed as the weighted harmonic mean of the CAMEL's z-scores, scaled in [1,100]. Refinements include the penalization of forced deleveraging (abrupt reduction in M and increase in C) and leveraged expansion (abrupt increase in M and reduction in C).

and ensure a well-behaved distribution.[33]

3. Aggregation. We aggregated the z-scores for each bank-year observation into a synthetic measure of fundamental soundness, defined as the weighted harmonic mean of these indexes.[34] Weights are defined via Principal Components Analysis (PCA) based on how much each factor contributes to the overall variability across banks' performance, that is, PCA assigns more weight to the factors that better differentiate the banks one from another.[35] PCA is computed on the standardized and winsorized indices targeting a 95% of explained variance. Then, weights are defined as the factor loadings of the first principal component normalized by the share of explained variance of each CAMEL. The resulting weights are:

$$C = 0.20, \quad A = 0.21, \quad M = 0.21, \quad E = 0.20, \quad L = 0.17. \tag{4.13}$$

Similarly to above, the *Index* is min-max scaled in $[1; 100]$, with a 1% cutoff. Summary statistics in Table 4.3.

The Index is refined with domain knowledge, explicitly targeting critical dynamics characterized by diverging CAMEL movements, which the harmonic mean may underweight by construction. In particular, we penalize the following dynamics: (i) Rapid decrease in M and increase in C, to target forced deleveraging, i.e., following a run on deposits; (ii) Rapid increase in M and decrease in C, to target unhealthy leveraged expansion. For each bank i, for each year t in which bank i has reported a balance sheet, we compute the annualized rate of change (CAGR) between t and the previous balance sheet t-k,[36] with

$$\text{CAGR}(\text{X})_t = \left(\frac{\text{X}_t}{\text{X}_{t-k}}\right)^{\frac{1}{t-(t-k)}} - 1. \tag{4.14}$$

Then, we define a trend as critical if the magnitude of the annualized change is below (above) the 10$^{\text{th}}$ (90$^{\text{th}}$) percentile of the distribution of the CAGR. The Index for the selected critical

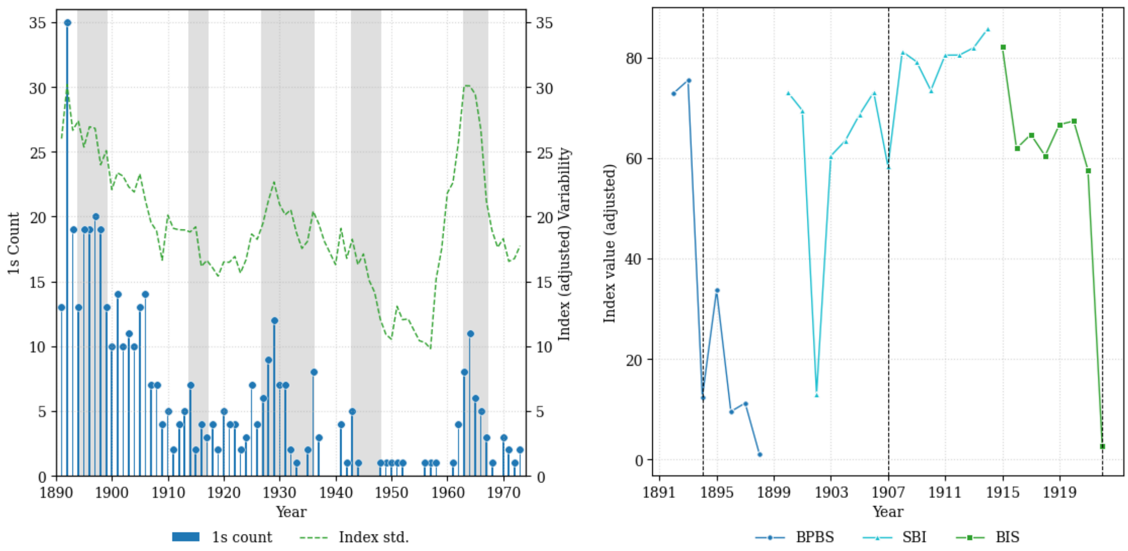
[33] That is, the lower and upper bounds for the min-max scaling are set at the 1st and 99th percentile. Values below or above these thresholds are set to 1 and 100, respectively.

[34] The harmonic mean is the optimal way to average ratios and, unlike a simple arithmetic average, it penalizes imbalances or weaknesses across dimensions. Thus, a low score in any single dimension significantly reduces the overall score, a well-desired property in our framework.

[35] Not having systematic historical data on bank distress, we cannot empirically set weights through supervised learning methods (e.g. logit coefficients).

[36] Note that if the bank has a balance sheet for all the years, then k=1 and the annualized rate of change converges to the arithmetic rate of change.

Figure 4.4: The Index, preliminary validation



(a) Number of 1s

(b) Selected distress episodes

Plot 4.4a (left axis) shows the number of banks with an Index of value 1 in each year. This measure provides a lower-bound estimate of the level of latent fragility in the system. The right axis plots the standard deviation of the value of the Index in each year. Grey-shaded areas mark phases of bank stress identified in chapter 2. Plot 4.4b bank-level trajectories around selected episodes. We plot the cooperative bank of Brescia, seen above (BPBS, crisis in 1894), Società Bancaria Italiana (SBI, crisis in 1907), and Banca Italiana di Sconto (BIS, crisis in 1922).

observations has a penalization of 75%. Summary statistics of the adjusted (refined) Index can be found in Table 4.3.

Note that the Index is not designed for prediction tasks, but to measure structural risk as inferred by a bank's fundamentals: it's a proxy of latent fragility.[37] What makes the Index suboptimal for prediction tasks is the lack of distress labels, which imperils a systematic assessment of its accuracy. Still, ex-post historical checks show a great alignment with known episodes of distress, both at a bank-level and system-wide.

In Figure 4.4a, we report the number of banks scoring an *Index* of value 1 for each year: a simple and yet informative proxy of latent systemic fragility, providing a lower-bound estimate of widespread distress in the banking sector.[38] The correlation between spikes in this indicator and the periods of stress identified in chapter 2 offers a preliminary robustness check.[39] Notably, the two most significant economic downturns—the depression of the 1890s and

[37]Note that if signals of weakness (e.g., significant losses) are not correctly reported to the supervisory authority—for any legitimate or not-so-legitimate reason—then the Index will not signal the distress.

[38]We tested other indicators, both in levels—like the number of banks with an Index 2.5 standard deviations lower than the median— and in changes—like the median and standard deviation of the changes (CAGR) in the scores in each year. Results are consistent; we are presenting the 1s for the sake of simplicity.

[39]A thorough presentation of the accuracy of the Index when classifying distress at the bank level is left to future work.

the 1927-1936 period—are both clearly captured. Consistency is further validated by negative signals, most notably, the Fifties. Of particular interest is the pronounced increase in banks flagged during 1962-1967. While this period is not typically classified as a banking crisis in existing chronologies, the signal is consistent with broader macro-financial trends, as described in the previous chapter.[40] Conversely, the crises of Società Bancaria Italiana in 1907 and Banca Italiana di Sconto in 1921-1922 do not correspond to a notable rise in the count, hinting at a lack of broad contagion or systemic spillovers. Still, a closer inspection of bank-level trajectories in Figure 4.4b reveals that the Index does correctly capture localized deterioration in these cases.[41] A more extensive historical analysis and interpretation of these intuitions is offered in section 4.3.

While the Index reveals meaningful historical correlation, linking it to the Map allows for further insights (see Figure 4.5). In fact, overlaying the Index on the Map broadens the very scope of the analysis: alone, the Index can answer "when is fragility high? Which banks are more at risk?" The Map complements this perspective, moving toward "where in the balance sheet space does fragility concentrate? Which are the discriminant factors?" This facilitates a structural interpretation of fragility that is not obvious from the time series alone. Moreover, for its ability to display patterns, the Map fosters comparability, identifying whether new fragility episodes resemble earlier ones in structural terms.

The overlay process assigns a score to each neuron proportional to the median *Index* of the banks i belonging to it, corrected for the standard deviation of the same observations. Formally, the score of a neuron $l \in \Lambda$ is defined as:

$$\text{score}_l = \frac{\text{median}(\text{Index}_{i \in l})}{\text{std}(\text{Index}_{i \in l})}. \tag{4.15}$$

We can enhance interpretability by rendering the overlay of the Index on the Map as *contour lines*, de facto drawing the boundaries between homogeneous risk areas. The contour lines serve as thresholds indicating variations in the risk landscape. Each line represents a level of uniform risk, and areas between contours indicate different risk categories.[42] This process allows tracking risk directly onto the density map, developing a single, intuitive visualization, with an immediate comparison of both bank concentration and latent fragility within each region of the *Map*. Thus, it strengthens the link between balance sheet composition and risk. Note that, the contour lines are computed using the pooled dataset. This is a deliberate design choice aimed at establishing a universal association between risk and the Map—creating a time-invariant *metric space* that enables consistent comparisons across the entire analyzed period.[43]

Viewed through this universal lens, the most significant concentrations of risk become clearly

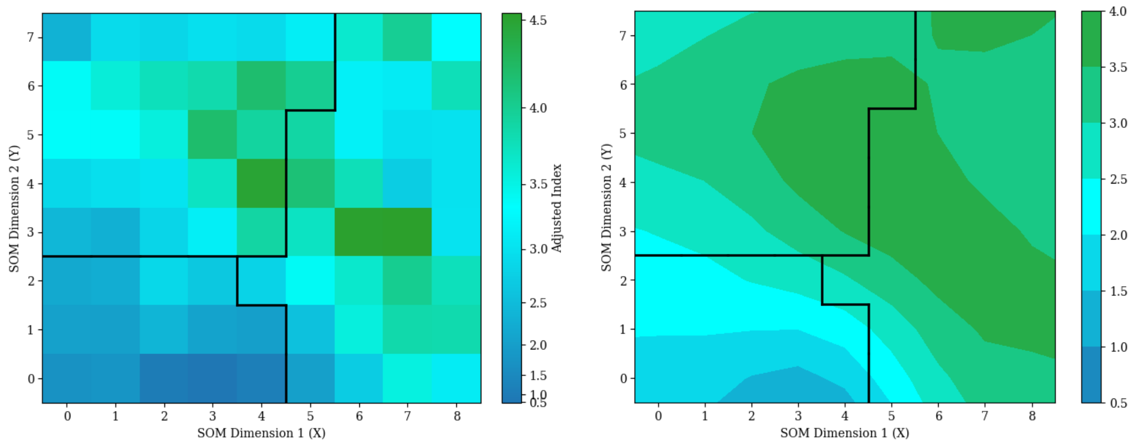
[40] A thorough analysis of the banking behavior around the crisis of 1964 is explored in chapter 5.

[41] The use of the *Index* at a bank level must consider both levels and changes.

[42] If a grid node is intersected by a contour line, we interpret it based on the majority area.

[43] By anchoring latent risk to the full historical experience, we ensure that the risk gradient remains clearly defined even when the density of banks varies, which often leaves specific regions "depopulated" during stable regimes. For a discussion on the statistical necessity of this approach and the instability inherent in regime-specific estimations, see appendix C.1.

Figure 4.5: Map space overlays. Balance sheet structure and the Index



(a) Signal-to-noise ratio

(b) Contour lines

Figure 4.5a overlays information from the Index on the Map. It shows the median score of the banks belonging to each neuron corrected for its standard deviation. Blue areas depict a lower score (more risk) than the green ones (less risk). Figure 4.5b summarizes the overlay process mapping areas that share similar risk profiles. Blue shades represent a higher risk.

visible. It is interesting to note that the lowest scores are concentrated in two distinct areas of the map: the NW corner— indicating a higher latent risk associated with loans-intensive banking, featuring both relatively low equity and liquidity—and the Southern region, related with a deteriorated asset quality (high Other assets).

Still, it is important to acknowledge a trade-off when projecting variables onto the Map's space: structural interpretation versus resolution on extreme events. For instance, if a particular balance-sheet structure is systematically associated with high *Index* values, this association will be reflected on the Map. Then, if only one—or a very small number—of banks within that neuron experience a crisis, the signal may be diluted, lacking sufficient influence to shape the neuron's visual representation. As a result, the overlay may not visibly highlight the crisis, while the underlying data contains it. We employ all the due diligence to mitigate this trade-off, and we claim that the results are historically robust. Still, the overlay should not be interpreted as a precise distress locator, but rather as an indicator of systematic associations between certain balance-sheet structures and risk.[44]

[44] One may think of the *Map* as a satellite image, depicting the structural landforms: mountains and valleys, forests and glaciers. Overlaying the Index on this map is similar to adding contour lines or elevation shading: it allows one to visualize a systematic association between certain geographical structures (e.g., snow) and height.

4.3 The SCoPE and the Long-Run Evolution of the Banking Sector

How can the SCoPE System be effectively leveraged to gain new insights on the long-run development of the Italian banking sector and its reaction to the numerous shocks of the period 1890-1973? This section puts the methodology to work, moving from novel descriptive insights to historical reassessment. We focus on pivotal episodes to demonstrate how a bottom-up, data-driven perspective can enrich, refine, and at times challenge the established historical narratives.

Our analysis is guided by the three core questions raised in the introduction. First, we compare the downturns of the 1890s and the Great Depression of the 1930s. Were these two distinct events, as the literature suggests, or do they share common features, rooted in bank business models? Second, we investigate the classic dichotomy between large, speculative banks and a supposedly stable periphery of smaller institutions around the crises of 1893, 1907, 1921, and 1930. Was risk confined to the apex of the system or between specific segments of the banking sector? Finally, we examine the engines of structural change, comparing the impact of crisis and top-down regulation (most notably the banking laws of 1926 and 1936). This exploration is not intended to be exhaustive, but rather to showcase how the SCoPE framework can effectively uncover new insights and guide deeper, more focused historical inquiry. A thorough historical and economic analysis of all the insights gained from the SCoPE is left to future works.

4.3.1 The Banking System Through the Long Depression (1891-1901) and the Great Depression (1925-1935)

Traditional historiography draws a sharp line between the crisis of the late 19th century and the Great Depression: different underlying causes, same internationally-rooted trigger (Di Martino, 2022; Fratianni and Spinelli, 2001). The former is typically portrayed as a consequence of a real estate bubble, culminating in the Banca Romana scandal of 1893, while the latter is linked to the unhealthy link between universal banks and industry during the 1920s boom (Conti, 2007; Toniolo, 1995).[45] In turn, notable political and institutional differences shaped a distinct financial system: While the period of 1891-1901 is characterized by a liberal government and *laissez-faire*, the 1925-1935 events unfold under an established fascist presence. In turn, institutional innovations such as the establishment of the Bank of Italy (1893) and the banking law of 1926 frame distinct regulatory contexts (Galanti et al., 2012; Toniolo, 1995, 2022).

[45] During the 1880s, the process develops through extensive investments—then, speculation—in the housing market, with a considerable involvement of banking institutions (Negri, 1989; Pani, 2017). On the contrary, between 1922 and 1926, solid economic growth and a process of financial deepening created profit opportunities, fostering an unprecedented banking expansion, inevitably intertwined with the industrial boom (Toniolo, 1995). Between 1921 and 1925, GDP growth reached 6.1% (Toniolo, 2017), the number of banks grew by 30%, and the number of branches by 100% (Molteni, 2023, 2024).

Thus, while the institutional and macroeconomic context makes the catalysts and the trigger of the crises undoubtedly different, the two periods 1887-1901 and 1925-1935 share similar features, particularly interesting for this analysis. Both periods are marked by a significant economic dynamism preceding the crises, catalyzed by an abundance of capital and resulting in a significant asset-price inflation, particularly in the non-tradables. In turn, a lacking regulation led to a self-reinforcing collateral mechanism, with an over-exposure of the banking sector often with speculative traits (Gigliobianco and Giordano, 2010).[46] This creates a central tension: were these crises inherently unique (Bordo, 2018), or were they different manifestations of a common fragility pattern (Kindleberger, 1978; Minsky et al., 1960)?

The SCoPE allows us to directly confront this dichotomy by moving from macro-narratives to micro-level evidence. It allows us to ask: Did instability propagate in the same way in the two periods? Did the vulnerable banks share similar characteristics? Figure 4.6 provides a powerful visual insight by mapping the distribution of banks during these two critical decades.[47]

A Common Path to the Crisis?

The Map reveals a compelling similarity in the system's response to rising instability. In both of the periods, the banking system's transitions from the North-West (loan-intensive business models) towards the South (higher shares of Other Assets, that notably includes non-performing loans), indicating a significant substitution effect in the asset allocation.[48] This shared trajectory indicates a common pattern: as economic conditions deteriorated, a growing number of banks saw a rise in impaired assets. However, the timing and intensity of this shift challenge the conventional narrative.

The years 1891 and 1893 show a system that is highly polarized in the North-West—averaging 92% of the total assets devoted to loans and 90% of the funding covered by deposits—but with no significant cluster of banks in the relatively-higher-risk Southern region (see the contour lines and the Index).[49] It is particularly interesting to note that in both 1891 and 1893, years flagged as banking crises, there's no sign of a significant displacement of the credit allocation process, with a predominantly loans-to-deposits intermediation. This evidence challenges the

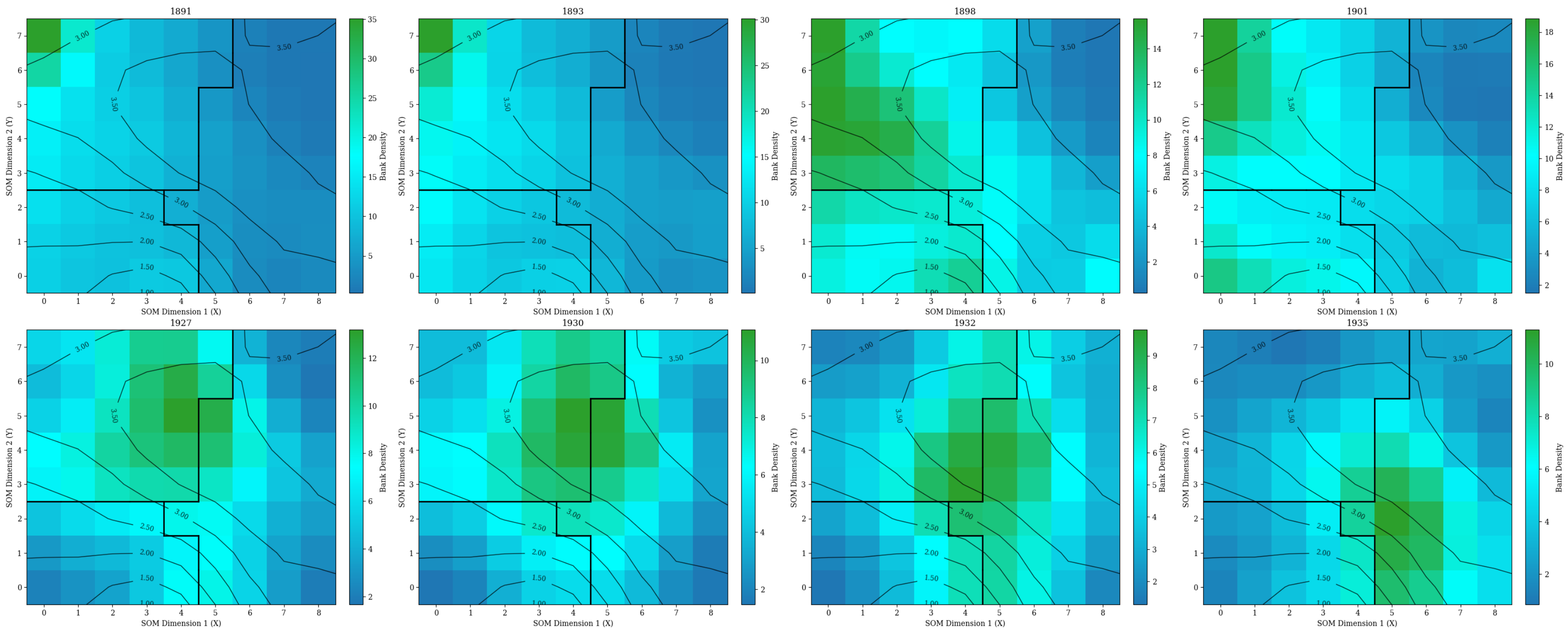
[46] Following the dating of Bartoletto et al. (2019), the described dynamics peaked in 1888 and 1926 respectively, when the economic cycle reverses. The deterioration of the real economic conditions spread to the banking sector, with a contraction in the supply of money and decreasing asset prices. In the 1880s, the monetary contraction was mainly driven by a reversal of international capital flows; in 1926, it was the result of internal economic policy decisions aimed at controlling the exchange rate. Our narrative follows a slightly different dating due to data restrictions. For the events at the end of the 19th century, the analysis starts in the first available year: 1891. For the interwar period and the Great Depression, we consider 1927 to avoid any sample bias from the lack of cooperative banks from 1927. To complement this gap, Figure C.2 offers a perspective on the position of BP in 1925 and 1936; the results are consistent with those described here.

[47] Aside from the starting and finishing boundaries (1891/1901 and 1927/1935), we report the years with the lowest concentration (HHI) in the balance sheet composition (1898 and 1932), and the years signaled as a banking crises by the chronologies (1893 and 1930).

[48] If initially unfamiliar with the Map's geography, don't worry! Remember that you can always refer to Table 4.2 or Figure 4.3 for a summary to support the historical interpretation.

[49] Remember that the neurons are not just abstract bank prototypes. Every moment, we can exactly see which banks belong to each neuron, making it possible to derive summary statistics.

Figure 4.6: Balance sheet composition dynamics: 1891-1901 vs 1925-1935



The figure shows the distribution of banks in the Map in the periods 1891-1901 and 1927-1935. For both of the episodes, four benchmarks are reported: the start and end years (1891/1927 and 1901/1935), the crisis year signaled by the chronologies (1893 and 1930), and the year with the lowest concentration (i.e., HHI) in the balance sheet composition (1898 and 1932). Green shades indicate a higher number of observations at the corresponding neuron, which represents a distinct balance sheet structure.

notion of a prolonged, widespread banking crisis lasting until 1891/1893. While the Banca Romana failure was a critical event that catalyzed the creation of the Bank of Italy, our analysis suggests it was predominantly an institutional and political scandal rather than a symptom of a systemic, sector-wide collapse, with no shift towards more defensive business models at that time.[50]

The interwar period presents a more complex picture. Unlike the highly concentrated system of 1891, the banking landscape in 1927 shows a more diversified assets and liabilities mix, with a center of gravity shifted to a more central position on the Map. It is reasonable to interpret this transition as the sector's direct adaptation to the 1926 banking law (Molteni and Pellegrino, 2021). By imposing the first modern forms of supervision and capital requirements proportional to the activities undertaken by the institutions, the law successfully nudged the average bank towards a more balanced business model. This legislation is a compelling empirical evidence of how top-down regulatory policy can actively reshape the banking system's structure by changing the costs and benefits of selected activities.

However, this aggregate shift must confront divergent paths. Most notably, the cluster of banks visible in the high-risk Southern region before the commonly cited peak of the crisis indicates pre-existing latent fragility, providing the balance sheet anatomy for the evidence of the preceding chapters. This group of vulnerable institutions well aligns with the rising financial stress we detected by the barometer in chapter 2, while the density around riskier models is a characteristic consistent with the "bad boom" identified in chapter 3. Therefore, our analysis provides strong quantitative support for the view that the Great Depression did not cause the fragility but rather exposed a pre-existing condition (Molteni, 2023, 2024). The global shock landed on a system where a significant segment had already become structurally vulnerable during the preceding boom and the policy shifts of 1926-27.[51]

The Unfolding of the Crises: Fragmentation

A compelling parallel between the two periods is the system's reaction to the initial shock, manifested as an increased dispersion in the balance sheet structures.[52] The years 1898 and 1932 report the highest volatility in the balance sheet Map, indicating a significant fragmentation of the system. The spike in 1932 well aligns with the acme of the Great Depression signaled by the bank stress barometer developed in chapter 2 (see Figure 2.7). The signal of 1898 helps to characterize the period of instability detected by the barometer, less studied by mainstream crisis narratives, and yet representative of a renowned period of economic, social, and political tensions: the *crisi di fine secolo*. In both cases, we observe a general diversion

[50] Our evidence aligns with Gigliobianco and Giordano (2010, p. 18), that stresses the political impact of the crisis: it was a scandal that well represented the intense "public debate concerning the banks of issue [...] and speeded up the legislative process towards a new law," leading to the creation of the Bank of Italy.

[51] In particular, the monetary tightening and the deflationary policies protect the Lira on the exchange rate market.

[52] The effect is not driven by a substantial increase in the number of banks among the different benchmark years, largely stable for the 1891-1901 decade: 573 (1891), 572 (1893), 558 (1898), 592 (1901). On the contrary, the number of banks shows a decreasing trend in the 1927-1935 period, both for exits and forced consolidations: 462 (1927), 405 (1930), 355 (1932), 309 (1935). This may imply that, when describing the balance sheet structure concentration, we may be underestimating the variation.

from the standard loans-deposits business model, toward more defensive asset classes (liquidity and securities) and an increase in the number of institutions with a significant share of deteriorated assets. This heterogeneity is key: it suggests how systemic stress amplifies micro-level asymmetries, segmenting resilient institutions from fragile ones and intensifying intra-sectoral divergence (top vs worst performers).

Is this segmentation driven by size or geographical location? The classic narrative often posits a dichotomy: a few large, speculative universal banks taking excessive risks, compared to a vast, stable network of smaller savings and cooperative banks (Baron et al., 2023; Battilossi, 2009; Brambilla, 2012; Confalonieri, 1974, 1994; Polsi, 1996). The SCoPE system allows us to test this empirically by examining which banks actually populated the riskiest regions of the Map.

Table 4.4 dissects the anatomy of the banks located in the most fragile business models (the Southern neurons) during our two periods of analysis.[53] The evidence shows that risk was more democratic than the narrative suggests, pointing to a more complex picture. Fragility was not the exclusive domain of large universal banks, while still present.[54] In the 1891-1901 period, cooperative banks (BP) constituted the largest single category (46.4%) of institutions in the higher-risk zone, followed by savings banks (38.8%). While larger (XL) banks represent 27% of the institutions, fragility is spread across all of the size quintiles. During the 1927-1935 period, joint-stock banks (SOC) are the most present (67.5%), with a notable concentration of smaller institutions (XS and S), accounting for 49% of the sample (consistently with Molteni, 2023). Nor was geography a simple determinant. Risk is evenly distributed across all three macro-regions in both periods, debunking any simple North-South explanation for instability. Still, looking at the riskiest banks (those with an Index score of 1), the smallest banks (XS and S size quintiles), and the South are heavily overrepresented.[55] This challenges the narrative of inherent stability among small and local banks, suggesting that during periods of stress, a reduced diversification and limited ability to attract deposits (flight-to-safety) can be as critical (see Baron et al., 2023). Finally, the SCoPE system reveals a fundamental difference in the nature of the risk itself. The distress of the 1890s is dominated by an asset-quality deterioration (109 out of 121 banks flagged as 1), reflecting the legacy of the real estate bubble. In contrast, the 1930s show greater fragility in Earnings (10 of 16), pointing toward a severe effect of the macroeconomic contraction.

This micro-level evidence, therefore, offers a nuanced perspective on our initial question. The path to distress and the anatomy of the at-risk population share remarkably similar dynamics across both periods, revealing a recurring economic pattern of how instability unfolds. And yet, the balance sheet "fingerprint" of the instability—an asset-quality crisis versus an earnings crisis—remains unique, clearly reflecting the distinct institutional and macroeconomic

[53] We define particularly "risky" neurons $i \in \{(2,0), (3,0), (4,0), (5,0), (4,1), (5,1)\}$. Both episodes show a comparable density of unique banks in these neurons—3.6% of the total number of banks for 1891-1901 and 4.1% for 1927-35.

[54] Both periods include emblematic cases of distress. In the period 1891-93, Banco di Roma, Banca di Torino, Banco di Sconto e Sete, and Banca Tiberina are correctly flagged (all XL). During the Great Depression, we can see the notable burst of Banca Agricola Italiana.

[55] Note that if smaller banks are located in the South, then the two signals are mechanically correlated.

Table 4.4: Risky neurons: descriptive insights

	1891-1901	*1927-1935*
Observations	675 (10.8%)	351 (10.2%)
Unique banks	221 (3.6%)	145 (4.1%)
Top-3 years by density	1895-1900-1898	1935-1927-1932
Worst-3 median *Index*	1892-1896-1898	1928-1929-1935
Categories	BP (46.4%), SOC (38.8%), CRO (14.8%)	SOC (67.5%), CRO (24.5%), MDP (6.3%)
Regions	North (36.9%), Center (22.2%), South (40.9%)	North (39.6%), Center (24.8%), South (31.1%)
Size	XL (27%), L (20%), M (18%), S (23%), XS (12%)	XL (19%), L (19%), M (17%), S (13%), XS (33%)
n. 1s	121	16
1s concentration	XS, CRO, South	XS/S, SOC, Center/South
Critical dimension	Asset quality (109/121)	Earnings (10/16)
Flagged run on deposits	39	32
Notable banks	Banco di Roma (1891:1893)	Banca Agricola Italiana (1930)
	Banca di Torino (1891:1894)	Banca di Firenze (1927:1930)
	Banco di Sconto e Sete (1892:1895)	***Banca Commerciale Italiana (1931)
	Banca Tiberina (1891:1901)	***Banca Nazionale Agricoltura (1932)

The table reports descriptive insights for the analyzed sub-periods on the nodes characterized by the lowest Index ("risky"): {*(2,0), (3,0), (4,0), (5,0), (4,1), (5,1)*}. Observations *reports the cumulative number of banks in these neurons (share over the cumulative number of banks in parenthesis);* Unique banks *reports the total number of unique banks in these neurons (share over the cumulative number of banks in parenthesis);* Top-3 years by density *reports the year with the highest number of observations in decreasing order;* Worst-3 median Index *reports the years with the lowest median Index in decreasing order;* Categories *and* Regions *reports the distribution of banks based on juridical category and macro-region of the HQ respectively;* Size *reports the distribution based on asset size categories. Size categories are defined by in-years quintile (i.e., XL represents the top-20% banks according to total assets for year 19XX);* n. 1s *reports the total number of banks with an Index value of exactly 1;* 1s concentration *reports the idiosyncratic categories in which there's the higher concentration of 1s;* Critical dimension *report the worst CAMEL dimension across the banks with Index 1, in parenthesis the number of banks with a score of 1/100 in this dimension;* Flagged runs *report the number of deposit run risk according to the Index (increase of capitalization and decrease of total asset in the top-5%);* Notable banks *reports renown banks classified at risk. The sample is a selection of XL banks (year of the flags in parentheses). ***Note, for the sake of this example, we added Banca Commerciale Italiana and Banca Nazionale Agricoltura to the list, even though their risk signals are located in neurons (1,5) and (7,5), respectively.*

triggers of each historical episode.

The Aftermath of the Crises

While the build-up to the crises shared common features, their aftermath is profoundly different. This divergence traces to the distinct historical and political contexts and sets the stage for our third research question. By 1901, the banking system had largely returned to the pre-crisis loan-intensive balance sheet composition in the North-West corner of the Map, thanks to the industrial boom of the Giolittian age.[56] The crisis of the 1890s, while severe, did not permanently alter the dominant business model of Italian banking. On the contrary, the aftermath of the Great Depression marks a significant structural break in bank business models. By 1935, the system had undergone a permanent transformation: The center of gravity significantly shifted toward the Southeast, indicating an increase in holdings of securities. This was arguably a state-directed reconfiguration, driven by the financial needs of the fascist regime and soon to be codified by the 1936 banking law.[57]

This stark contrast provides a powerful preliminary insight. It suggests that while the market turbulence of the 1890s crisis led to a temporary dispersion followed by a reversion to the mean, the combination of the Great Depression and state intervention in the 1930s caused a fundamental and lasting structural break. This directly suggests that what makes a crisis a landmark in banking evolution is not the "creative destruction" of the crisis itself, but rather the regulatory intervention it catalyzes (see Gigliobianco and Giordano, 2010).

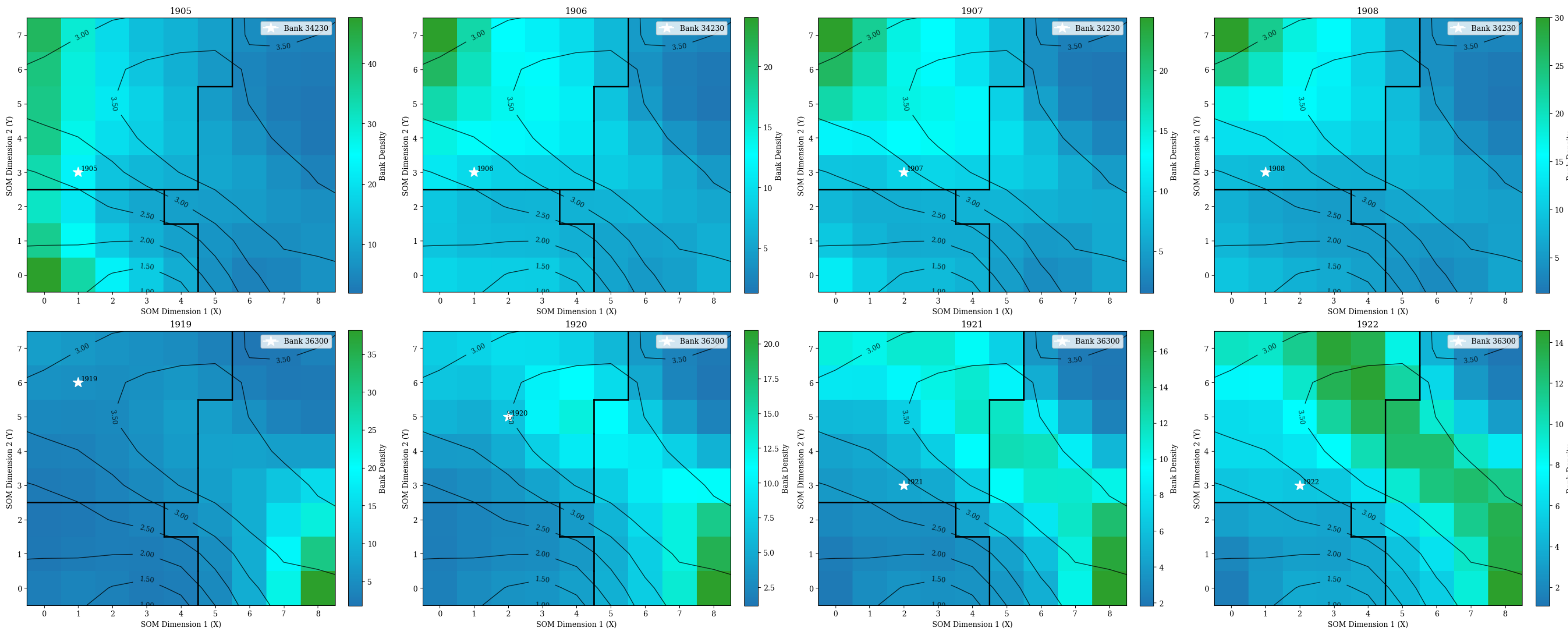
4.3.2 Banking Crises or Crises of Banks? The Distress of Società Bancaria Italiana (1907) and Banca Italiana di Sconto (1921)

The distress of the Società Bancaria Italiana (SBI) in 1907 and the Banca Italiana di Sconto (BIS) in 1921 are long-recognized landmarks in Italian financial history. The systemic importance of the institutions involved, the high-profile bail-outs, and the public intervention have unanimously cemented their place as banking crises in traditional chronologies (see section 2.1). While the distress of these major banks is undeniable, the crucial question is whether it triggered the "string of similar outcomes for other financial institutions" required for a systemic crisis (Reinhart and Rogoff, 2008, p. 81). This is a critical distinction, as historical narratives agree that regulators in both cases acted swiftly to prevent contagion (Bonelli, 1982; Gigliobianco and Giordano, 2010; Vercelli, 2022). Indeed, in the preceding chapters, we showed how these two events had a limited impact on the aggregated sample. The SCoPE system, by tracing both the path of the single institutions and the entire banking population, allows us to directly test whether the micro-level evidence supports the narrative of a system-wide contagion, or if it points to severe, but ultimately contained, crises of individual banks. Figure 4.7 presents some intuitions.

[56] The increased density reported in the South-West corner is largely related to the introduction of pledge banks (MDP) in 1899, structurally characterized by non-deposits funding. Indeed, looking at neurons $\{(0,0),(0,1),(1,0)\}$, 34% of the 47 banks are MDP.

[57] In 1935, the government deficit reached nearly 10% of GDP (Baffigi, 2013).

Figure 4.7: Banks' distribution and risk dynamics around the distress of Società Bancaria Italiana and Banca Italiana di Sconto



The figure plots the distribution of the banking sector in the Map for the years around the distress of Società Bancaria Italiana (ID 34230) in 1907 and of Banca Italiana di Sconto (ID 36300) in 1921. Green shades indicates a higher number of banks in the corresponding neuron, blue shades sparser populated ones. The white stars represent the position of the two institutions in the corresponding year.

The Paths to Distress

From Figure 4.7 we can note that both SBI and BIS faced distress in the same neuron (2,3), while presenting notably different dynamics.[58] SBI is characterized by low dynamism, indicating a balance sheet structure stable over time, lacking a clear differentiation between normal regimes and the distress of 1907. In particular, the Index reflects a generally acceptable condition even in 1907 (score 58/100), yet with a non-negligible deterioration year-on-year (-26%, starting from a score of 73/100 in 1906), mainly driven by a reduced capitalization and lower earnings.[59] On the contrary, the BIS shows a gradual movement toward the South between 1919 and 1920, indicating a diversion from the loans-deposits-driven banking.[60] The drop in 1921-22 toward riskier neurons marks a clear distinction between pre- and post-distress. In particular, the movement from neuron (2,5) to neuron (2,3) is linked to growing anomalies in the balances sheet composition, with a substitution between Loans and Other assets and between Deposits and Other liabilities.[61] From the same figure, we can notice how these dynamics lead to an overall riskier balance sheet composition, which matches a 15% drop in BIS' Index between 1920 and 1921, collapsing to 1/100 in 1922, burdened by extreme losses (Earning score: 1/100).

Both of these situations are met with concern, acknowledging the high risk of contagion. Similar actions are taken, pooling liquidity from a consortium of the major banks and from the Bank of Italy to provide the necessary resources to ease the crisis. The too-big-to-fail SBI is quickly rescued (Bonelli, 1982; Vercelli, 2022), while the resources gathered for the too-big-to-save BIS were insufficient, leading to the liquidation of the institute in 1922 and government intervention to insulate other banks from systemic repercussions (Gigliobianco and Giordano, 2010).

The Systemic Contagion?

While the distress of these institutions is of paramount importance, the evidence for a wider, systemic contagion is absent in our framework. This represents a key discrepancy with the established view, and an important micro-level validation of the findings of the previous chapters.

As seen in Figure 4.7, neither the banking sector's center of gravity nor the movement on the Map is significantly altered by the distress of the two institutions. Around 1907, the vast majority of Italian banks remained clustered in the loan-intensive regions of the Map—i.e.,

[58] Neuron (2,3) represents a balance sheet composition characterized by a high share of Other liabilities, complemented with a relatively higher share of Equity and Other Assets (that includes non-performing loans) with respect to a loan-deposits-driven balance sheet structure.

[59] On the Earnings (E) dimension, in 1907 the SBI scores 42/100 in 1907 (-33% YoY), promptly recovered in 1908 (64/100). Similar dynamics are shown by the Capitalization (C), 18/100 in 1907 (-33% YoY), recovered by 1908 (31/100).

[60] Between 1918 and 1920 the share of Loans reduces from 86% to 79%, complemented by a higher share of Sight assets, from 6% to 10%, and Other assets, from 1% to 4%. On the liabilities side, the share of deposits decreases from 86% to 79%, entirely complemented by higher Other liabilities, from 4% to 13%.

[61] Indeed, the share of Loans between 1920 and 1921 decreases from 79% to 62%, complemented by a sharp increase in Other assets, from 4% to 21%. Similarly, the reduction in deposits, from 79% to 55%, is reflected in an increase of Other liabilities, from 13% to 38%.

indicating no displacement of the broad credit activity—seemingly unaffected by the turmoil of SBI. Similarly, the system's post-World War I reconversion process continued unabated through 1921, with the broad population gradually substituting securities with loans (North-West movement).[62] We see no mass migration towards riskier areas and no widespread fragmentation. The "string of similar outcomes" that defines a systemic crisis is simply not visible in either the Index or the Map.

As a result, our analysis leads to a significant reinterpretation of these landmark events. They were unquestionably severe crises of banks, but the widespread distress implied by the "banking crisis" label is not supported by the evidence. The crisis of the two major banks seems to be effectively rooted in idiosyncratic causes—i.e., the stock market speculation for the SBI and the unhealthy link with the Ansaldo for the BIS. The regulatory efforts to insulate the system from contagion appear to have been successful, a conclusion validated by both the stability of the stress barometer (chapter 2) and the lack of contagion on the business model Map.

4.3.3 The 1936 Banking Law and a New Financial Order

Which force was more powerful in shaping the long-run structure of the Italian banking system: the "creative destruction" of market crises, or the technocratic hand of the state? Our analysis has already provided compelling insights. The crisis of the 1890s, despite leading to the creation of the Bank of Italy, was ultimately a temporary shock that did not fundamentally alter the dominant bank business model. In contrast, the 1926 Banking Law, enacted in response to an overheating system, prompted the first subtle but deliberate shift toward a more diversified asset and liabilities mix. It was the Great Depression, however, that represented a clear rupture in the long-run development, thanks to an unprecedented state intervention.

That the resulting 1936 banking law represents a fundamental structural break is a cornerstone of Italian financial history (see section 2.1). The contribution of our work, therefore, is not to simply micro-identify this break. Rather, we use the SCoPE system to precisely characterize its impact on the anatomy of the banking sector and, most importantly, to analyze the subsequent dynamics of the post-war period—challenging the implicit assumption of a static stability. In doing so, we can qualify and enrich the findings of the previous chapters.

How the banking system changed after the banking law of 1936 is represented on the Map in Figure 4.8.[63] Two features stand out:

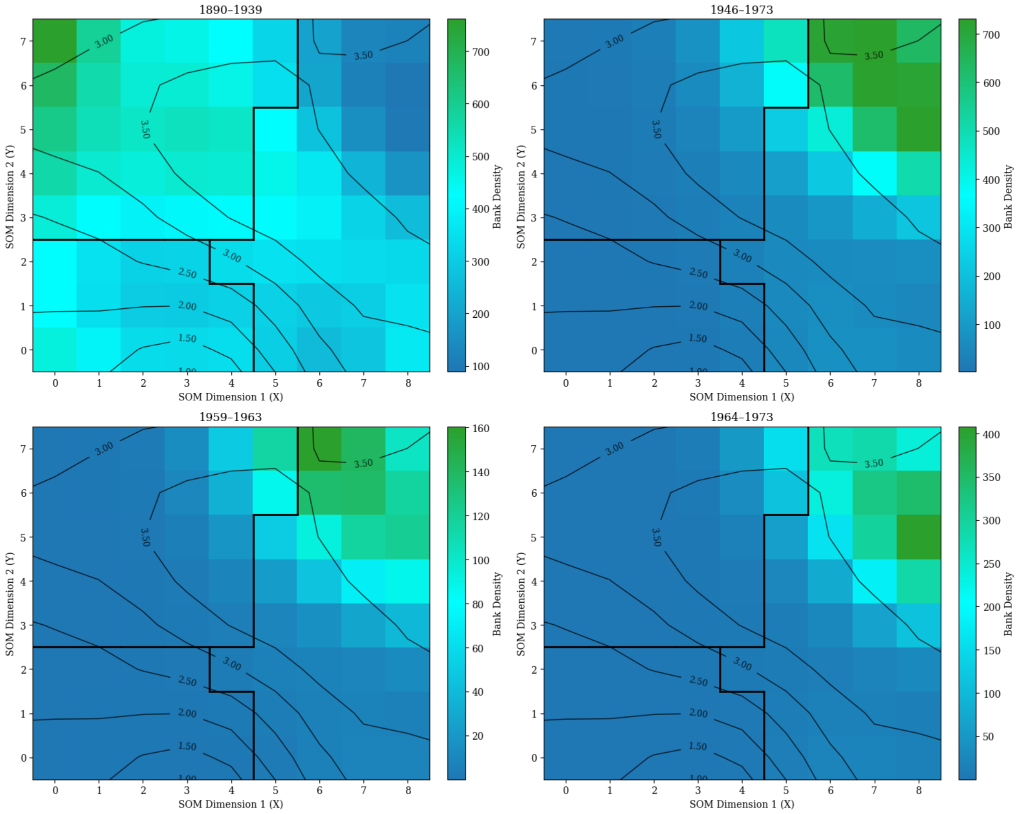
1. The emergence of a distinct business model. The post-war system is characterized by a new cluster in the North-East of the Map, a region sparsely populated before 1936. This new model is characterized by higher liquidity and a reduced reliance on direct commercial lending, outsourced to the state-backed Special Credit Institutes (SCI). Deposits became the dominant source of funding.

2. A homogenization of business models. In this period, the system's heterogeneity significantly

[62] The reconversion will be effectively over just by 1925.

[63] A more granular annual perspective in Figure C.3.

Figure 4.8: The Impact of the Banking Law of 1936



The figure plots the cumulative distribution of banks in the balance sheet composition Map before and after the banking law of 1936 and the instability of 1963. Green shades indicate a higher density in the neuron, blue shades indicate a lower density.

shrank. The Herfindahl-Hirschman Index (HHI) of business model concentration on the Map tripled from an average of 252 to 785 in the post-war period. The banking sector effectively transitioned into a narrow regulatory corridor, eliminating the wider range of strategies previously observed.

It is widely argued that this new regulatory order laid the institutional foundations for the prolonged period of financial stability and growth that followed World War II—often referred to as Italy's economic "Golden age" (Cotula, 1999). Our evidence strongly supports this view. Between 1946 and 1961, signals of high risk from our Index are at their lowest frequency.[64]

However, this post-war resilience was not absolute. The SCoPE system allows us to see a subtle drift in this stable framework, providing the critical, balance-sheet-level explanation for the signals detected in our previous chapters: the renewed instability flagged by our stress barometer (chapter 2) in 1963 and the "bad boom" we identified for the same periods (chapter 3). The Map reveals that the system's response to the macroeconomic downturn of the

[64] Between 1946 and 1961, the Index rises only 8 signals of high risk (see Figure 4.4a).

mid-1960s was a subtle but persistent migration toward a new dominant business model (neuron 8,5). This shift represents a profound change in asset allocation. Unlike the pre-war booms characterized by a risky migration toward the South of the map (impaired loans), the system now shifted East, toward a model where the median share of securities rose from 8% to 25% at the expense of loans.

This demonstrates a profound change in the system's business model. The instability signals of the 1960s were not driven by the familiar risk manifestations—like an increase in non-performing loans—but by a new dynamic where banks adapted to economic pressure by absorbing securities. As we will analyze in chapter 5, while this maintained face stability, it simultaneously created a latent securities-bank nexus. This chapter, therefore, provides the micro-level evidence that qualifies and explains the nature of the instability that the aggregate tools had identified.

4.4 Concluding Remarks

In this work, we have revisited the long-run evolution of the Italian banking system from 1890 to 1973 through a novel combination of historical data and machine learning techniques. We introduced the SCoPE System, a framework tailored to provide a new lens on Italian financial history by visualizing the anatomy of bank business models and tracing their evolution through decades of transformation, crisis, and stabilization. By moving from macro-level narratives of the previous chapters to granular, balance-sheet-level evidence, we have effectively distinguished between the symptoms of distress (profitability metrics) and its structural dynamics and legacy (anatomy of the business models), confronting and complementing traditional narratives in several key aspects.

First, as in the previous chapters, we offer a valuable contribution to the general debate on the nature of banking crises. We both provide a refined understanding of the chronologies of instability and empirically prove that not all financial shocks result in a structural change. The central finding is that while market crises acted as catalysts for restructuring, it was the deliberate hand of the state that crystallized a crisis's "creative destruction" into a lasting structural transformation. For instance, the events of the 1890s, while politically and institutionally relevant, resulted in a "reversion to the mean" in banking practices precisely because the regulatory response focused on the bank of issues (with the creation of the Bank of Italy) without targeting the pre-existing financial *laissez-faire* (Gigliobianco and Giordano, 2010; Fratianni and Spinelli, 2001). We confront the risk of "big bank bias" in narrative descriptions by empirically showing how the famous events of 1907 and 1921 unfolded not as systemic contagions, but as severe—yet ultimately contained—"crises of banks", with limited consequences on the rest of the banking sector stress and business model. In contrast, the top-down intervention of the 1936 banking law represents a permanent structural break, with the entire system entering a novel and homogenized business model, characterized by a lower share of loans complemented by higher liquid assets and securities.[65] Preliminary

[65]This links directly to the decreasing efficiency identified for the 1950s in chapter 3.

narrative evidence suggests that this was not a "flight to safety" driven by market forces, but a regulatory-induced homogenization: the law effectively suppressed the biodiversity of business models, freezing the system into a static, state-sanctioned cartel.

Second, our re-examination of the long-run development of the banking system enriches traditional views on the spread of distress during the major crises. We show that, during these events, distress was more democratic than traditionally assumed—i.e., widely spread across all institutional types and geographical regions rather than confined to large mixed banks. Crucially, instability did not drive a convergence toward safety—as implied by the "flight to quality" hypothesis (e.g. Bernanke et al., 1994)—but rather manifested as an increasing segmentation of the sector, which amplified asymmetries between a resilient and vulnerable institutions, with the smaller ones particularly hit. This evidence aligns with the comparative inefficiency we documented in chapter 3, questioning the interpretation of the peripheral banking system as a safe-haven. Results are particularly robust during the crisis of the 1890s and in the late 1920s, directly challenging the historiographical view of the local bank as an inherent stabilizer of the liberal system (Confalonieri, 1974; Polsi, 1996), and aligning our findings with the widespread distress documented by Molteni (2023) at the onset of the Great Depression.

Third, our long-run structural perspective validates the previous chapters by suggesting a reassessment of static post-war stability. By dissecting the business model dynamics of the 1960s, we identify the micro-level trend behind the rise in stress and the "bad boom." We show how the system adapted to the cyclical economic pressures of 1963 by reallocating financial resources into a higher share of securities, creating a persistent market-bank nexus and an increase in latent risk, which aligns with the reduced allocative efficiency of a financially repressed system (Faccio and McConnell, 2025).

While the SCoPE system has allowed us to visualize complex dynamics over time, this exercise is far from exhaustive. Important dimensions—such as network exposure, interbank relationships, and institutional dynamics—remain essential avenues for future extensions. Ultimately, however, our data-driven perspective reveals a century of profound transformation and adaptation. We have documented a system that, throughout the *Age of extremes* (Hobsbawm, 1994), persisted not by remaining static, but by continuously reshaping its anatomy to meet the constraints of its time. In this sense, the history of Italian banking confirms that the systemic structure was neither a Darwinian "survival of the fittest" nor a "survival of the biggest" (Baron et al., 2023) but a continuous alignment of business models with the shifting institutional environment. As Megginson (1963, p. 4) puts it:

> Yes, change is the basic law of nature. But the changes wrought by the passage of time affect individuals and institutions in different ways [...] it is not the most intellectual of the species that survives; it is not the strongest that survives; but the species that survives is the one that is able best to adapt and adjust to the changing environment in which it finds itself.

Chapter 5

Unstable Stability: Banks' Business Model in the Years When Banking Was Boring (1951-1969)

"[After the Great Depression, banking] was tightly regulated, far less colorful than it had been before the Depression, and far less lucrative for those who ran it. Banking became boring."

— Paul Krugman (2009)

"When the goal of sustaining the employment substitutes the one of price stability, and when looking for solutions to short-run problems becomes dominant, [the monetary policy] not only is incapable of counteracting the destabilizing impulses that hit the Italian economy, but becomes itself a source of instability."

— Fratianni and Spinelli (2001, p. 400, tr.)

In this chapter, we synthesize the findings of the previous analyses about the post-war period to offer a comprehensive new perspective on Italian banking during the "Golden age," directly linking its unique economic and institutional context to the granular dynamics of the bank-level activity.

The period is traditionally characterized by an archetypal triad: strong regulation (i.e., financial repression), low instability, and exceptional economic growth (Hodgman, 1973; Monnet, 2018). If we were to translate these peculiarities to the financial sector by paraphrasing a renown claim by Paul Krugman, it would entail the controversial definition of *boring banking*.[1] Yet, as the preceding chapters have demonstrated, beneath the surface of monolithic

[1]Applying this notion to the context of the Italian Golden Age, *boring banking* could entail an unwillingness

financial stability, cracks were forming. In chapter 2, our stress barometer detected a significant rise in banking sector fragility between 1963 and 1967. In chapter 3, we identified a "bad boom" beginning in 1963, sharing quantitative traits with the 1920s—i.e., characterized by declining margins despite rising volumes. In chapter 4, a bank-level analysis preliminarily qualified these findings, identifying a subtle but persistent substitution of loans for securities: a trend associated with an increase in latent fragility.

This chapter addresses the question that naturally emerges from these results: *what drove these distortions?* Here, we go beyond the *what* to study the *why*, offering a novel perspective that explicitly links changes in the institutional framework to bank-level dynamics. While narrative (and institutionally-focused) descriptions of the period are abundant,[2] a systematic quantitative assessment that connects the regulation to the granular behavior of the banking sector remains, to the best of our knowledge, underexplored.

Filling this gap, this work offers a three-fold contribution.

First, the chapter enters the historical debate on the allocative efficiency of the banking system in the Golden Age. Recent scholarship has argued that, despite heavy regulation, the Italian banking system efficiently supported the industrial boom, channeling resources to the most promising sectors (Battilossi et al., 2011). However, this positive assessment typically relies on aggregated data, which, by construction, mask the heterogeneity of bank behavior. In this work, by leveraging granular, bank-level data, we provide an empirical reassessment of the activities of the Italian banks, testing whether the claimed allocative efficiency held up under the growing economic pressures of the 1960s, or if the policy response to the crisis of 1964 effectively marked not only the "decay of the Italian economy" (De Cecco, 2004, p. 103, tr.) but also that of its banking sector under tightening financial repression.

Second, we offer valuable empirical evidence to the literature on the effects of financial repression. While often analyzed as a functional tool for liquidating public debt (Reinhart and Sbrancia, 2015) or guiding credit (Monnet, 2018), the structural impact of such policies on financial intermediaries remains debated. We contribute to this discussion by investigating the specific mechanisms through which repression may distort bank behavior: (i) whether the policy tools used to stabilize the 1960s—by shifting the burden of fiscal policy onto bank balance sheets—weakened the incentives to lend to the private sector;[3] (ii) whether, consistent with the theoretical framework of Crosignani (2021), this shift was driven by capital constraints, where under-capitalized banks are structurally more prone to tilt their portfolios toward government securities.

Third, we offer a contribution to policy analysis regarding the "middle-income trap" (Gill and Kharas, 2007). Interestingly—while bearing in mind the specificity of the historical context—the Italian experience of the "economic miracle" provides a case study for contemporary

of the banking industry to take on risks—with a consequent resorting to safer activities—caused either by regulatory bounds, central pressures, or internal decisions.

[2]See, among others, De Cecco (1968); Galanti et al. (2012); Fratianni and Spinelli (2001); Mastromatteo and Esposito (2023); Strangio (2017); Toniolo (2017, 2018, 2022).

[3]As argued, for instance, by Acharya et al. (2011) regarding the crowding-out effects of fiscal burdens on intermediaries.

emerging economies facing the trilemma of short-term stabilization, long-term development, and state intervention. By analyzing the structural transformation of the Italian banking sector, we seek to understand how policies designed to buffer temporary macroeconomic shocks can permanently distort the incentives of financial intermediaries, with potential implications for the capacity of firms to invest and develop.

Empirically, by analyzing the business model of Italian banks from 1951 to 1969—i.e., the evolution of their assets and liabilities mix—with machine learning techniques, we detect a subtle but persistent substitution between loans and securities, consistent with the findings of chapter 4. Most importantly, we document that this substitution effect dramatically accelerated after the economic downturn (*congiuntura*) of 1963-1964.

The central thesis of this work is that the policy response to the *congiuntura*, designed to stimulate investment through public subsidies, created a set of controversial incentives that catalyzed a systemic shift away from traditional retail lending and towards the holding of public and semi-public securities (as implicitly suggested by Carnevali, 2005). In a "flight to safety" a lá Bernanke et al. (1994), this trend was most pronounced among financially weaker institutions, for which the government-supported asset class offered insulation from market competition and volatility. We claim that this process created a regime of "unstable stability" that, while suppressing volatility in the short-run, fostered a persistent distortion in the financial system.

The catalyst was the institutionalization of a system of "double intermediation," where commercial banks collected deposits not to directly grant loans, but to provide financial resources to the state-controlled Special Credit Institutes (SCI), which then allocated capital often under political guidance (as noted for the 1970s by Battilossi et al., 2011). This not only altered the allocative function of the Italian banking system but, at the systemic level, it created the preconditions for a "diabolic loop"—the pernicious link between sovereign and bank risk (Brunnermeier et al., 2016; Farhi and Tirole, 2018)—making the health of the banking system tied to that of sovereign debt quotations. As a result, and perhaps most importantly, it compromised the ability of the central bank to implement a consistent monetary policy, as the sheer volume of public debt on bank balance sheets required a commitment to defend the quotations of public securities as a microprudential tool.

This is the very process that Governor Guido Carli looked at with concern in 1966 when he warned how:

> A continuously expanding supply of public securities, coupled with price stability, will inevitably distort the banking system's structure over time [...] gradually replacing core banking operations (Relazione for 1966, p. 364, tr.).[4]

To understand the origins, the mechanisms, and the consequences of the transformation process that led to this statement is the central objective of this chapter.

[4] "Relazione" refers to the Bank of Italy's report to the stakeholders (see section 5.1). All the quotes referring to Italian documents were translated into English by the author. For the sake of conciseness, this procedure will be signaled by the abbreviation *tr.* in the rest of the document.

After this introduction, the remainder of the chapter is structured as follows. Section 5.1 presents the sources for the analysis: We employ balance sheet data from ASCI, and complement the quantitative insights with a qualitative perspective on the evolving institutional framework as described in the Bank of Italy's annual *Relazioni*. This evolving framework is then discussed in section 5.2, presenting the institutional banking landscape of post-war Italy, and how it related to the monetary policy. To go beyond the institutional description, in section 5.3 we present a data-driven approach tailored to identify distinct and persistent "business models" adopted by the banks in the analyzed period. In section 5.4 we complement static modeling with a perspective on how business models changed over time, identifying three distinct phases in the banking activity: 1951-1957, 1958-1963, 1964-1969. In section 5.5, with a link, the macro-dynamics are linked to their micro-determinants, analyzing the significant drivers of a business model's switch. Lastly, section 5.6 concludes.

5.1 Data description

Quantitative Data: Archivio Storico del Credito in Italia

Our analysis relies on the balance sheet data from the Archivio Storico del Credito in Italia (ASCI), as presented in section 2.2. We focus on the period 1951-1969 for two primary reasons. First, these years provide high data consistency, as all banks reported using the same accounting standard (the "Modulo 81 di Vigilanza"). Second, the period aligns with the broadest historical definition of "Golden age," beginning as Italy exited the Marshall Plan (1951) and ending just before the widely recognized structural break of 1969. As Fratianni and Spinelli (2001, p. 401, tr.) note, these years represent "the best sub-period of the whole post-unification history."

After the preprocessing described in section 2.2, our final sample is highly comprehensive. It is composed of 6,906 bank-year observations from 413 unique institutions, covering between 95% and 98.1% of the total assets in the ASCI dataset. The panel is remarkably stable, with a median bank presence of 19 out of the 19 possible years. The sample includes all major bank categories: 145 cooperative banks, 79 savings banks, 141 joint-stock banks, and 9 public banks (Public-law banks and Banks of National Interest). Descriptive statistics are provided in Table 5.1. Notably, these 9 public banks alone account for an average of 48% of the total assets in our sample, highlighting the concentrated, state-influenced nature of the system (see section 5.2).

Qualitative Data: Bank of Italy's "Assemblea Generale dei Partecipanti"

To complement our quantitative data, we draw documentary evidence from the Bank of Italy's *Assemblea Generale dei Partecipanti* (general assembly of the stakeholders)—hereafter, the *Relazione*.[5] These annual reports, published from 1894 to 2003, provide a thorough description of the country's economic and financial situation. Each *Relazione* offers a comprehensive, data-rich assessment of the global economy before providing a granular analysis of

[5] The report for a given year (e.g., 1965) was formally presented at the assembly in the following year (1966). For clarity, we will cite the Relazione by the year to which the analysis pertains (e.g., Relazione for 1965).

Table 5.1: Sample numerosity and total assets: descriptive statistics (billions of Lira)

Category	Nº Banks	Count	Mean	Std.	Min	25%	50%	75%	Max
BIN	3	57	1414.1	1043.4	289.1	579.2	1095.3	2038.1	4464.8
BP	145	2413	15.0	68.1	0.0	0.9	2.7	7.8	1282.6
CRO	79	1478	53.7	146.9	0.4	5.9	16.6	44.3	2140.1
DB	32	443	3.8	6.1	0.0	0.6	1.5	4.5	52.5
IDP	6	110	818.7	899.0	21.7	258.0	513.5	1066.3	5011.0
MDP	8	127	19.4	28.3	0.1	2.1	8.5	22.8	155.5
SOC	141	2278	32.6	86.6	0.0	1.8	6.5	22.8	1206.0

The table reports the descriptive statistics of the sample in terms of numerosity by category and asset size. Note: the number of banks reports the maximum numerosity of the category in the sample in the analyzed time-period, the observations are bank-year observations, the percentiles are expressed in billions of Italian Lira.

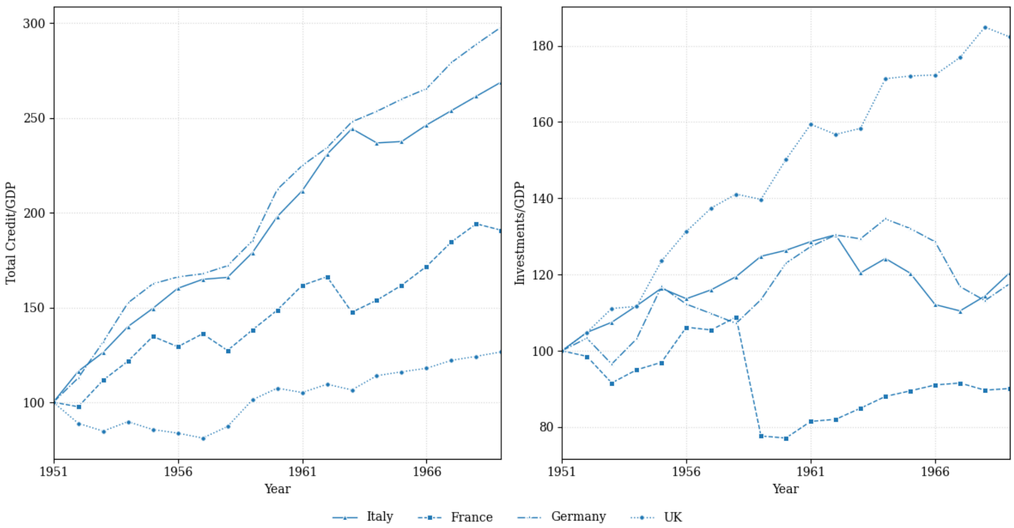
Italy's national accounts, balance of payments, credit sector, and securities markets, using data from international institutions (IMF, OECD), ISTAT, and the Bank's own supervisory activities.

Of particular interest for our analysis are the *Considerazioni finali* (concluding remarks) delivered by the Governor. While the main body of the Relazione is quantitatively descriptive, the Considerazioni are more qualitative and forward-looking. In a more direct, *vis-a-vis* tone, they convey the predominant sentiment of the Bank, its main concerns, and, most notably, its view on latent threats not yet visible in the data. As such, relevant information can be drawn not only from what the Governor says but also from how he says it (Astuti et al., 2020). These remarks provide an invaluable window into the internal debates that shaped the economic policy.

5.2 A Quiet Hand: Monetary Policy and the Banking System of the Golden Age

The post-war period in Western Europe is widely understood as an era defined by state-led growth and active economic management (Hodgman, 1973). Operating within the fixed-exchange-rate discipline of the Bretton Woods system, European central banks faced a common challenge: how to use domestic monetary policy to pursue the national objectives of reconstruction, full employment, and industrial development while maintaining a stable peg to the dollar. Despite the "rebirth of the monetary policy at the beginning of the 1950s," conventional market-based tools were seen as incapable of promoting economic growth, their effective implementation being subordinated to the stability of the balance of payment (Cotula et al., 1997, p. 21). Consequently, direct state intervention in credit markets became the norm, particularly in countries where weak financial markets made bank credit the main source of funding for industrial firms, as Italy and West Germany (Crafts and Toniolo, 1996, see also Figure 5.1). As Monnet (2018, p. xvii) effectively summarizes, the prevailing belief was that:

Figure 5.1: Credit and investments: comparative figure (1951=100)



The figure reports the total credit and the total investments as a share of the GDP for the major European economies. Source: Macrohistory database (Jordà et al., 2017).

> market mechanisms were incapable both of promoting sufficient credit growth to finance investment and of controlling credit growth to avoid overly high inflation and banking crises [...] the heart of the system of control over credit and investment was the central bank. While it did not ignore the existence of private markets or limit itself to targeted policies, the state nevertheless intervened on all fronts, at different levels, thus erasing the boundary between public and private credit.

While state intervention was the leitmotif, the instruments varied significantly, creating a fragmented landscape in which Italy emerges as a compelling case study. The post-war "economic miracle" transformed the nation in a context of remarkable monetary stability, and yet, as Ackley (1972, p. 164, tr.) observes, this was apparently achieved by doing... *nothing*:

> In Italy, the officials of the Bank of Issue love to talk a lot about their continuous and tireless efforts to regulate the supply of money to preserve the integrity of the lira. One might think that price stability is the result of their fine maneuvers. Yet, the Bank of Italy didn't do any open market operation, changed the interest rate only once in ten years (lowering it), changed the rate of mandatory reserve only once in ten years (lowering it) [...] we draw the attention to the contrast between declarations and actions, and on the contrast with the actions of other central banks.

How did Italy achieve such a "stability and growth" (Cotula et al., 1997; Cotula, 1999) if not with conventional tools? The answer, as we will explore, lies in the Bank of Italy's "quiet hand": an *ensemble* of structural management, moral suasion, and direct state influence embedded within the banking system itself.

5.2.1 The Institutional Landscape of Post-War Italian Banking

The Paradigm of Stability

The interventionist paradigm just described found particularly fertile ground in Italy: monetary policy's role was to "guide money and credit with an eye to the needs of the real economy, and to the goals of capital accumulation and growth" (Fazio, 1999, p. 5, tr.). This objective was pursued by ensuring that the necessary preconditions were met. As the Bank of Italy's governor Donato Menichella (1948-1960) clearly states, the central bank can only sustain growth by shielding monetary stability, while supervising on the soundness of the financial system:[6]

> In all cases, it is only a contribution to stability that can be given. This needs to be said quite clearly, especially because, [...] less well-informed and more impatient, expect of it things of which it is not by itself capable. [...] it is, alas, the fate of the central bank to be without friends, as are all those who often say "No" and only rarely say "Yes" (Menichella, 1956, p. 6).

A Repurposed Institutional Framework

The institutional framework established by the banking law of 1936 was particularly well-suited to sustain this monetary paradigm. It granted the Bank of Italy extensive supervisory powers and, after the war, the existing apparatus of "financial repression"—including capital controls, tight regulation of banking activities, and a state-overseen "bank cartel"—was repurposed from military goals to developmental ones (Toniolo, 2018). This formal authority was amplified by two key factors:

1. Credibility. The credibility of the governor Menichella—combined with the frequent rotation of less technically adept finance ministers—gave the Bank a de facto autonomy and a leading voice in economic policymaking (Fazio, 1999; Fratianni and Spinelli, 2001; Toniolo, 2018). The Bank used this credibility to "influence upstream the push for the creation of monetary base deriving from public needs, with a constant work of persuasion towards the treasury ministers." Cotula et al. (1997, p. 21, tr.)

2. State ownership. Following the Great Depression and the creation of the Institute for Industrial Reconstruction (IRI), the state inherited a significant footprint in the financial sector. Adding on the state-run Special Credit Institutions (SCIs), Public-law Banks (IDP), and the Banks of National Interest (BIN) were state-controlled, with charters and management subject to government approval. The scale of this influence was notable: between 1951 and 1969, these nine publicly-linked banks accounted for an average of 48% of the total assets of the entire banking sector (Natoli et al., 2016).

The Credit Sector as the Main Monetary Policy Tool

This unique context allowed the Bank of Italy to effectively leverage an active structural management of the credit sector as its main policy tool, sparingly resorting to the "conventional"

[6] This idea shows a full internalization of Keynes' "you can't push on a string", that is, of what the monetary policy can efficiently achieve and of what, while useful in the short term, may lead to future imbalances.

policies, as Ackley noticed (Cotula et al., 1997). The guiding principle laid by the law of 1936 was that "banking is a function of public interest" (Art. 1). This straightforward sentence represents a profound change in the paradigm of banking, as Menichella made explicit in a striking address to the Italian Bankers' Association (ABI):

> You have the duty—*since you are a service*—to provide this service at the lowest cost possible. Everyone needs to be convinced that banking is not a rich profession and that no one can get rich by practicing this profession (Albareto and Trapanese, 1999, p. 130, tr.).

This non-speculative view of the banking sector subordinated the credit sector to the needs of the real economy, a process that unfolded along three main channels:

1. Structural management of the bank population. The Bank of Italy strictly controlled the opening of new branches, favoring the expansion of a dense network of small, local banks (savings and cooperatives) while discouraging the further growth of the majors.[7] The trade-off was clear: sacrificing competition and efficiency for pluralism.[8] As (Ciocca, 2003, p. 3, tr.) notes:

> Menichella sacrificed competition and efficiency in the banking sector to ensure that competitive impulses emerged from the pluralism of banks and reached industrial firms: "The multiplicity of credit institutions is a guarantee of the fair distribution of savings... and this comes at a cost. One could reduce operational costs, but this would require a significant reduction in the number of institutions; however, this could lead to a concentration that is very dangerous for the freedom of initiatives by citizens" (Ciocca, 2003, p. 3, tr.).

This structure was necessary to match the industrial and financial networks: it was paramount to have a banking sector that could dialogue with the vast web of small and local firms and to gather deposits also in the rural areas of the country.[9] By 1962, 63% of Italian banks were operating in just one municipality, and 92% in just one province (Relazione for 1962, p. 333). Though commercial banks were legally barred from long-term lending, the Bank of Italy tacitly allowed them to indefinitely roll over short-term credit to small-and-medium enterprises, compensating for their limited access to the SCI long-term credit.[10] As Menichella itself notes in the Relazione for 1958 (p. 374, tr.):

> The credit to small and medium enterprises is inherently a credit that is based and cannot but be based on the personal qualities of the owners [...] The credit that is granted to them is indeed *formally* short-term, but [...] they know that the continuation of the credit assistance is strictly conditioned on their conduct (tr., emphasis is our own).

[7] The expansion of the major banks was limited both by denying the opening of new branches and by constraining their capital, making capital requirements binding (Cotula, 1999).

[8] See how this relates to the quality of the credit boom in chapter 3.

[9] In 1951, 31% of the Italian manufacturing firms had less than 10 employees (Albareto and Trapanese, 1999, p. 59).

[10] As Albareto and Trapanese (1999, p. 34, tr.) notes, this procedure was also common in the relationship between the Bank of National Interest (BIN) and the major firms, effectively inheriting "traits that characterized the activity of the former mixed banks: the provision of long-term credit through the continuous renewal of short-term credit."

2. Soft power and moral suasion. Adding on the structural management of the branch network, the Bank of Italy possessed a toolkit of "soft" controls, including the ability to deny rediscounts or loans of foreign currency, "suggesting" how to use credit from foreign correspondents, and requiring authorization for credit lines above certain thresholds.[11] However, Menichella consistently resisted direct, administrative control over credit allocation. He believed the central bank's role was to guide, not to "replace the banker in the delicate and essential function of the distribution of credit" (Cotula et al., 1997, p. 20). The Bank's soft power was effectively used to limit the emergence of distress:

> For distressed banks, and especially those that supported or absorbed them, after 1947 Bank of Italy authorized the opening of branches (which were more valuable because they were rationed); it eased the burden of mandatory reserves; and it granted refinancing at discount rates that were significantly lower than the market rates. In a banking crisis, "avoiding the noises, the guilty are forced to sacrifice what remains to them, credit is preserved, and *depositors are unaware of the danger they faced* (Ciocca, 2003, p. 4, tr., emphasis is our own).

3. Interest rate controls. Finally, the Bank of Italy directly managed interest rates via the "bank cartel" to influence the public's preference for bank deposits over other assets. Between 1949 and 1954, deposit rates were systematically raised while lending rates were lowered, compressing the spread and reinforcing the "public service" model of the banking sector (Cotula et al., 1996).[12]

Summing up, the Bank of Italy's "quiet hand" was finely tuned for the conditions of reconstruction. Shaping the very structure and behavior of the banking sector, the Bank of Italy ensured stability and successfully channeled resources toward national development. The resilience of this system would soon be tested by the new economic pressures of the 1960s.

5.3 Business Models Modeling: A Two-Steps Procedure

To go beyond the institutional description and empirically investigate the behavior of Italian banks, this study adopts a quantitative and data-driven approach based on bank-level information. The core idea is that, by analyzing the composition of bank balance sheets, it is

[11]As Menichella (1956, p. 16) outlined, "[1] The central bank can allow or refuse the commercial banks rediscounting facilities and advances on securities. [2] The Italian Foreign Exchange Office, which, in turn, is financed by the central bank, may grant or refuse loans to commercial banks in foreign currencies. [3] The banks can be requested to be more liberal, or more sparing, in their use of credit granted to them by their foreign correspondents, especially American or British banks. [4] The central bank can apply, with varying degrees of liberality, its powers to authorize the commercial banks to grant credits which exceed a certain percentage, fixed by law, of their share capital and reserves. Finally, a constant watch is kept on the level of the funds held by the banks in the form of free or tied deposits at short term with the central bank."

[12]Between 1952 and 1954 the minimum interest rate on fiduciary deposits rose from 1.5% to 2.5% for 3-months deposits, from 2% to 3.25% for 6-months deposits, and from 2% to 4% for 12-months deposits; between 1949 and 1951, the interest rate of current account loans decreased from 8.77% to 7.50%, the rate on bills discounting decreased from 6.27% to 5.25% (Cotula et al., 1996, p. 940).

possible to identify distinct, persistent strategies, or "business models," and to track how the relevance of these models changed over time.

5.3.1 Methodological Setting

Following the literature, we define a bank's business model (BM) as the set of its "balance sheet characteristics, intended as asset and liability composition, examined in their temporal evolution and in their tendency to converge towards homogeneous structures and groups" (Savona, 2024, p. 3, tr.). By looking at a bank's BM, we are studying the holistic process of intermediation undertaken by the institute and, consequently, "the fundamental way in which the bank pursues its economic objectives [...] in fact, is above all a model of financial intermediation" (Ayadi et al., 2018, p. 24).

The notion of business model is paramount for an endemic friction between the formal definitions of banking and real-world practices. Think of the banking law of 1936: it defines banking as "the gathering of savings among the public, in every form, and the exercise of credit" (Art.1, tr.). And yet, it is indubitable that the banking activity goes far beyond the textbook definition of transforming savings into loans: financial intermediaries are involved in a plethora of complementary activities, with an intrinsic heterogeneity in banking: in other words, not all banks are created equal. This is precisely where the notion of a BM comes in. The notion of BM has notable properties that draw the attention of academics and regulators alike. Most notably, it has been shown to be significantly related to both the idiosyncratic dynamics of a bank and systemic factors. Largely reported is the link between a bank's BM and its risk-returns profile.[13] Chiaramonte et al. (2013) studies how the mix of banks' BM affects the systemic financial stability. Nucera et al. (2018) and Savona (2022, 2024) investigate the link between banks' BM and the monetary policy, the regulatory framework, and systemic shocks.

To identify these models, we adopt a two-step process designed to first find the stable underlying structures and then to track their evolution over time.

Step 1. Business models identification (Clustering)

First, we identify a set of "archetypal" business models. We treat the entire bank-year panel as an i.i.d. sample to ensure long-run consistency, and apply the *K-medoids* (PAM) clustering algorithm, characterized by its efficiency and robustness to outliers (Kaufman and Rousseeuw, 1990).[14] This unsupervised machine learning algorithm partitions the input set into subgroups (clusters) with respect to a set of individual characteristics of each point (features), under the constraint that the center of each cluster (medoid) must be an actual data point, not a synthetic instance obtained as the center of gravity of the group. Each observation is then allocated into a cluster so that the members of each cluster share as similar as possible features, consequently being as diverse as possible to the members of other clusters.

[13] See, among others, Ayadi et al. (2011, 2018); Chiaramonte et al. (2015); Demirguc-Kunt and Huizinga (2010); Marques and Alves (2021); Roengpitya et al. (2014, 2017).

[14] See also Savona (2024).

Let $\mathcal{X} = \{\mathbf{x}_1, ..., \mathbf{x}_N\}$ be input set of N observations, where each observation $\mathbf{x}_i \in \mathbb{R}^d$ is a vector of d features. Given a pre-specified number of clusters K, the objective of the K-Medoids algorithm is to find the set of medoids $\mathcal{M}^* = \{\mathbf{m}_1, ..., \mathbf{m}_K\} \in \mathcal{X}$ and a partition of the data into K clusters $\mathcal{C} = \{c_1, ..., c_K\}$ that minimizes the sum of dissimilarities between each point and the medoid of its assigned cluster. The objective function $C(\mathcal{M}, \mathcal{C})$ to be minimized is defined as:

$$C(\mathcal{M}, \mathcal{C}) = \sum_{k=1}^{K} \sum_{\mathbf{x}_i \in C_k} d(\mathbf{x}_i, \mathbf{m}_k) \tag{5.1}$$

with $d(\cdot, \cdot)$ being a chosen distance metric, in our case the Euclidean distance, such that

$$d(\mathbf{x}_i, \mathbf{m}_k) = ||\mathbf{x}_i - \mathbf{m}_k||_2 = \sqrt{\sum_{j=1}^{d} (x_{ij} - m_{kj})^2}. \tag{5.2}$$

The algorithm proceeds in two phases:

1. *Build phase (Initialization):* An initial set of medoids is selected. We use the common heuristic, a greedy approach where the first medoid is the most central point in the dataset (the one that minimizes the sum of distances to all other points). Subsequent medoids are then chosen iteratively to provide the greatest reduction in the objective function $C(\cdot)$.

2. *Swap phase (Iterative Refinement):* This phase iteratively improves the set of medoids until convergence. The steps are repeated until the cluster assignments no longer change:

   (a) *Assignment:* Each non-medoid point $\mathbf{x}_i \in \mathcal{X} \setminus \mathcal{M}$ is assigned to the cluster c_k of its closest medoid. Thus,

   $$c_k = \{\mathbf{x}_i \in \mathcal{X} \setminus \mathcal{M} \mid d(\mathbf{x}_i, \mathbf{m}_k) \leq d(\mathbf{x}_i, \mathbf{m}_j) \forall j \neq k\} \tag{5.3}$$

   (b) *Update:* For each cluster c_k, the algorithm considers swapping its medoid $\mathbf{m}_k$ with every non-medoid point $\mathbf{x}_j \in c_k$. It computes the change in the total cost function $C(\cdot)$ for each potential swap. The swap that results in the largest decrease in the objective function is executed.

The algorithm stops when no swap can further reduce the total cost, indicating that a local minimum has been reached.

In our exercise, we let the optimal number of clusters K be endogenously defined as the one that maximizes the Silhouette score (Rousseeuw, 1987), which measures how well-defined the clusters are in terms of cohesion (similarity within the clusters) and separation (heterogeneity between clusters). The result is a data-driven taxonomy of the stable business models present in the Italian banking system during the period 1951-1969.

Step 2. Dynamic Reallocation (Tracking)

To track how banks moved between these models over time, we partition the data into yearly cross-sections. For each year, we allocate every bank to the business model (i.e., the clusters identified in Step 1) to which it is most similar. This dynamic allocation allows us to trace the evolution of the banking system's structure and the strategic shifts of individual institutions in response to the changing economic and regulatory environment.

5.3.2 Business Model Identification

The Input Set

Our clustering exercise is based on the composition of banks' assets and liabilities. We partition the balance sheet into eight key categories, five assets and three liabilities, which offer a robust and comprehensive representation of allocative choices available to banks in the period. All the variables are measured as the share of total assets and liabilities to net out the effect of size.

The asset mix includes: (i) *Liquidity*, measured as the share of sight assets held by a bank. Among sight assets, cash reserves and current account deposits at the central bank or other financial institutions are included. This dimension is related to the liquidity of a bank's fundamentals. (ii) *Retail loans*, indicating the reliance on traditional banking activities, that is, the issuing of loans to non-financial customers. In this category, portfolio bills, current account loans, mortgages, advances, and REPOs are included. This dimension is related to the credit risk faced by a bank. (iii) *Bank loans*, indicating the importance of interbank activities, consequently approximating the contagion risk from interconnectedness. This dimension groups current account loans to other financial institutions (SCI included). (iv) *Government securities*, measuring the involvement of a bank in the financing of the treasury and the exposure to liquidity and market risk. Government securities include both short and long-term claims issued or guaranteed by the central government and by local administrations. (v) *SCI securities*, measuring the involvement of a bank in the financing of SCI credit. It includes mortgage bonds backed by tangible assets (i.e., land and buildings) named *cartelle fondiarie*.[15] It relates to the exposure to liquidity and market risk.

The liabilities mix covers: (i) *Equity*, indicating the share of capital and reserves, that is, the importance of internal funding. (ii) *Retail deposits*, indicating the reliance on the "traditional" form of financing, that is, the gathering of deposits, both current account and fiduciary, among non-financial actors. (iii) *Bank deposits*, indicating the reliance on an interbank form of financing. Current accounts from other financial institutions, advances, and REPOs are considered. Summary statistics are presented in Table 5.2.

The Three Business Models of the Golden Age

Our data-driven identification identifies three distinct and persistent business models. Table 5.3 presents the centroids for each cluster, which represent the average balance sheet composition of a bank following that particular model.[16]

[15] A presentation of the *credito fondiario* and of the related *cartelle fondiarie* is presented in section D.1.

[16] From here, the terms "BM" and "clusters" are used interchangeably.

Table 5.2: Assets and liabilities composition: descriptive statistics (share over total assets and liabilities)

	Count	Mean	Std.	Min	25%	50%	75%	Max
Sight assets	6,909	0.17	0.08	0.00	0.12	0.16	0.21	0.62
Bank loans	6,906	0.11	0.08	0.00	0.05	0.09	0.14	0.58
Retail loans	6,906	0.48	0.10	0.01	0.41	0.48	0.54	0.92
Government securities	6,906	0.11	0.08	0.00	0.05	0.09	0.14	0.83
Special-Credit Institutes securities	6,906	0.07	0.08	0.00	0.01	0.04	0.10	0.73
Equity	6,906	0.05	0.05	0.00	0.02	0.04	0.06	0.81
Bank deposits	6,906	0.05	0.06	0.00	0.02	0.03	0.07	0.90
Retail deposits	6,906	0.83	0.08	0.02	0.80	0.85	0.89	0.98

The table reports the descriptive statistics of the balance sheet ratios used as inputs for the analysis. The asset and liabilities composition is expressed as the share of total assets or liabilities.

Table 5.3: Banks' business models and their assets and liabilities mix

	Cluster 0	Cluster 1	Cluster 2
Sight assets	18.6 (8.9)	15.5 (6.7)	17.9 (8.1)
Bank loans	8.3 (4.9)	6.7 (4.2)	*16.0* (8.4)
Retail loans	39.4 (7.9)	*56.8* (6.9)	43.6 (7.1)
Government securities	7.1 (5.3)	11.6 (7.3)	11.6 (9.2)
Special-Credit Institutes securities	*19.5* (8.4)	3.5 (3.7)	3.6 (3.3)
Equity	3.2 (1.9)	5.3 (5.3)	5.2 (4.8)
Bank deposits	3.8 (3.8)	5.4 (5.8)	5.7 (6.4)
Retail deposits	85.6 (6.3)	82.7 (8.3)	82.8 (8.7)
Business model	Securities-focused	Retail-focused	Banks-focused

The table reports the centroids for each cluster, that is, the average assets and liabilities composition of a bank following the business models. Measures are presented as the share of the items with respect to the total assets and liabilities. Standard deviations (%) in parentheses.

A preliminary analysis of the clusters reveals several key features. The liability composition was found to be remarkably stable across the clusters, reflecting the gathering of savings "public service" discussed above, and indicating that strategic differentiation occurred primarily on the asset side of the balance sheet. On this, all three business models present a diversified asset allocation, with different strategic focuses.

Cluster 0, the *"securities-focused" business model*, is characterized by a significantly lower share of Retail loans and a correspondingly higher share of SCI securities, 19.5% of the total assets. On the liabilities side, the cluster operates on a lower level of equity compared to its peers. This suggests a business model relatively less focused on direct lending to the real economy and more on indirect financing via the SCIs.

Cluster 1, the *"retail-focused" business model*, represents the traditional commercial bank, with a significantly higher share of Retail loans (56.8%) in a diversified asset allocation. These banks are the most engaged in the direct financing of firms and households.

Cluster 2, the *"bank-focused" business model*: is defined by a relatively higher share of Bank loans (interbank lending), up to 16% of the total assets, and a lower share of Retail loans. This suggests a specialization in acting as an intermediary within the financial system itself.

Having identified these stable structures, the next step is to analyze their dynamics over time by reallocating each bank to its best-fit cluster in each year of the sample period. This dynamic perspective allows for a precise tracking of how the Italian banking sector evolved through the Golden Age.

5.4 Business Model Dynamics and the Unstable Stability

By dynamically allocating each bank to one of the three identified business models on a yearly basis, a compelling narrative of structural transformation emerges: The analyzed period is characterized by three distinct phases, 1951-1957, 1958-1963, and 1964-1969. The most notable and persistent business model shift appears in the wake of the 1963-1964 economic downturn. Results are presented in Figure 5.2.

1951-1957: The Reconstruction Period

The years from 1951 to 1955 reflect the very stability that the Bank of Italy's policy was designed to foster. Our results show that at the heights of the reconstruction period, the retail-oriented business model was dominant, representing on average 58% of the total assets in the sample (5.2b). The securities-oriented banking was a residual business model (less than 10% of the total assets), exclusively adopted by savings banks.[17] Following Fratianni and Spinelli (2001, p. 419, tr.), this is tightly linked with both "the correct choice of the objectives of the monetary policy" and the "favorable circumstances", which meant that "the external constraint was never threatening. Consequently, monetary policy never had to abruptly stop internal demand." In this stable environment, the "public service" model of banking—gathering deposits and granting loans—could thrive without distortion.

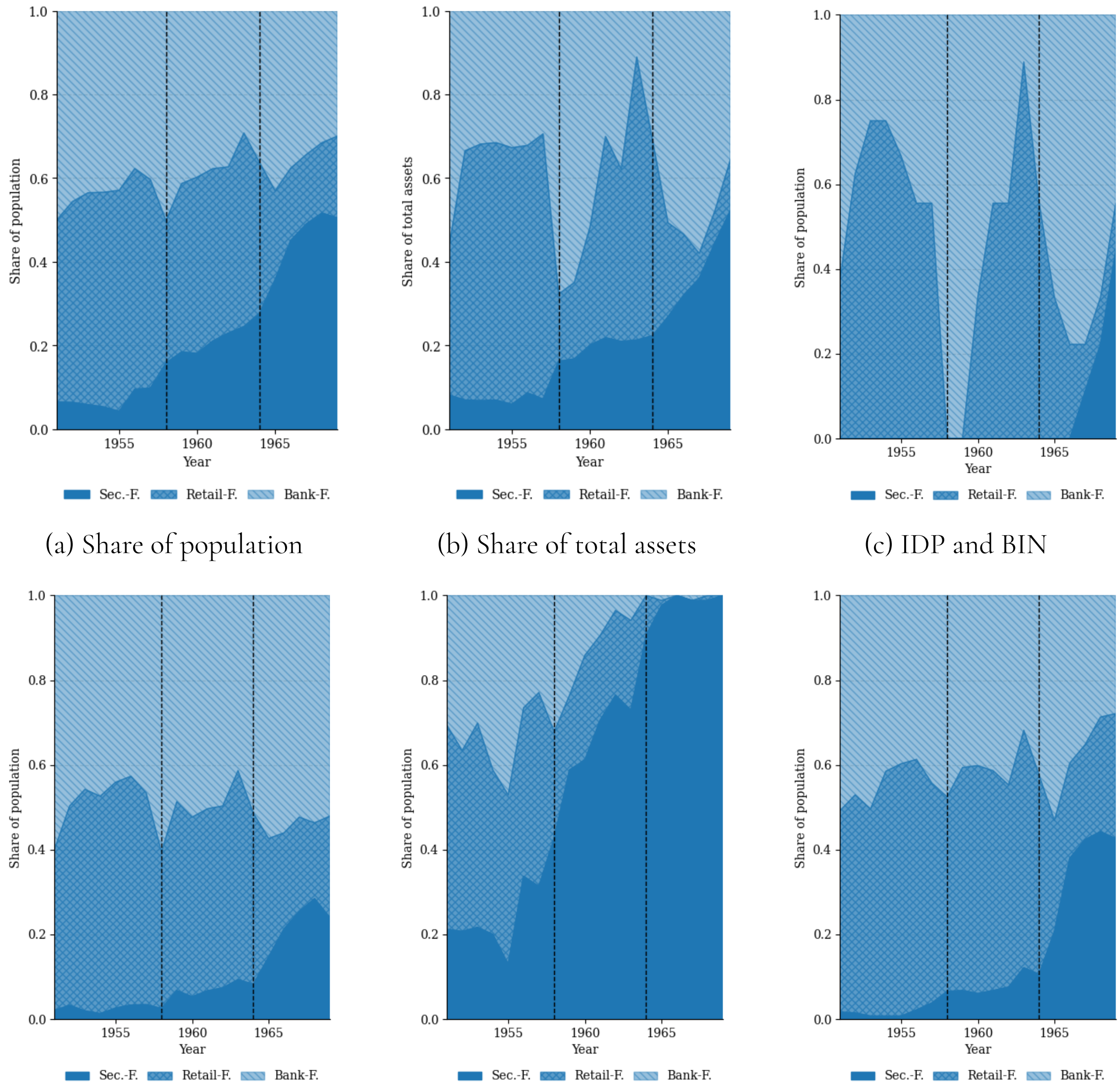
1958-1963: First Stress, First Response

The first signs of structural change emerge in tandem with the international economic downturn of 1956-1958.[18] While Italy avoided a recession, the slowdown prompted a decisive counter-cyclical policy response from the Bank of Italy. The main policy lever was an injection of liquidity, marked by the 1958 reduction of the official discount rate from 4% to 3.5%

[17] Savings banks were legally compelled to invest a share of their assets in public or publicly-guaranteed bonds (Galanti et al., 2012).

[18] This phenomenon traces its root in a surge of geopolitical instability following the crisis of the Suez Canal in 1956. The response is a wave of monetary tightening to control inflation and the balance of payments, mainly in the US and the UK. The FED increases the interest rate in August 1957 from 2.88% to 3.5%. In the same period, the Bank of England raised the policy rate from 5% to 7% (source: FRED). Between 1957 and the first half of 1959, the economic growth of most developed countries stagnated or entered a recession (Relazione for 1959).

Figure 5.2: Business models: dynamic reallocation results

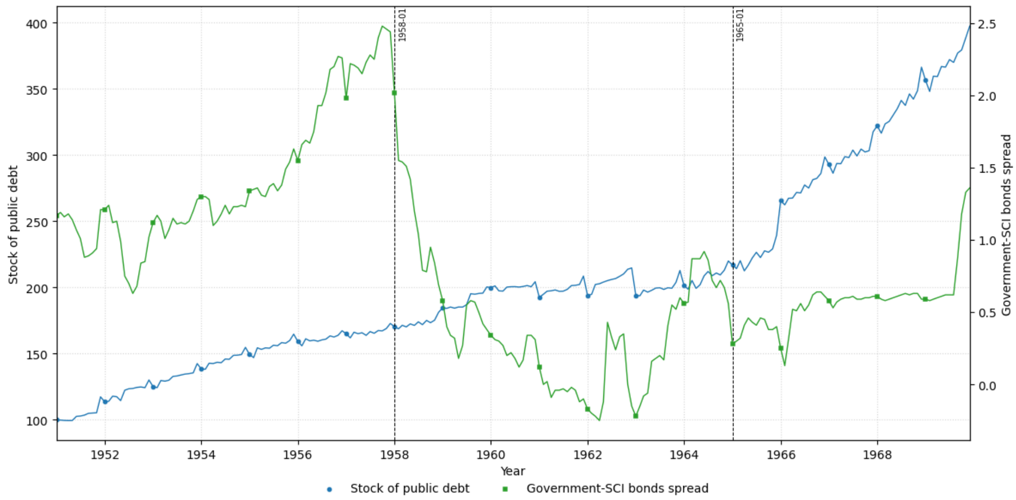


(a) Share of population (b) Share of total assets (c) IDP and BIN

(d) SOC and DB (e) CRO and MDP (f) BP

The figures show the results of the dynamic reallocation process: Each year of the sample period, each bank is allocated to its best-fit cluster. The three business models define the asset and liabilities mix presented in Table 5.3. The securities-focused business model (Sec-F.) indicates a higher share of SCI's securities; the retail-focused business model (Retail-F.) indicates a higher share of retail loans; the bank-focused business model (Bank-F.) indicates a higher share of bank loans. Panel 5.2a shows the share of the total number of institutions in each business model. Panel 5.2b shows the share of the total assets in the sample in each business model. Panel 5.2c to 5.2f splits the results by bank category, showing the share of the category's population in each business model: the major public banks (IDP and BIN) in panel 5.2c, the joint-stock and private banks (SOC and DB) in panel 5.2d, savings and pledge banks (CRO and MDP) in panel 5.2e, and cooperative banks in panel 5.2f. The vertical dashed lines indicate 1958 and 1964, respectively.

Figure 5.3: Debt of the public administration and spread between M/L-term government bonds and the *cartelle fondiarie*



The figure reports the monthly series of the total debt of the public administration (1951-01-01=100), as reconstructed by Francese and Pace (2008), on the left-axis. On the right axes, the figure reports the monthly spread between the return on medium-to-long-term government bonds (Piselli and Vercelli, 2023) and the nominal return on the cartelle fondiarie, fixed at 5% across the whole period.

(the only change Ackley noted).[19] This maneuver, carefully managed with strong moral suasion to prevent inflation, had two notable and direct consequences, which are clearly visible in our business model data:[20]

1. Excess liquidity. The growth in liquidity outpaced the demand for short-term credit. In turn, banks allocated the "excess" liquidity—i.e., funds they could not lend to loans—into securities. Moreover, the lower interest rate compressed the spread between government bonds and *cartelle fondiarie*, making the latter more attractive (see Figure 5.3).[21] Indeed, our data shows a sharp spike in the securities-oriented business model in 1958 (from 7% to 16% of total assets), peaking to 21% by 1963. This process changed the opportunity cost of holding government securities and retail loans, particularly affecting the savings banks' asset allocation (see 5.2e), with a permanent shift in their business model.

2. Countercyclical bank loans. The downturn also prompted a countercyclical response within the banking system: We observe a sharp, albeit temporary, spike in the bank-focused business model, which moved from 29% to 68% of the total assets. As the sub-samples show (5.2c), this shift is driven entirely by public banks (IDP and BIN) increasing their exposure to the interbank market, hinting at a countercyclical form of liquidity provision to the correspondents.

[19] Contributing to the increase in liquidity there were the positive balance of payments, the price stability, and the reimbursement of long-term government bonds, all increased the amount of money in the economy, not sterilized by the Bank of Italy (Fratianni and Spinelli, 2001).

[20] As Menichella states in the Relazione for 1958 (p. 356, tr.), the increase in liquidity was coupled by warning the intermediaries "that we would not hesitated to take energetic measures if, taking advantage of the considerable liquidity released into the market, operators had gone beyond the limits of sound conduct."

[21] The spread steadily decreased from 2.5% in October 1957 up to -0.25% in April 1964.

Italy managed to exit the slowdown of 1958 with significant dynamism, making this event just a jolt in the tendency of stability and growth that started in 1948.[22] The retail-focused model peaked in 1963, accounting for 68% of all banking assets, thanks to a substantial involvement of the public banks. But this peak was a precipice, and the system was about to arrive at its "traumatizing end" (Gelsomino, 1999, p. 354).

1964-1969: The Fading Golden Age

The year 1964 marks the most prominent structural break in our results. This turning point was the direct consequence of a severe balance of payments crisis and, more importantly, the specific policy response enacted to resolve it.

1. The problem. In 1963, the virtuous cycle of the "economic miracle" broke down as wage growth outpaced productivity, fueling inflation, a sharp decline in the investment rate, and a deterioration of the current account (Gelsomino, 2024). The Bank of Italy initially maintained an expansionary stance, "breaking the rule of the game" (Fratianni and Spinelli, 2001, p. 423) to sustain a failing stock market and to protect corporate profits from wage increases.[23] This policy is harshly judged by contemporaries as a mere "palliative" (Modigliani and La Malfa, 1966, p. 247, tr.). In a fixed-exchange rate regime, preventing current account deficits from leading to a monetary tightening was inherently unsustainable. Indeed, by 1964, with a balance of payments in a deep deficit, the Bank was forced to abruptly switch to a restrictive policy.[24] It urged commercial banks to close all external positions, in a "sudden stop" that crunched domestic credit. As Sylos Labini (1999, p. 61, tr.) vividly puts it: "When you are driving at 150 or 200 km/h, faced with an obstacle, braking cannot be but hard and sudden." Stability was restored, but the engine of the "economic miracle"—capital accumulation and high investments—was broken.[25]

2. The policy response. The abrupt monetary tightening caused the economy to fall into deep stagnation.[26] To try and simulate the ailing investment, the state intervened in 1965, lever-

[22] From 1959 to 1962 the real GDP growth averaged 7.3% per year, inflation averaged 2.1% (data from Gelsomino (2024), except when otherwise noted). Between 1959 and 1961, Italy was a net importer of capital, with a balance of capital that averaged +141 million dollars between 1959 and 1962 (Fratianni and Spinelli, 2001, p. 422); this fueled investments and growth, both reducing the cost of money and providing funds to the capital market. For the period, investments averaged 30% of GDP, and productivity of work averaged a growth of 7.5%. Between 1958 and 1960, the cost of labor decreased by 8.5%, more than the prices, with a consequent increase in profits that further pushed for new investments (Gelsomino, 1999). Public debt decreased from 35% to 28%, with a consequent reduction in the interest rate on long-term bonds (BTP) from 7.3% in 1957 to 5% in 1961. Exports and imports grew as a result of the greater competitiveness of Italian products and an increase in the internal dynamism of both investments and consumption.

[23] As Gelsomino (1999, p. 364, tr.) effectively summarizes that the monetary policy objective was to "finance the imbalance in the accounts of companies caused by the wage explosion, through the increase in bank credit. Sylos Labini (1999) comments on political reasons affecting the decision.

[24] The balance of payments declined from +\$202M in 1961 to -\$308M in 1962, up to -\$485M in 1963 (Fratianni and Spinelli, 2001, p. 422).

[25] And yet, perhaps, the most important loss does not figure among economic statistics: "The crisis was the symptom of more profound changes: it was the first manifestation of a transformation process that, in the space of about a decade, would radically change the monetary situation of the country [...] In those measures, substantially, structural and cyclical reasons were mixed together" (Gelsomino, 1999, p.351-371, tr.).

[26] "Investments were slow to recover [...] Internationally, the capital accumulation rate of Italy was lower

aging the Special Credit Institutions (SCIs). This intervention was a two-fold strategy. On the demand side, public subsidies were introduced to stimulate the demand for SCI credit (whose scope was extended), and SCIs were permitted to expand their lending up to 30 times the amount of capital and reserves.[27] On the funding side, to make sure that no quantitative limits would constrain SCIs' ability to lend, a new regulation made the *cartelle fondiarie* eligible as mandatory reserves for all banks.[28] This regulatory change is explicitly designed to artificially inflate the demand for SCI's securities.[29]

3. The reaction of the banking system. This policy, designed to channel idle bank liquidity into the SCIs, created a set of controversial incentives that catalyzed a systemic shift away from traditional retail lending and towards the holding of public and semi-public securities. It provided a backdoor solution to the banks' most pressing problem: idle liquidity.[30] In the stagnant post-crisis environment, with the demand for short-term loans severely depressed, the regulation effectively made the *cartelle* a second best choice: more profitable than holding cash, and the eligibility for reserve compensated for the lower return compared to government bonds (see Figure 5.3).[31]

The consequence of this policy intervention is precisely captured by our empirical exercise. We can notice a structural collapse of the retail-focused business model, whose presence decreased from the 68% of total assets in 1963 to 6% by 1967. Mirroring this contraction, the securities-focused business model gains strength, covering up to 52% of the total assets in the same period. The results show that this shift was initially led by cooperative banks and, to a lesser extent, joint-stock banks (5.2f and 5.2d)—switching from the retail-focused business model—then met by the public banks by 1967 (5.2c).

The policy would not just be an "accident along the way" but rather the "first manifestation of a transformation process [...] that would radically change the monetary situation of the country" (Gelsomino, 1999, p. 351, tr.).

The Vicious Cycle

than most European countries. The other side of investment's laziness was the current account surplus [...] deriving from a low propensity to invest, not from an increase in the amount to save. Italy was exporting capital and labor: its economic system seemed incapable of utilizing all the available resources to grow" (Gelsomino, 2024, p.20f., tr., emphasis is our own).

[27] Subsidies involved both contributions for the payment of interest and a partial state guarantee. Initially directed toward specific sectors (i.e., agriculture and the housing industry), the span was gradually broadened, including all the SME in 1965.

[28] Previously, only savings banks were allowed to hold medium and long-term securities as reserve.

[29] "In the last two years, significant portions of the needs of these institutions [the Treasury and public entities] have been satisfied with short-term credit; since this could not continue indefinitely in the future, it is to be presumed that issues will increase considerably. It follows that *it will be increasingly difficult to create the necessary space to include larger issues by the ICS*" (Relazione for 1965, p.497, tr., emphasis is our own).

[30] In 1964, the contribution of the banking sector to the financing of the economy was as low as 17%, against the 50% of 1962 (Relazione for 1965, p.306).

[31] The government had indeed no incentive to let idle liquidity financing the public debt. Indeed, the goal was to "transfer funds from one category of uses to another and channel them towards those deemed most in line with the general interests" (Relazione for 1965, p. 451, tr.) Regulation denied the possibility of investing abroad.

This policy was effective in fostering new investment, yet it contained a critical flaw: the government's inability to cover the new expenses from credit subsidies without resorting to new debt. As the Bank of Italy's Relazione for 1966 identifies:

> The expansion of the fixed-income market is related to the increasing needs of the public sector: *the continuous overlapping of new expenses* deriving [...] by the intervention arranged between the end of 1964 and the spring of 1965 [...] in the presence of a sharp decline in public savings (Relazione for 1966, p.232, tr.)

To cover this "overlapping of expenses," the Treasury had to issue a continuously expanding supply of new public debt (see Figure 5.3). This set in motion a vicious, self-reinforcing cycle:

(i) Commercial banks gather retail deposits.

(ii) Following the 1965 regulation, banks use these funds to buy SCI and public securities: low-risk, liquid, and counted as an interest-paying mandatory reserve.

(iii) The SCIs use this funding to grant the subsidized loans.

(iv) The State, in turn, must issue new public debt to pay for these subsidies.

(v) To ensure this ever-growing supply of securities is placed without raising interest rates, the Bank of Italy commits to stabilizing its price, guaranteeing a floor on the secondary market (effectively a put option on public securities).[32]

(vi) Price stability further discourages banks from engaging in complex and riskier retail lending. The cycle repeats, strengthening with each rotation (Crosignani, 2021; Reinhart and Sbrancia, 2015).

This new equilibrium consolidated a system of "double intermediation." The banking sector was no longer primarily a creator of credit and assessor of risk; it was becoming a passive channeler of funds, moving money from household deposits directly to the state and the SCIs. And this leads to the quote that started this very analysis. Bank of Italy's governor Guido Carli, looking with concern at the situation, in 1966 warned how:

> a continuously expanding supply of public securities, coupled with price stability, will inevitably distort the banking system's structure over time [...] gradually replacing core banking operations (Relazione for 1966, p. 364, tr.).

While "double intermediation" is not an inherently bad equilibrium—it conveyed safer assets to banks and created economies of scale at the SCI level—its side effects in this specific context were profound: (i) as more securities enter the balance sheet of commercial banks, their soundness becomes progressively intertwined with the quotation of these securities. (ii) the

[32] The rationale here is clear: stable quotations lead to stable returns, and stable returns increase the demand. This is a winning bet, with a sizable surge in the demand for public securities in 1966, both from the banking sector—as a holder and a retailer—and from the private sector, a notable exception in Italian post-war history.

policy created privileged (subsidized) credit circuits and made the securities market reliant on public support (Relazione for 1966). (iii) The Bank of Italy, now obliged to defend securities quotations to safeguard the stability of the entire banking system, found its monetary policy autonomy fatally compromised (see Brunnermeier et al., 2016; Farhi and Tirole, 2018).

Thus, while the authorities seemingly managed an unprecedented crisis—investments grew robustly in 1966 and 1967—the short-term solution of 1965 had laid the ground for future tensions.

5.5 The Roots of Migration

The narrative of the vicious loop, however, leaves a critical question unanswered: why did banks willingly abandon their core business for this new model? The very fact that such an artificial incentive had to be created in 1965 suggests that *cartelle fondiarie* were otherwise a suboptimal investment.

Our data confirms this hypothesis. A simple investigation of the Return on Assets (ROA) for each business model reveals that, between 1951 and 1964, the securities-oriented cluster was a consistent underperformer in terms of profitability, without offering any significant reduction in risk—as measured by the Z-score (see Table 5.4).[33] The effects of the regulatory changes described above correlate with a marked difference in the analysis: after 1965, the profitability of the securities-oriented cluster aligns with the other models as it benefits from direct regulatory support.

Indentifying the Switchers: A Machine Learning Approach

While widespread, the migration toward a securities-oriented business model was not undertaken by all the intermediaries. Thus, to understand which factors significantly influence the probability of switching, we predict the probability at time t of switching to a securities-oriented business model in time t+1. To do this, we employ a Random Forest (RF) classifier, a machine learning algorithm well-suited for capturing the complex, non-linear relationships that a traditional logit model might miss.[34] The results are presented in Table 5.5.

In chapter 2 we found evidence of a major stress across small and medium banks (see Figure 2.8). The results of the Shapley regression highlight a subtler pattern: the primary driver was latent fragility. Banks with lower capitalization, lower liquidity, lower profitability (ROA), and higher non-performing loans (NPLs) were all significantly more likely to mi-

[33] The Z-score is an index of the distance-to-default of an institute, where the default event is defined as the moment in which the losses exceed the disposable capital and reserves. Formally Z-score$_{it}$ = [Equity$_{it}$ − μ_3(ROA$_{it}$)]/σ_3(ROA$_{it}$), where Equity$_{it}$ measures the share over total liabilities of capital and reserves of bank i at time t, and μ_3 and σ_3 are respectively the three periods rolling mean and standard deviation of the ROA of bank i at time t. The higher the Z-score, the lower the probability of experiencing a loss higher than the capital and reserves, and thus, the safer the bank.

[34] A full description of the model specification, the SHAP framework, and the controls is presented in section D.2.

Table 5.4: Multiple comparison tests

	Return on Assets (ROA)			Z-Score		
Year	KW	0v1	0v2	KW	0v1	0v2
1953	11.456**	-0.003**	-0.002**	1.7	-6.057	-14.456
1954	14.309***	-0.003***	-0.002*	1.359	-9.442	-27.812
1955	9.786**	-0.003***	-0.002	2.023	-1.926	-6.731
1956	18.601***	-0.003***	-0.002***	1.924	11.856	6.719
1957	6.176*	-0.002**	-0.002**	1.728	7.222	19.292
1958	8.585*	-0.002**	-0.000	2.601	17.508	7.985
1959	15.399***	-0.002**	-0.001	3.093	21.227	11.659
1960	14.252***	-0.002***	-0.001**	7.175*	30.532*	37.429*
1961	16.535***	-0.002***	-0.001***	2.167	28.802	22.027
1962	9.371**	-0.001**	-0.001*	0.017	0.034	-0.743
1963	7.236*	-0.001*	-0.001	0.207	-1.107	7.773
1964	15.171***	-0.002***	-0.001	4.059	29.668	23.526
1965	4.520*	-0.001	-0.000	2.464	-0.895	12.823
1966	0.950	-0.001	-0.000	0.020	5.028	2.504
1967	7.939*	-0.001	0.000	0.287	11.699	5.099
1968	6.254*	-0.001	0.000	0.066	15.832	5.842
1969	7.275*	-0.001	0.000	0.213	6.370	8.918

*The table presents the Kruskal-Wallis test to check the hypothesis of clusters originating from the same distribution. The test statistic is reported. The median difference between a specific couple of clusters is also reported; statistical significance is the result of the Conover-Iman test. Note: p-values are Bonferroni-Holm corrected for the problem of multiple comparisons. ***, **, *, denote significance at 0.1%, 1%, and 5% respectively.*

grate to the securities-oriented business model.[35] While further research on this point is needed, this may hint at a competitive disadvantage of those types of institutions in actively competing on the retail market, compared to the relative safety of holding public securities with stable returns, insulating them from cyclical fluctuations.

This "flight-to-safety" is then significantly catalyzed by the macroeconomic conditions. Unsurprisingly, the probability of switching increases in years with low GDP growth, as the prospects for traditional lending shrink. Still, the most powerful predictors of a switch are the interest rates, which precisely capture the opportunity costs at play: Higher long-term rates decrease the probability of switching. When long-term bonds offered a higher return, banks were less likely to lend on SCIs' securities. The *cartelle*, with a fixed 5% nominal rate of return, were an inferior, inelastic asset. Banks only preferred them when other long-term assets were unattractive.[36] On the contrary, higher short-term rates increase the likelihood

[35] This holds true even controlling for savings banks and geographic regions. Conclusions are consistent when subsampling for distinct starting business models (with only minor exceptions).

[36] To keep the *cartelle fondiarie* attractive, their nominal interest rate of 5% was increased to 7% in 1970, to match the significant increase of the BTPs interest rate, which surged from 5.8% to 7.7% between 1969 and 1970 (Gelsomino, 2024).

Table 5.5: Shapley regression results

(From, To):	(All, Sec.-F.)	(Retail-F., Sec.-F.)	(Bank-F., Sec.-F.)
Asset size (norm)	-0.0452	-0.0826***	-0.0631
Capitalization (MA)	-0.0183***	-0.0736***	-0.0749
Liquidity (MA)	-0.0254***	-0.0623***	-0.0715***
ROA	-0.0397***	-0.0873***	-0.0776***
Non-Performing Loans	+0.0456	+0.0578***	+0.0565***
Saving bank	+0.0175***	+0.0294	+0.0444
Systemic bank	+0.0011	+0.0028***	+0.0010
HQ in the North	-0.0031**	-0.0169	-0.0132***
GDP growth	-0.0619***	-0.0593	-0.0766***
Real Long-term IR	-0.1324***	-0.1313***	-0.1015
Real Short-term IR	+0.3042**	+0.2285	+0.0232
Post-64	+0.3056	+0.1683	+0.1879***
AUC	0.76	0.76	0.72
N	4827	2363	2464

of switching. This captures the indirect effect of a weakening macroeconomic condition.[37]

This evidence, taken together, paints a consistent picture. The 1965 regulation appears to have functioned as a form of regulatory support for the system's weakest players. It offered them an exit from a competitive retail market in which they were already underperforming, allowing a flight to a state-guaranteed, low-risk asset class.

5.6 Concluding Remarks

This chapter set out to provide a granular, bank-level perspective on the Italian Golden Age (1951-1969), challenging the monolithic narrative of stability. By identifying and tracking the evolution of bank business models, we have demonstrated that the period was, in fact, one of profound structural change.

Our analysis documented a "great reversal" in the mid-1960s, where the retail-focused business model, dominant during the "economic miracle" of the 1950s, collapsed. We showed

[37]Another compelling hypothesis may consider the indirect impact of monetary policy. As observed by coeval newspapers, banks used to directly intervene on the secondary market to sustain the price of their *cartelle* (*L'Unità, August 4th, 1974: "I piccoli risparmiatori delle cartelle gettati in pasto alla speculazione"—small savers of the cartelle thrown to speculation).* Thus, we may think that, as short-term rates rise, the demand for SCI-securities—and especially the inelastic Cartelle Fondiarie—declines, as investors shift towards more attractive short-term instruments. In response to this weakening demand, banks seem to intervene by purchasing more (or selling less) SCI securities, possibly to sustain prices in the secondary market, and match the declining demand. This behavior would naturally lead to an increase in the share of SCI-securities in their balance sheets, reinforcing the observed shift towards a securities-oriented business model. Still, those narrative, while suggestive, requires further analysis to be proved.

this was not a market-driven change, but a pseudo "flight to safety" where regulatory actions directly targeted the opportunity costs of bank assets, resulting in a distorted incentive structure for commercial banks.

In particular, the main argument of this work is that the policy born as a short-term response to the 1963-64 slowdown created a permanent and self-reinforcing vicious cycle of "double intermediation" that represents a critical counterpoint to the view of the Golden Age as a period of consistently high allocative efficiency (Battilossi et al., 2011). While the system successfully mobilized savings, our micro-level evidence suggests that post-1964, the allocative function of the banking sector largely resorted to the "boring" channeling of resources towards SCIs. This confirms the critical intuition of Guido Carli (1966) regarding the distorting effects of the "double intermediation" mechanism that ended up "gradually replacing core banking operations." We also empirically validate the hypothesis of Crosignani (2021), as weaker institutions were the most involved in this allocative involution. While the policy response was effective in stabilizing the cycle and managing public needs in the short run, the absorption of public-related securities by the banking sector (aligned with Reinhart and Sbrancia, 2015) started the "diabolic loop" that inextricably linked the solvency of the banking system to the stability of the bond market. This severely compromised the central bank's ability to implement an independent monetary policy, as financial stability became synonymous with stable securities quotations, setting the stage for the instability of the following decade.

These findings allow us to re-interpret the stress signals detected in the previous chapters. Those signals were not, as one might assume, linked to declining asset quality or plummeting earnings from bad loans. Rather, they were the symptom of an induced suboptimal capital allocation which swapped explicit credit risk for a latent, systemic overexposure to market risk—a fragility that remained hidden only thanks to the era's positive economic cycle and the Bank of Italy's active support.

The fragility of this new system was immediately exposed by its first real test. When international interest rates rose in 1969, the Bank of Italy was trapped. It could not raise domestic rates to defend the Lira without destabilizing a bond market "addicted" to the intervention of the central bank. In the summer of 1969, when the Bank was forced to suspend its support to stop the balance of payment deterioration, the result was telling.[38] As Gelsomino (2024, p. 33, tr.) notes, "this decision threw the bond market into crisis, which came to an almost complete halt." The Bank had to immediately reactivate the stabilization policy.

To conclude, we may say that, facing a novel challenge, the authorities managed to solve the short-term slowdown, and yet, they inadvertently created a long-term structural trap. A trap laconically summarized by Gelsomino (2024, p. 62): "the system was inconsistent and highly unstable." One may call this the unstable stability of the Golden Age.

[38]Committing to a stark defense of the long-term interest rates on a level lower than the international average prompted massive capital outflows from Italy.

Chapter 6

Concluding Remarks

This thesis began by confronting a central friction in Italian financial history: the reliance on "one-size-fits-all" analytical frameworks, often derived from the Anglo-American experience, which are ill-equipped to capture the unique, state-permeated dynamics of the Italian financial sector. As argued by Bordo (2018), treating banking crises as homogeneous events risks oversimplification. Indeed, we argued that the peculiar institutional context of Italy, defined by "backdoor" interventions and a deep bank-state nexus, creates non-negligible analytical challenges—from biased crisis chronologies to the identification of credit booms—that may obscure the true nature of financial instability (e.g., by hiding the presence of episodes of widespread distress that have escaped traditional narratives).

Our research addressed these challenges by developing a set of institutionally sensitive, data-driven tools applicable where traditional indicators may falter. Leveraging the granular richness of balance sheet data in the *Archivio Storico del Credito in Italia* (ASCI), we aimed to move beyond the "narrative approach." We did so not by substituting the established accounts, but by complementing them, extracting new information from a dataset whose potential had previously been only partially realized.

This is the process entailed in the "new perspective" that titles this work: a methodological bridge between macro-narrative financial history and micro-level bank analysis. By leveraging machine learning tools and composite risk frameworks, we demonstrated that the evolution of the banking sector is not characterized by the binary occurrence of major events alone, but by the continuous mutation of business models and the divergent adaptations of its actors to external forces (e.g., competition, the international context, or the regulation)—structural shifts that may reveal a silent accumulation of risk even without manifested panic. This perspective allows us to intervene in three fundamental debates in financial history.

First, we challenge the consensus in international macro-finance, which relies on "event-based" binary indicators to define financial instability (Bordo et al., 2001; Reinhart and Rogoff, 2008; Schularick and Taylor, 2012). Our findings demonstrate that in bank-based contexts with high state intervention, systemic risk does not always manifest as a visible crash. We showed that the canonical crises of 1893, 1907, and 1921 were largely idiosyncratic events, where the narrative resonance of the collapse of major actors fostered an overestimation of the systemic contagion (aligning with the recent revisions by Vercelli, 2022; Battilossi et al., 2011). Conversely, we uncovered a "ghost" rise in systemic stress in the mid-1960s, a period largely overlooked in narrative accounts. These results align with Baron et al. (2021) on the existence of "banking crises without panic": distress episodes where regulatory forbearance masks the more resonant symptoms of failure. Yet, we conclude that in contexts characterized by thin stock markets, profitability metrics may serve as a robust alternative to equity prices for an objective, quasi-real-time, and quantitative proxy for distress, offering both a corrective to the "big bank bias" inherent in narrative history and a robust indicator where market signals are unreliable. Moreover, our reassessment of long-run instability extends to the predictors of distress: While aggregate credit booms are traditionally considered the single best predictor of banking crises (see, e.g., Schularick and Taylor, 2012), our micro-level evidence suggests they are not a universally valid proxy, particularly in historical settings undergoing a financial deepening (Bartoletto et al., 2018; Rajan and Zingales, 2003). We demonstrate that, historically, credit expansion correlates with instability only given certain conditions—specifically, when growing volumes of credit are decoupled from its efficiency. By methodologically framing the distinction between "good" and "bad" booms (Dell'Ariccia et al., 2016; Gorton and Ordonez, 2020), we identified two distinct regimes of "bad" expansion: the exuberance of the period 1925-1930 and the inefficient growth of the 1960s. This parallel suggests that both the laissez-faire of the interwar period and the financial repression of the Golden Age fostered suboptimal capital allocation, increasing the latent fragility of the intermediaries by a slow erosion of their efficiency (Berger and DeYoung, 1997; Engle and Ruan, 2019).

Second, we intervene in the historiographical debate regarding the structural (in)stability of the Italian banking system, challenging the dichotomy that characterizes local banks as stabilizers and universal banks as vectors of instability (Polsi, 1996; Confalonieri, 1974, 1994). We align with both historical and economic literature in highlighting that, despite their local roots, small banks were structurally exposed to risk due to reduced efficiency (Di Martino, 2000; Molteni, 2023; Baron et al., 2023; Stimpert and Laux, 2011). Consistent with the credit channel literature (Bernanke, 1983; Kashyap and Stein, 2000), we show that these institutions bore a disproportionate burden of adjustment during both the major downturns of the 1890s and the Great Depression. As a result, we claim that the mixed banking model was not inherently flawed; rather, the regulatory vacuum surrounding it allowed for the proliferation of specific governance failures in the management of the bank-industry relationship (Battilossi, 2009).

Third, our work confronts the historiography of the post-war "Golden Age." While often interpreted as the legacy of the successful technocratic design of the banking law of 1936 that insulated the system from risk (Cotula, 1999; Guiso et al., 2006), our findings point to a reassessment rooted in the political economy of banking (Calomiris and Haber, 2014). We argue that the regulatory framework effectively subordinated the logic of market efficiency to political imperatives, a dynamic that accelerated after the economic downturn of 1963. Driven by a distorted incentive structure that favored the absorption of public securities over private lending (Carnevali, 2005), banks effectively underwent a profound risk transformation that progressively swapped explicit credit risk for a latent but systemic overexposure to market risk. This suggests that the stability of the "Golden Age" was not inherent, but politically induced and sustained by the exceptionally favorable international context. When those economic conditions cooled, the legacy of this institutionalized intervention was a growing capital misallocation and state dependence. This dynamic effectively incubated the "diabolic loop" (Farhi and Tirole, 2018) that would define the instability of the 1970s.

As a byproduct, this thesis delivers an original, flexible, and replicable methodological toolkit calibrated for financial contexts where market signals are thin or distorted by intervention. We introduce a continuous Stress Barometer based on profitability, offering a solution for measuring fragility when market signals are unreliable. We complement this with an original decomposition of ROE, to distinguish "good" from "bad" credit booms, providing a micro-founded perspective on *how* banks lend to complement traditional measures of *how much*. Finally, we present the SCoPE, a machine-learning framework that micro-validates macro trends, providing a dynamic mapping of how business models—and their inherent risks—evolve over the long run. These tools offer an alternative for scholars analyzing financial contexts with similar data and constraints.

To conclude, the overarching lesson of this analysis is that financial stability and fragility in Italy cannot be understood as purely market-driven phenomena. Rather, they are the endogenous outcome of an inextricable interplay of incentives, constraints, and political imperatives of the prevailing institutional framework.

This work is not an aseptic exercise: it is a contribution to my very view of financial history (and hopefully the reader will forgive moving from "we" to "I" for these last paragraphs). When I first read Kindleberger's *Manias, Panics, and Crashes*, the drawing of a discipline divided between historical uniqueness and economic regularities was striking.[1] I set out to defend the economist's view, to find the patterns that history might have missed, with an immature and blind ambition of changing history. Years later, I exit this fight defeated. My view did not change history (how could it have?), quite the contrary. Approaching history changed my view. In my work, I found both the uniqueness and the patterns, and I came to realize how inextricable they are. No, I don't view history as a sequence of unique events any more than I feel like patterns are the solution. As Mark Twain once said, "history doesn't repeat itself, but it often rhymes." I've come to appreciate this rhyming, not looking at these thousands of data as mere numbers anymore, but as a slow-moving ecosystem, a natural ecology in which multiple diverging forces—from the authorities' goal of stability, to the single speculative bank seeking to maximize its profits—interact, in a leitmotiv of stress and adaptation; and the results are not ubiquitous. As much as in the historical forces and between history and economics, it's not an exercise of strength, it's a necessary compromise in which "it is not the most intellectual of the species that survives" but rather "the one that is best able to adapt and adjust to the changing environment in which it finds itself" (Megginson, 1963, p. 4). As this analysis hopefully has shown, the results of this organic adaptation are compelling, thought-provoking, counterintuitive at times, and yet "fascinating, challenging

[1] The "Historians view each event as unique. In contrast economists search for the patterns in the data, and the systematic relationships between an event and its antecedents. History is particular; economics is general"—a quote you have stumbled upon multiple times during this thesis.

and of overwhelming importance to us today, as we seek to grasp our past's lessons for our future" (Diamond, 1997, p. 11)

Borrowing the eminent and self-deprecating closing line of Alessandro Manzoni's *I Promessi Sposi*, let me conclude this story with the hope that "if you did not dislike it entirely, you'll think kindly of the one who wrote it [...] But if, instead, we have succeeded in boring you, believe me, it wasn't on purpose."[2] A fitting epilogue, perhaps, for a work whose ambition has always been to provoke more thought than fatigue.

06/02/2026 09:37:20
MICHELE CALABRIA

[2]"La quale [storia], se non v'è dispiaciuta affatto, vogliatene bene a chi l'ha scritta [...] Ma se in vece fossimo riusciti ad annoiarvi, credete che non s'è fatto apposta."

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Appendix A

Appendix for Chapter 2: Bank Profitability and Financial Instability: A Barometer of Financial Stress for Historical Analyses

A.1 Additional Material

Figure A.1 reports the probability of stress computed for selected subsamples: size quintiles (XL, L, M, S, XS), legal category (SOC, CRO), geographic location (North, Center, South). These data are an expansion of Figure 2.8, presented in the main body.

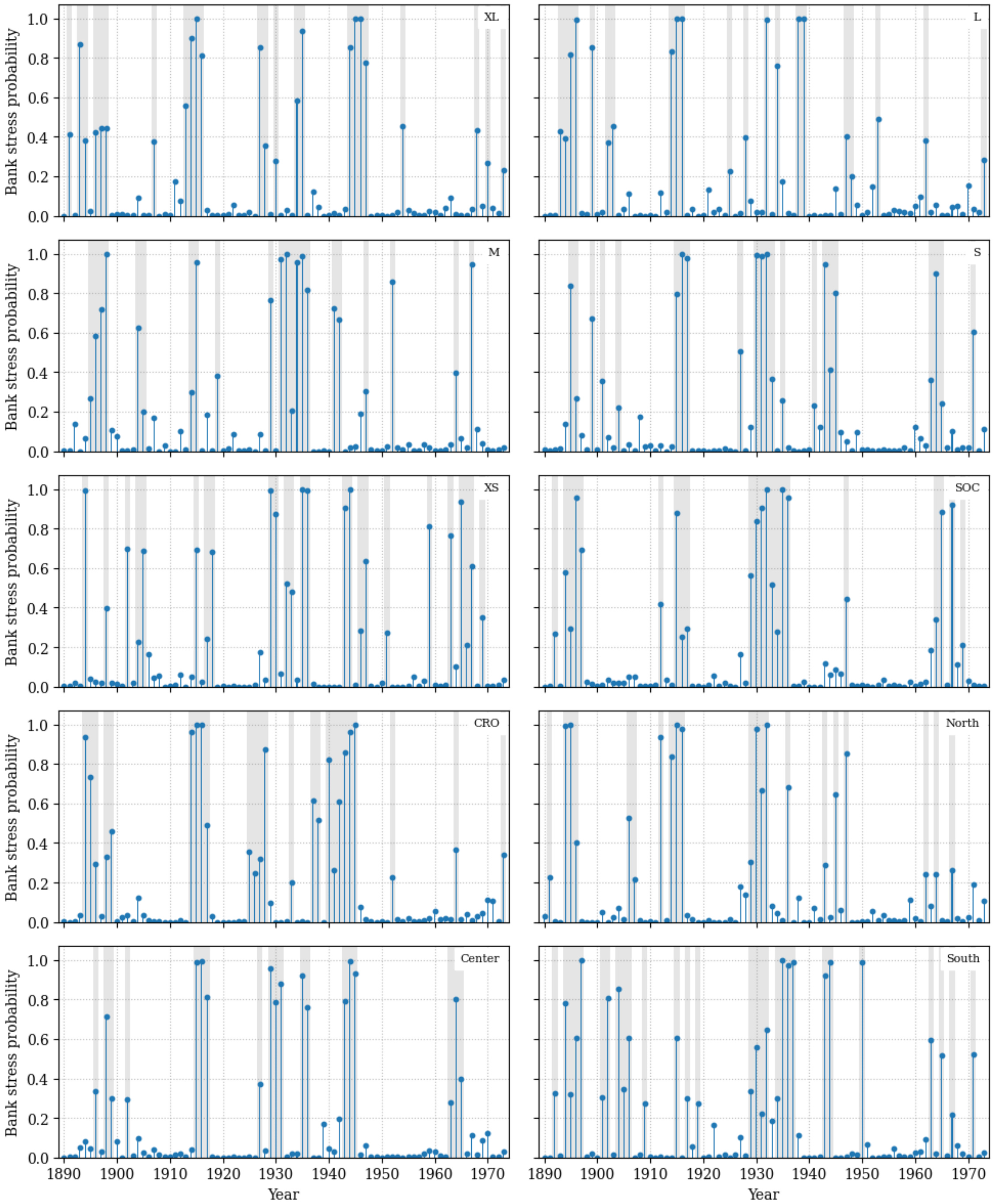
A.2 Robustness Checks

To ensure the reliability of our Bank Stress Index (BSI) and the related Bank stress barometer, we conducted a comprehensive sensitivity analysis to verify that its signals are not an artifact of specific modeling choices. Our approach tests the indicator's robustness across key dimensions of its design: the underlying data and the sample composition, the aggregation methodology, and the two primary assumptions of our calibration procedure.

Exposure to Sample Selection Bias

As a preliminary step, we address the likelihood of sample selection bias in our primary input variable, the Return on Equity (ROE), to confirm the representativeness of our dataset. Following the procedure proposed by Natoli et al. (2016), we checked whether sample selection bias is a statistically significant concern in our data by benchmarking the working sample against a closed panel composed of banks that survived the entire 1890-1973 window (24 banks, 2,016 observations). The authors show that closed samples replicate the growth dynamics of national aggregates with near-unit correlations, supporting the use of ASCI micro-data for macro-consistent inference. Here, for the ROE we tested for systematic differences between the two samples, both in levels and in growth rates, using HAC-robust

Figure A.1: The heterogeneous distribution of risk: full data



The figure reports the stress probability of the barometer for selected subsamples. XL, L, M, S, XS represent total assets quintiles computed within each year (i.e., in year t, a bank is classified as XL if its total assets fall within the top 20% of the year t total assets distribution). We considered only legal categories present throughout the sample, that is, joint-stock banks (SOC) and savings banks (CRO). North, Center, and South represent the macro-region of the HQ. Grey bars represent years with a stress probability above average (19%).

Table A.1: Bank stress barometer: alternative specifications

Parameter	Main exercise	Alternative specifications
Sample	Without BP	With BP
Weighting w	Variance	Equal weights
Crisis baseline S^c	90$^{\text{th}}$ percentile	$\{80^{\text{th}}, 85^{\text{th}}, 95^{\text{th}}\}$
Normal baseline S^n	50$^{\text{th}}$ percentile	$\{20^{\text{th}}, 30^{\text{th}}, 40^{\text{th}}\}$
Crisis probability p^c	0.8	$\{0.7, 0.9, 0.95, 0.99\}$
Normal probability p^n	0.02	$\{0.01, 0.03, 0.04, 0.05\}$

The table presents the set of alternative specifications tested to assess the stability of our main results.

mean-difference tests with Bonferroni-adjusted p-values. We do not detect any statistically significant difference at a 1% confidence level, suggesting that the working sample tracks the closed sample tightly, thus mitigating the selection bias concern. Result are robust to (i) using the Holm correction for multiple comparisons testing; (ii) running the testing year-by-year instead of the whole sample (repeated cross-section); (iii) using assets-size-weighted means instead of simple means.

Sensitivity to Sample Composition and Benchmarking

Next, we visually inspect the impact of two foundational modeling choices: the sample composition and the benchmarking of aggregated annual values. We plot our baseline indicator against two key alternatives. First, an indicator constructed using a broader sample that includes cooperative banks (see Figure A.2a). Second, an indicator constructed using a static, full-period median benchmark for normalization instead of the dynamic HP-filtered trend (Figure A.2b).

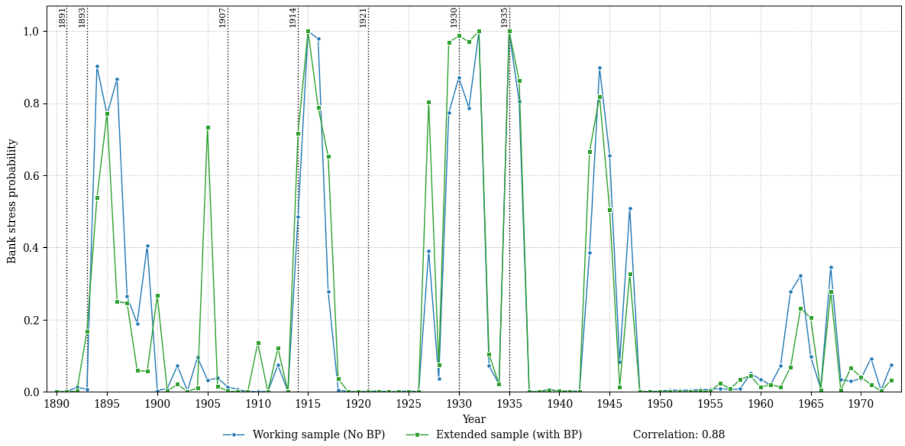
Both alternative series closely track the dynamics of the baseline indicator, indicating a strong robustness of the results. Notably, while minor deviations in the level of the index are expected, the timing and magnitude of key signals remain consistent during known historical banking crises and during the periods of financial stress signaled by the main indicator.

Iterative Testing

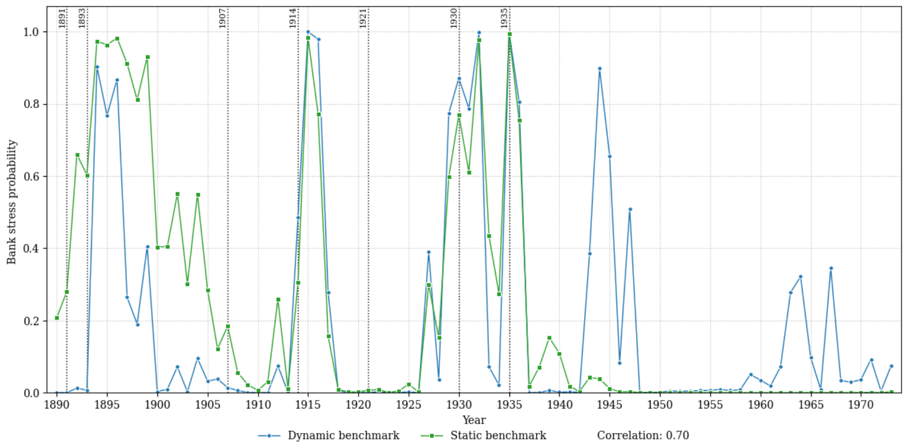
We quantify the overall consistency across a wide battery of alternative model specifications. We generated a full set of indicators by fitting every combination of the parameters outlined in Table A.1, for a total of 1,600 alternative specifications. Then, we computed a pairwise correlation matrix to assess the co-movement of the alternative specifications with the main model.

Table A.2 reports the descriptive statistics of the correlation of alternative specifications with the main model. On average, the 1,600 specifications show a remarkable correlation of 0.79 with the main specification. Then, to infer the relative importance of each dimension, we analyze how controlling for a specific parameter choice affects the correlation with the baseline. If holding a parameter constant between a subgroup and the baseline model increases the average correlation relative to the full sample, it demonstrates that varying this parameter was a significant source of model disagreement. For example, holding constant the variance

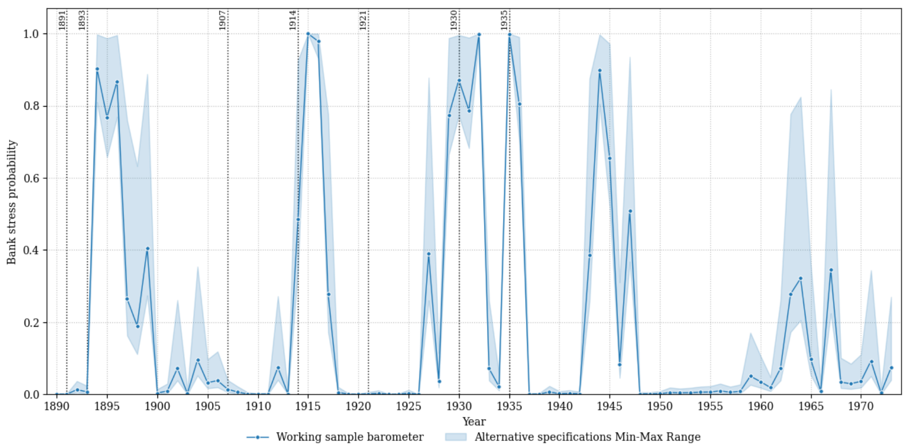
Figure A.2: Assessing the robustness of the barometer of bank stress



(a) Alternative sampling



(b) Alternative benchmarking



(c) Alternative calibration

The figure shows the barometer with different modeling choices. Panel A.2a includes the cooperative banks. Panel A.2b tests a static benchmark. Panel A.2c shows the min-max range of all alternative calibration parameters presented in Table A.1.

Table A.2: Correlation with the main model, descriptive stats

Controlling for...	–	Sample	w	S^c	S^n	p^c	p^n
N	1600	800	800	400	400	320	320
Mean	0.789	0.851	0.927	0.789	0.789	0.794	0.788
Std. Dev.	0.152	0.129	0.056	0.152	0.152	0.162	0.156
Min	0.543	0.686	0.838	0.543	0.543	0.546	0.562
25%	0.667	0.725	0.877	0.667	0.667	0.674	0.675
50%	0.788	0.830	0.907	0.788	0.788	0.806	0.793
75%	0.899	0.990	0.990	0.899	0.899	0.915	0.899
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000

The table presents the descriptive statistics of the correlation of each alternative specification with the main model (Sample without BP, w=variance-based, $S^c = 0.9,\ S^n = 0.5,\ p^c = 0.8,\ p^n = 0.02$), and holding constant selected dimensions.

weighting w, the correlation across the models increases from 0.79 to 0.93, indicating that altering the weighting is a key driver of model variability. Crucially, none of the calibration parameters, $S^c,\ S^n,\ p^c,\ p^n$, significantly alters the main prediction, with similar descriptive statistics to the non-controlled specification, providing strong evidence that our indicator's signal is not sensitive to these more subjective choices, and confirming its methodological robustness.

Sensitivity to Calibration Parameters

The calibration of the indicator to a probability scale involves the most subjective parameter choices. To assess their combined impact, we isolate the effect of calibration by generating a family of 400 indicators where only the calibration baselines and probability anchors vary, while the sample, benchmark, and weighting are held constant. We then plot our baseline indicator against the min-max interval of this family of specifications, creating an "uncertainty band" around the main signal (see Figure A.2c). A narrow band indicates that the indicator's core signal is robust, while a wide band suggests it is sensitive to the specific calibration assumptions.

The results confirm the indicator's robustness. The uncertainty band is exceptionally narrow during tranquil periods, indicating a high degree of consensus. As expected, the band widens moderately around high-stress episodes. This reflects minor differences in the timing and magnitude of the alerts, as some specifications are inherently more sensitive and signal stress earlier than others. Nonetheless, the core high-stress signals remain remarkably consistent across all calibration choices, confirming the reliability of the indicator's warnings.

Appendix B

Appendix for Chapter 3: Breaking the Cycle: Bank Profitability and the Anatomy of Italian Credit Regimes

B.1 Robustness Checks

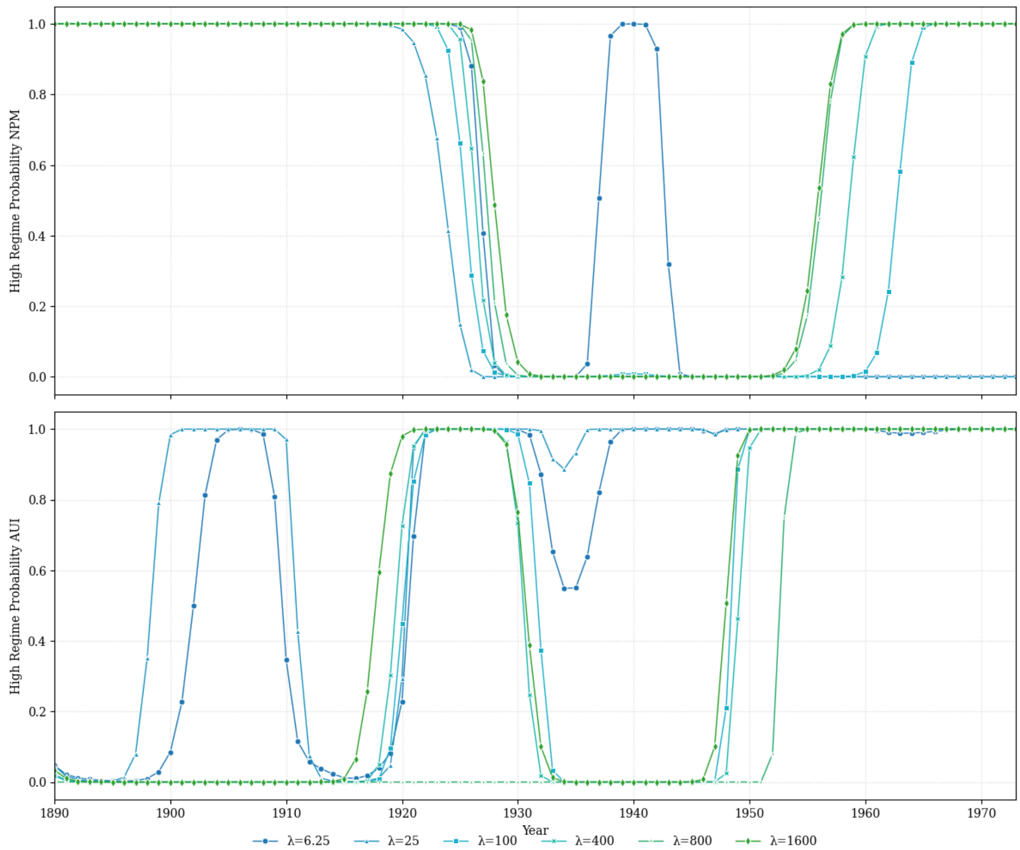
To ensure our identified regimes reflect structural shifts rather than short-term cyclical dynamics, the main empirical exercise relies on Hodrick-Prescott (HP) filtered trends. Our main results adopt the standard value for annual data (λ=100). Still, to ensure that the identified regimes are not an artifact of this specific parameter, we test the robustness of the Markov-switching model to a wide range of alternative λ values. Figure B.1 plots the smoothed probabilities for the high-regime state of both NPM and AUI across six different λ specifications, ranging from a highly flexible trend (λ=6.25), close to the original, unfiltered series, up to a very stiff, near-linear trend (λ=1600). The results show a high degree of robustness.

For the Net Profit Margin (NPM) (top panel), trends derived with very low λ values (e.g., λ=6.25) are, as expected, more sensitive to temporary shocks. They tend to misinterpret the induced overheating of World War II as a regime shift, which in turn masks the more subtle but persistent structural switch seen in the post-war period. However, for all specifications with λ higher than 25, the timing of the regime shifts is consistent.

A similar pattern holds for the Asset Utilization Intensity (AUI) (bottom panel). The timing of the high-activity regimes is remarkably stable across most specifications. The primary exceptions occur when the trend component includes a significant cyclical noise (i.e., $\lambda \leq 25$). In these cases, the model identifies the cyclical upturn during the Giolittian period and, notably, becomes highly uncertain during the Great Depression. This ambiguity is resolved by using a stiffer filter ($\lambda \geq 100$), which isolates the clear structural break of that era. In turn, the stronger filter (λ=1600) becomes insensitive to the boom of the 1920s.

Overall, this check confirms that our identified regimes are a robust feature of the data's long-

Figure B.1: Markov Switching Model: Alternative λ



The figure shows the sensitivity of the Markov Switching Model's results to a different λ for the HP-filter, indicating the "strength" of the filtering. With a lower λ, the series is more sensitive to short-run cyclical fluctuations, while a higher λ implies a stronger smoothing.

term structure, not a mere consequence of our baseline λ=100. Furthermore, it validates our methodological choice: by focusing on the moderately filtered trend components, our model successfully identifies persistent structural regimes while avoiding short-term cyclical dynamics that are, by design, not the focus of this analysis.

Appendix C

Appendix for Chapter 4: Laws, Orders, and Crises: the Italian Banking Sector Through the Age of Extremes

C.1 Time Varying Contour Lines

In the main analysis, the SCoPE system utilizes a *pooled estimation* strategy to generate the contour lines that define the risk landscape; that is, all the available data are used to calibrate the risk thresholds at once. As we argue in the main body, this was a deliberate prioritization of structural stability: By holding the topographic elements constant, we ensure that any regime dynamic is captured endogenously by the movement of banks (density) across the Map, rather than by altering the metric space itself, avoiding any "moving target problem".

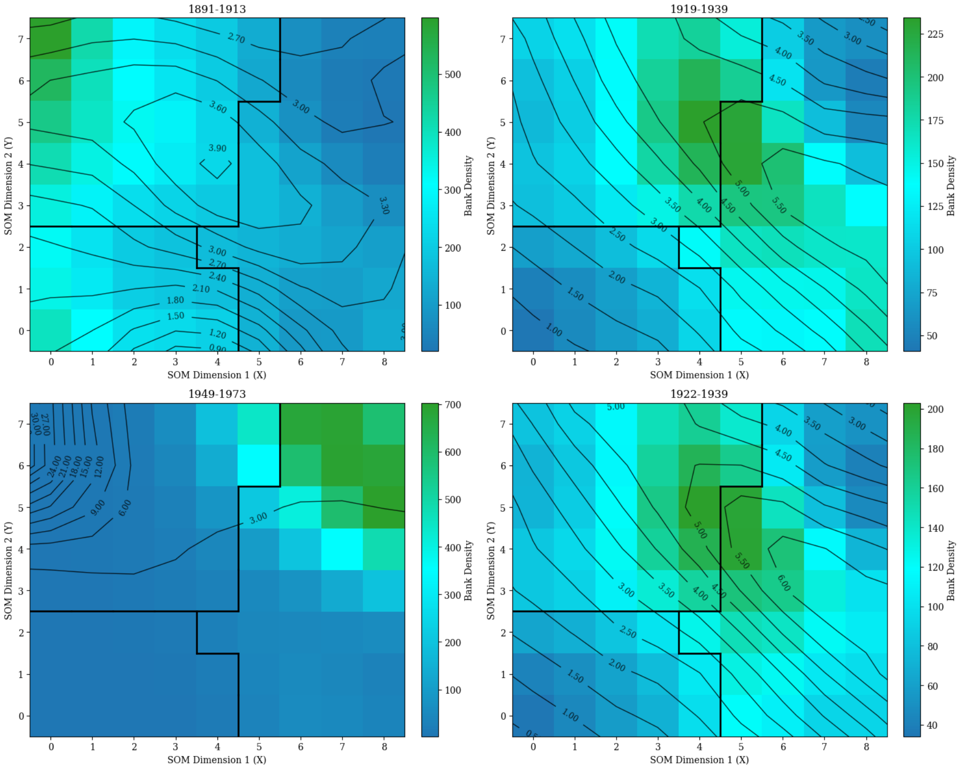
Yet, one may argue that the relationship between business model and risk is hardly time-invariant, but rather the result of a time-varying institutional framework and exogenous dynamics (e.g., market competition and macroeconomic conditions). To address this reasonable critique, in this appendix, we relax the assumption of time-invariance, re-estimating the contour lines for selected sub-periods, as presented in Figure C.1.

The comparison between regime-specific estimations validates the fundamental dichotomy in the historical evolution of the Italian banking sector found in the main analysis.

During the pre-WWII period, the banking sector was characterized by significant heterogeneity, with a well-defined risk landscape consistent with the one found in the main exercise. Conversely, the post-war period is characterized by structural homogenization, with a concentration of the entirety of the bank population in the North-East corner. This process effectively leaves the complementary zones sparsely populated, and creates a paradoxical visual dynamic: the risk gradient appears flattest where the banks are, and steepest where they are not.

This result highlights a critical interaction between the structure of the banking system and

Figure C.1: Time Varying Contour Lines



The figure shows the evolution of the relationship between business models and latent risk by allowing the contour lines of the Map to change. Four periods are presented: the liberal period pre-WWI (1890-1913), the interwar period (1919-1939), the post-WWII period (1949-1973), and the fascist period (1922-1939). The interpretation of the contour lines is consistent with the one presented in the main body of this chapter. The number of contour lines has been doubled compared to the main body to better grasp the patterns of interest.

the mathematical framework of the contour calibration. Splitting the sample into shorter, regime-specific sub-periods mechanically reduces the number of observations and compresses the variability of business models, particularly if banks within a regime exhibit higher homogeneity. It follows that the reduction in the sample support deprives the algorithm of the heterogeneity required to define a robust local gradient across the entire Map.

As the Map preserves the topology on the inputs, the clustering of observations in neighboring neurons reflects a lack of variance among structurally similar institutions. Mathematically, this results in a flat surface where contour lines are sparse or absent. In the empty regions, lacking empirical anchor points, the algorithm is forced to linearly extrapolate from the edge of the populated cluster. It projects a continuation of the local slope into the void, resulting in the steep but artificial gradient visible in Figure C.1.

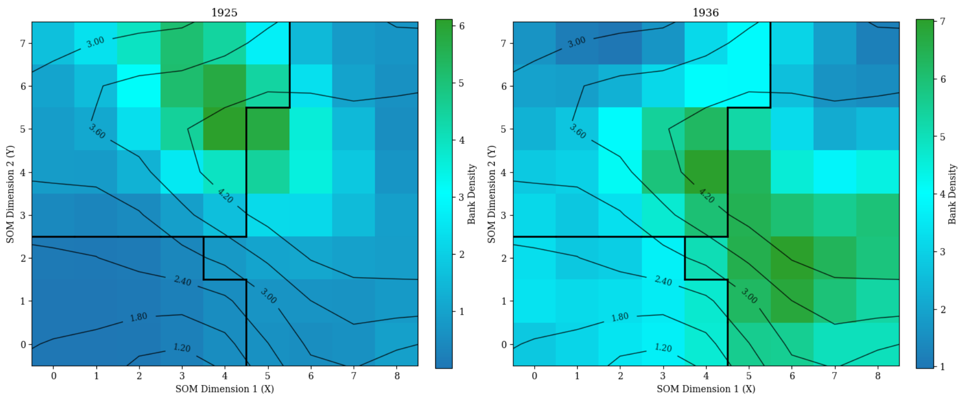
These results illustrate the inherent friction involved in overlaying mismatching objects: a fixed Map (which assumes a stable coordinate system) and time-varying contours (which require a well-defined local density). Still, they should be interpreted neither as a model flaw nor as a dismissal of the value of time-varying analyses. Rather, they serve as validation of a fundamental methodological principle: a fixed Map necessitates fixed contour lines. The reason is that, by pooling the dataset, we ensure that the Map retains the "historical memory" of fragility. The presence of pre-war failures in the training set anchors the risk coordinates, allowing us to accurately quantify (e.g.) that the post-war period is structurally safer than the pre-war era.

On the contrary, if the research objective were strictly to study the regime-specific association between business models and risk, the appropriate approach would be to re-train the Map for that specific sub-period. This would ensure that observations occupy the entire topological space within each regime, avoiding the extrapolation artifacts observed here. While such an exercise represents a compelling avenue for future research, it goes beyond the scope of this analysis.

C.2 Additional Material

The SCoPE system, being a visual and flexible tool, would have allowed for a plethora of alternative visualizations. For the sake of time and space, in the main body, we have provided just a minimal part of the available information. In Figure C.2 we present how the positioning on the Map of cooperative banks changed between 1925 and 1936, at the boundary of the data lacuna of 1926-1935. The movement from North toward Southeast is consistent with the one identified in the main body for the remaining institutions. In Figure C.3 we offer a complete picture by presenting the bank distribution on the Map for all the years in the sample (1891-1973).

Figure C.2: Cooperative banks before and after the Great Depression



The figure reports the distribution in the balance sheet composition Map of cooperative banks (BP) in 1925 and 1936. The dynamics are consistent with the one described in the main body.

Figure C.3: Bank density (all banks, 1891-1908)

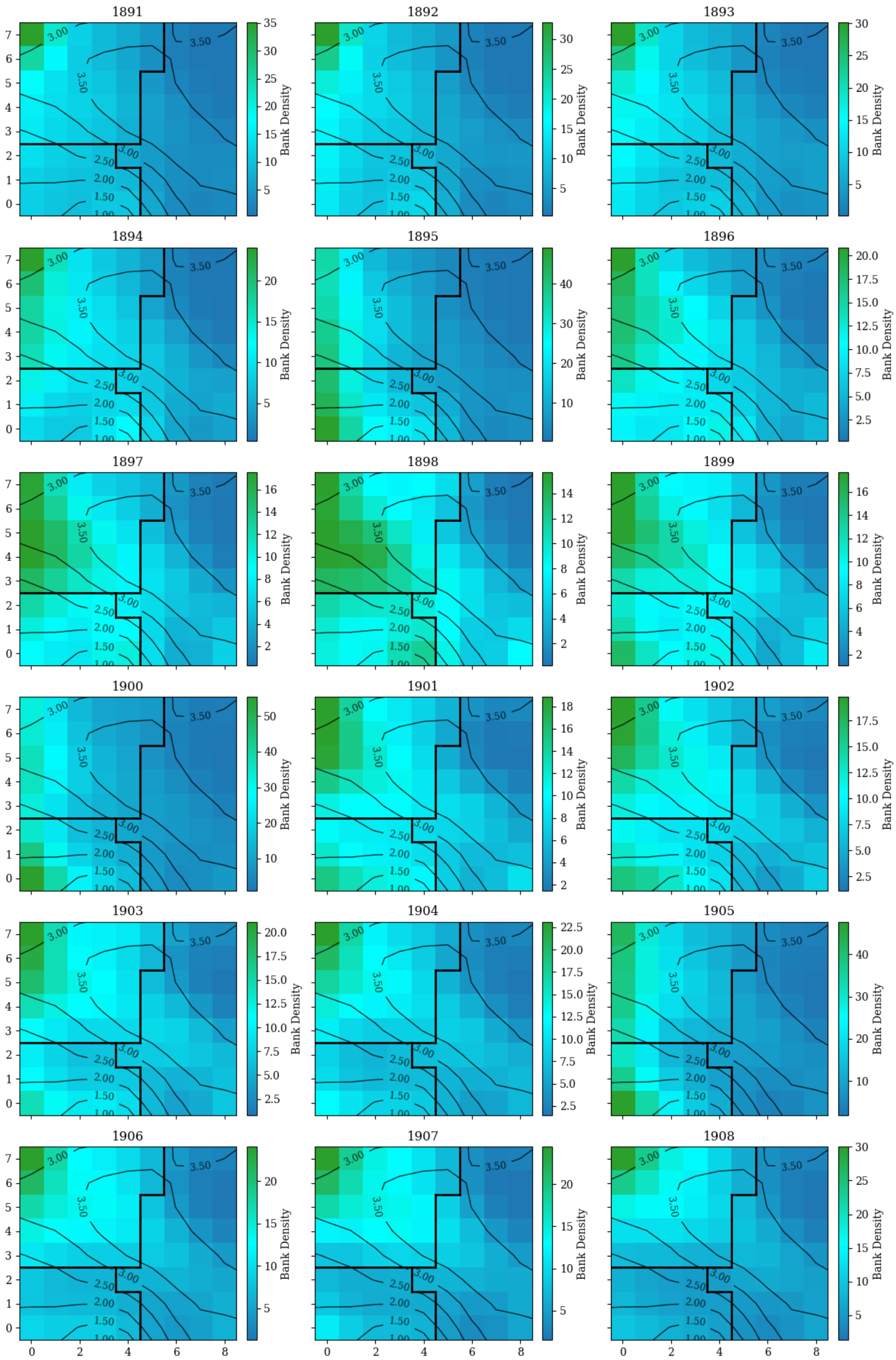


Figure C.3: Bank density (all banks, 1909-1926)

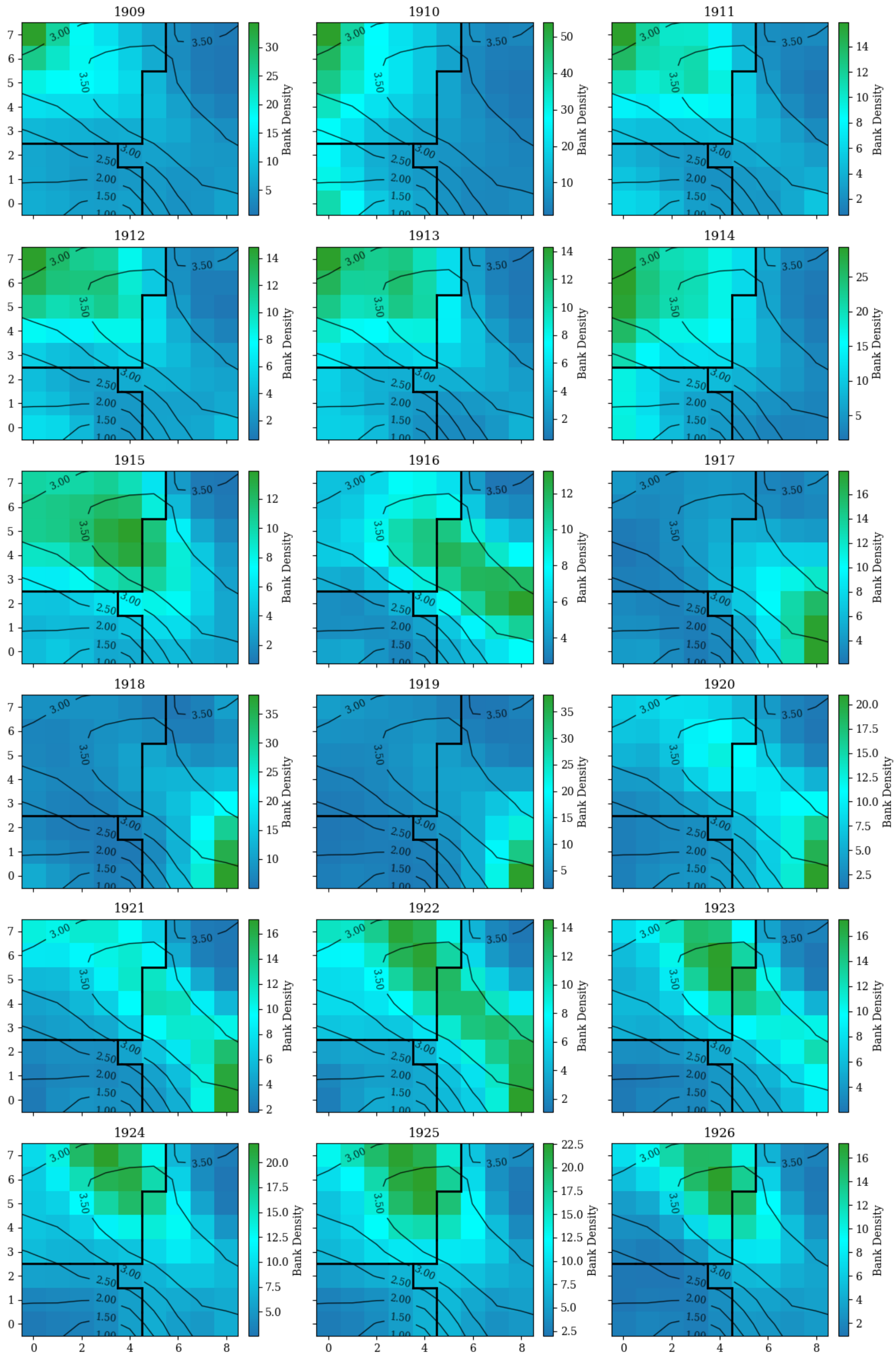


Figure C.3: Bank density (all banks, 1927-1944)

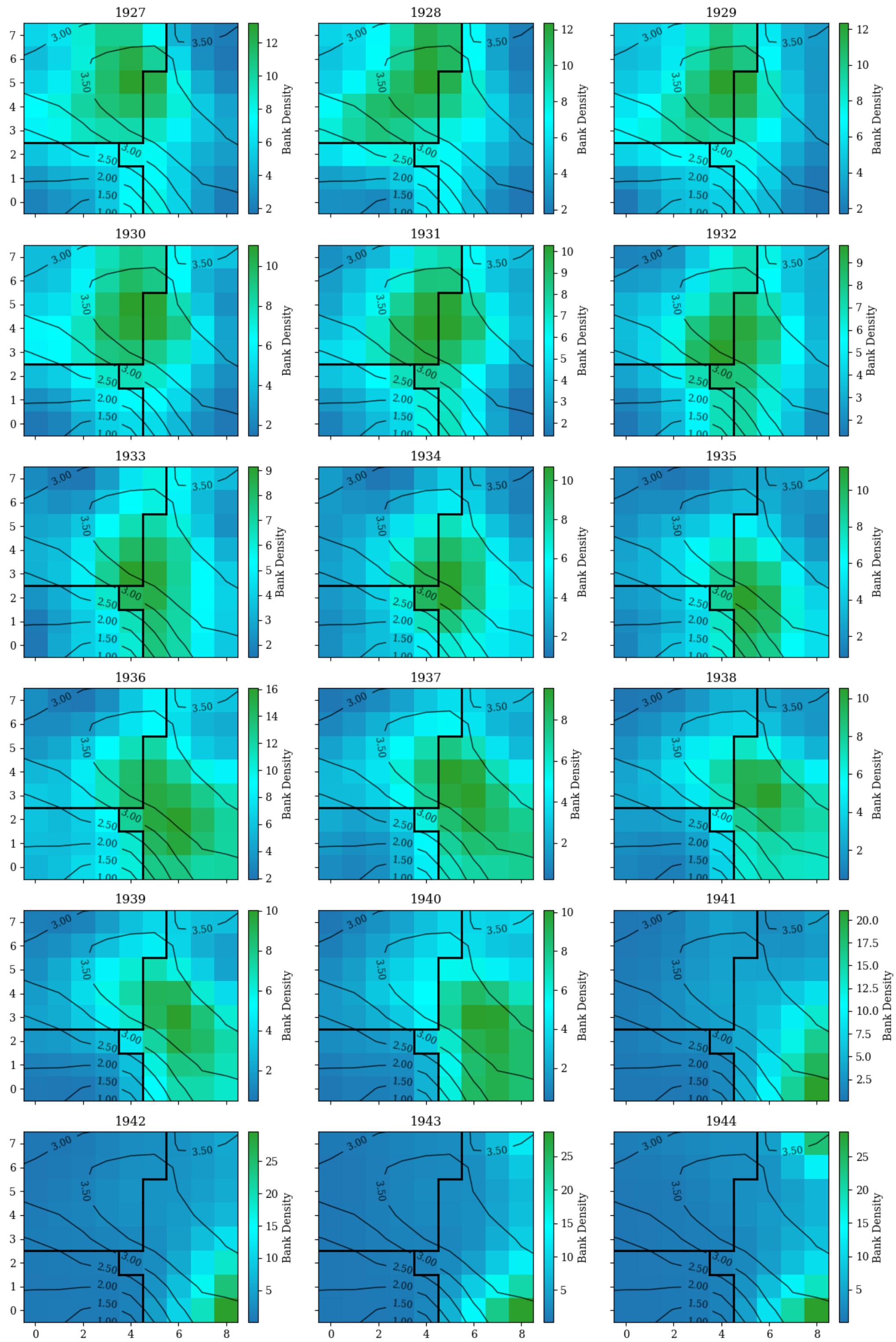


Figure C.3: Bank density (all banks, 1945-1962)

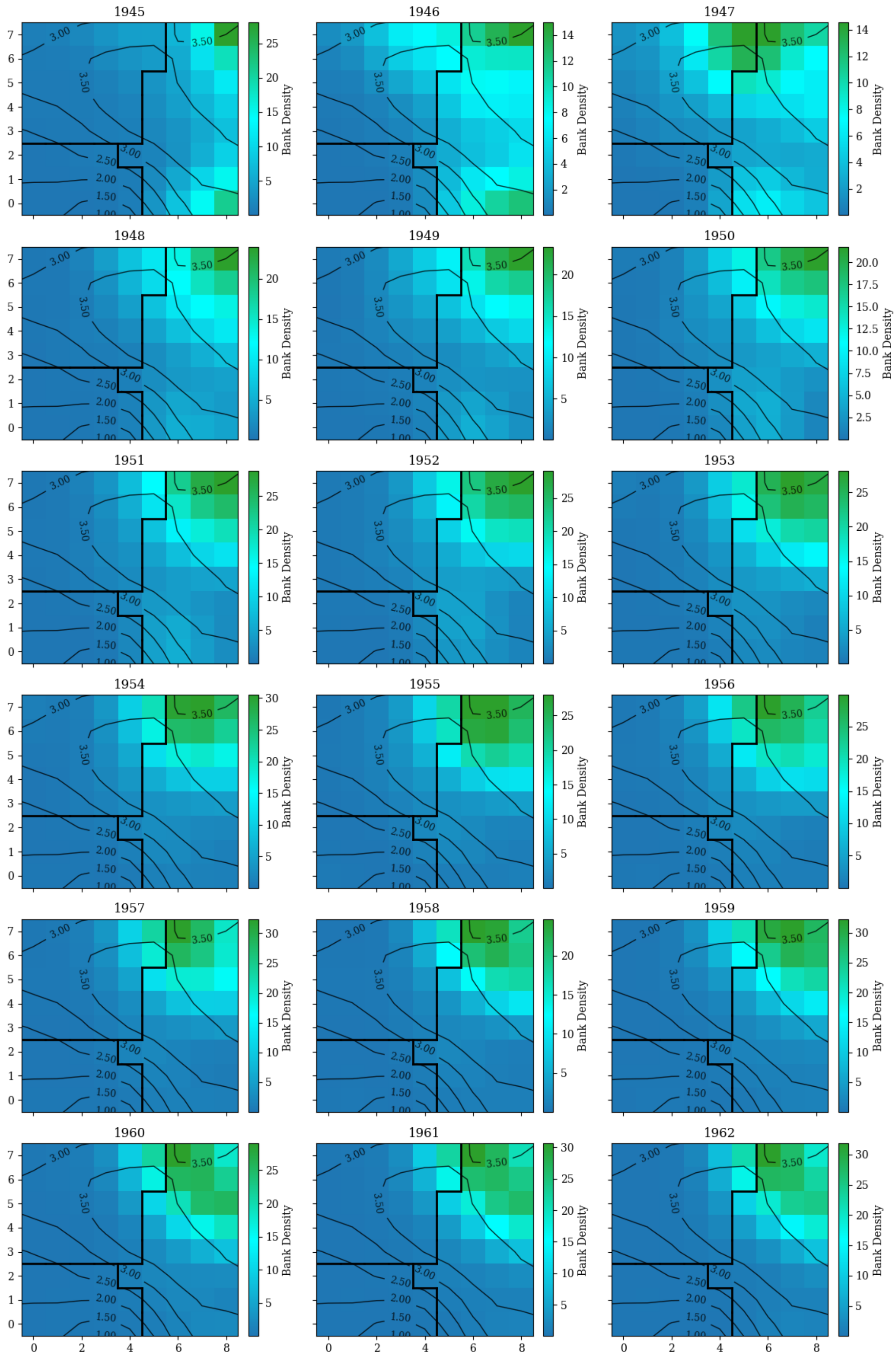
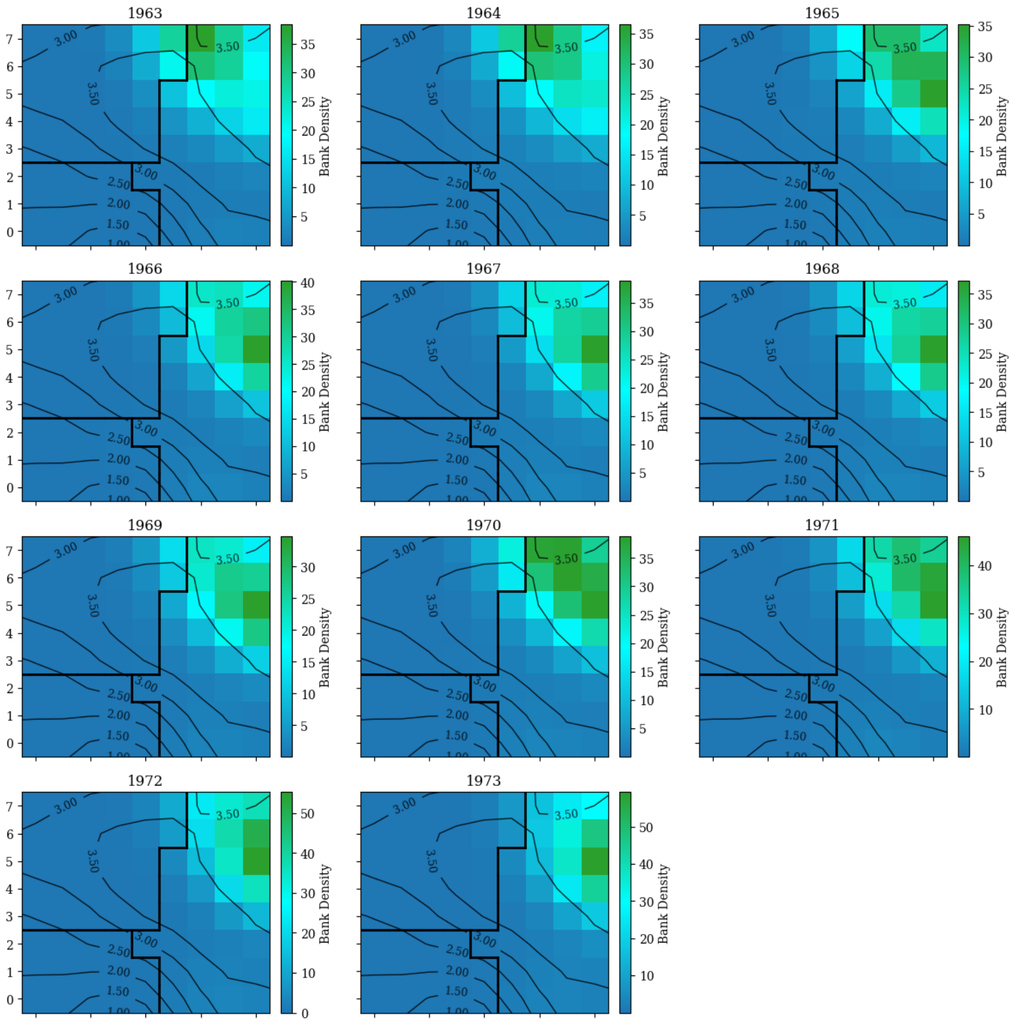


Figure C.3: Bank density (all banks, 1963-1973)



The figure plots the number of bank-year observations in each node of the Map for the analyzed time period (1891-1973). The position on the Map (and thus the movements) represents a distinct bank asset and liabilities mix (see Table 4.2). Green shades indicate a higher density of observations in the node, blue shades denote sparser populated ones.

Appendix D

Appendix for Chapter 5: Unstable Stability: Banks' Business Model in the Years When Banking Was Boring (1951-1969)

D.1 A Brief Presentation of the *Credito Fondiario*

Credito fondiario is a specialized system of long-term mortgage lending funded not by deposits, but by the issuance of special mortgage bonds known as *cartelle fondiarie*.

Introduced in Italy in 1866 (Law n. 2983) and later governed by legislation in 1905 (R.D. n. 646) and 1910 (R.D. n. 472), its primary goal was to provide liquidity to owners of urban and rural real estate. By mortgaging their properties, owners could raise capital. This specialized credit was provided only by authorized institutions, such as dedicated sections of public banks (e.g., Banco di Napoli), large savings banks (e.g., Cassa di Risparmio delle Province Lombarde), and Istituti di Credito Fondiario (a dedicated branch of the SCIs).

The institutions providing *credito fondiario* acted as pure intermediaries. They raised funds by issuing and selling cartelle fondiarie to savers.[1] *Cartelle fondiarie* were fixed-income securities directly backed by the mortgages on the real estate assets, tradable on the secondary market. A key feature, lasting until 1970, was that cartelle paid a legally fixed 5% nominal interest rate.[2] Furthermore, institutes could also issue bonds that were representative of a "basket" of *cartelle*, pooling multiple mortgages together (see Figure D.1). This practice effectively represents a form of securitization ante-litteram.

The transaction process was peculiar. Consider a firm seeking a £1 billion mortgage from an SCI: Once the SCI granted the mortgage, it would create £1 billion worth of *cartelle fondiarie*. Technically, these £1 billion in bonds were given to the borrowing firm. The firm would

[1] The institute's profit was the spread between the fixed interest rate paid to the bondholders and the (slightly higher) fixed interest rate charged to the mortgage borrower.

[2] We weren't able to reconstruct the mark-to-market rate of return of these securities. The task is left to future research.

Figure D.1: Cartelle Fondiarie

(a) Bond representative of one thousand *cartelle fondiarie* issued by the Istituto San Paolo of Turin (1905)

(b) Bond representative of two-hunderds *cartelle fondiarie* issued by the Banco di Napoli (1957)

then be responsible for selling them on the secondary market to get its cash. In practice, this physical delivery almost never happened. A specific clause in the mortgage contract authorized the SCI to act as an agent, taking care of managing the new bonds on the firm's behalf. Thus, in exchange for a haircut, the SCI would keep the bonds and then disburse the cash to the firm. On the SCI's balance sheet, this created a £1 billion loan (asset) that was perfectly matched by the £1 billion in cartelle it had issued, figuring among the liabilities, now owed to the savers who bought the bonds (see Figure D.2).

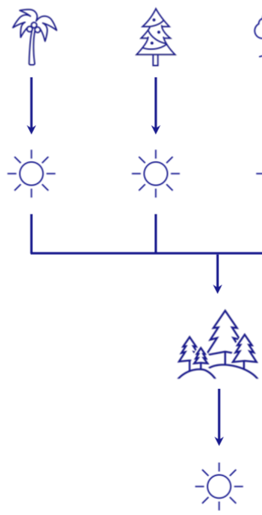
Crucially, there was no legal binding on the actual use of the *credito fondiario*; the borrower could use the liquidity from the mortgage in other ways.

Figure D.2: Simplified accounting relationships of *credito fondiario* (no profits)

Firm		Special Credit Institute		Bondholder	
Assets	Liabilities	Assets	Liabilities	Assets	Liabilities
Cash: £1B	Debt: £1B	Loans:£1B	CF:£1B	CF:£1B	…

Firm		Special Credit Institute		Bondholder
Pays the interest on the loans	⟶	Receive the interest on the loan		
		Pays the interest on the CF	⟶	Receive the interest on the CF

Figure D.3: How a Random Forest Classifier Works



The figure offers a sketch of the functioning of a Random Forest Classifier. Each tree classifies the outcome (Sun or Rain), fitted on a subset of features and observations. Then, the Forest takes the prediction of each tree and formulates a final classification based on majority voting. In the figure, three trees classify Sun and only one Rain, thus the Random Forest returns Sun as a final prediction.

D.2 A Methodological Note: Random Forest Classifier and Shapley Regression

To model the probability of switching to a securities-oriented business model, we utilize a Random Forest classifier (Breiman, 2001)—from here RF—a machine learning algorithm used for classification purposes, that is, to assign instances to a label class (e.g., 0/1). The algorithm is built on a forest of regression trees. In particular, each tree in the forest is fitted on a specific subset of features and observations. The forest's final prediction is an aggregation by majority voting of the predictions of the single trees. This process improves accuracy, corrects overfitting and multicollinearity, and accounts for non-linear relationships and interaction effects (see Figure D.3).

The main side effect of the RF is a reduced interpretability compared to traditional counterparts (the black box critique). To overcome this issue, we make use of the *SHAP values framework* (SHapley Additive exPlanation), a model-agnostic approach designed to explain the output of any machine learning model.[3] SHAP values are a computationally efficient extension of the notion of Shapley values.[4] Transposing the intuition to the field of interpretable

[3] See `https://github.com/shap/shap?tab=readme-ov-file#citations`. SHAP values are computed following Lundberg et al. (2018) TREESHAP methodology.

[4] Shapley values are a game-theoretic concept that solves the problem of allocating a payoff among the elements of a coalition. The payoff is distributed based on the marginal contribution of each element to the result, estimated by checking the outcome for all the possible permutations of elements in the coalition (Shapley,

machine learning (Štrumbelj and Kononenko, 2010), the SHAP value $\phi_k^S[f(x_i)]$ measures the contribution of the feature k in the outcome predicted by the model $f(\cdot)$ for the instance x_i.[5] SHAP values benefit from local accuracy; thus, the sum of the SHAP values of each feature $k = 1, ..., d$ exactly sums up to the predicted outcome $f(x_i)$, that is

$$\phi^S[f(x_i)] = \phi_0^S + \sum_{k=1}^{d} \phi_k^S(x_i) = f(x_i). \tag{D.1}$$

Other desirable properties of the SHAP values are missingness and consistency, that is, missing features have no contribution to the prediction, and a change in the model changes the SHAP values accordingly.

To transpose the local decomposition of the SHAP values and derive the global importance of each feature, we compute the *Shapley regression*, as presented in Buckmann et al. (2019), that linearly regresses the SHAP values of each feature on the predicted outcome of the Random Forest classifier y_i:

$$y_i = \sum_{k=0}^{d} \phi_k^S(f, x_i)\beta_k^S + \epsilon_i \tag{D.2}$$

With $\phi_k^S(f, x_i)$ being the SHAP value of the feature $k = 1, ..., d$ of the i-th observation and $k = 0$ being the intercept. The results can then be summarized as the *Shapley share coefficient*:

$$\Gamma_k^S(f, \Omega) = \left[\text{sign}(\beta_k^{\text{lin}}) \left\langle \frac{\phi_k^S(f)}{\sum_{j=1}^{d} \phi_k^S(f)} \right\rangle_\Omega \right]^{(*)} \in [-1, 1]. \tag{D.3}$$

$\Gamma_k^S(f, \Omega)$ is a summary statistic of the global contribution of the feature k in the sample space $\Omega \subseteq \mathbb{R}^n$. It is composed of three parts:

1. $\langle \cdot \rangle$: representing the *Shapley share coefficient*, that measures the share of model's output explained by feature k (variable attribution) averaged over Ω. Shapley share coefficients sum up to 1, and their sign is not informative by construction.

2. $\text{sign}(\beta_k^{\text{lin}})$: sign of the corresponding linear model (logit for a classification exercise), it measures the alignment of the feature k with the target variable y.

3. $(*)$: significance level defined by the (one-sided) p-value of the SHAP regression (H_0: $\beta_k^S \leq 0|\Omega$)

In the empirical exercise, we control for three broad categories of factors: (i) balance sheet fundamentals (capitalization, asset quality, relative size, profitability, and liquidity); (ii) idiosyncratic features (bank category and geographic location); (iii) macroeconomic context (GDP growth, interest rates, term structure). Lastly, a dummy to control for the years after 1964 is included. Additional information is reported in Table D.1.

The model significantly outperforms a standard logistic regression, achieving an AUC score of 0.76 vs. 0.67.

1953).

[5] Notation from Buckmann et al. (2019).

Table D.1: Random Forest classifier controls

Control	Measure	Source
Capitalization	5y- moving average of $\text{Equity}_i/\text{Tot. Assets}_i$	ASCI
Asset quality	$\text{Non-Performing Loans}_{it}/\text{T. Loans}_{it}$	ASCI
Relative size	$\log(\text{T. Assets}_{it})/\log(\max(\text{T. Assets}))$	ASCI
Earnings	$\text{Return}_{it}/\text{T. Assets}_{it}$	ASCI
Liquidity	5y. moving average of $\text{Sight Assets}_i/\text{Tot. Assets}_i$	ASCI
Saving banks	$\mathbb{I}_{\text{category}_i \in [\text{CRO; MDP}]}$	ASCI
Systemic bank	$\mathbb{I}_{\text{category}_i \in [\text{IDP; BIN}]}$	ASCI
North	$\mathbb{I}_{\text{HQ location}_i = \text{North}}$	ASCI
GDP growth	$\Delta \log(\text{GDP}_t)$	Baffigi et al. (2013)
Short-term IR	Interest rate on short-term 10m BOT	Jordà et al. (2017)
Long-term IR	Interest rate on long-term 5y BTP	Jordà et al. (2017)

The table presents a description of the controls used in the main classification exercise.

D.3 Robustness Checks

To validate the stability and robustness of the business models identified in our main analysis, we perform four additional checks. The results, summarized in Table D.2 and Figure D.4, confirm that our findings are not dependent on specific methodological choices or sample definitions.

1. Clustering by Bank Category. To test for heterogeneity across institutional types, we ran the K-medoids algorithm separately on each bank category. The resulting business model dynamics, shown in Figure D.4a, D.4b, D.4c, are highly consistent with our main findings, confirming the major structural breaks around 1958 and 1964. The check also adds important nuances. First, the dynamics for savings and pledge banks (CRO and MDP) clearly capture their persistent, long-term drift toward SCI securities. Second, the analysis of joint-stock and public banks (SOC, DB, IDP, BIN) reveals that the post-1964 shift away from the traditional retail model was driven by the rise of a hybrid model high in both bank loans and SCI securities. A similar trend is visible for cooperative banks (BP). While with minor differences, these results confirm the presence of a widespread strategic shift, not confined to a single institutional category.

2. Clustering on Asset Mix Only. To confirm that our findings are driven by strategic asset allocation rather than the largely homogeneous liability structure, we re-ran the analysis using only asset-side metrics (Figure D.4d and D.4e). The results are consistent. The model adds granularity by identifying five distinct clusters, each heavily specialized in one of the primary asset classes (e.g., retail loans, SCI securities). The resulting business model dynamics mirror those of the main analysis, clearly capturing the structural breaks around 1958 and 1964. The business model dynamics closely match the main exercises, identifying a structural break around 1958 and 1964, in which a "defensive shift" occurs, with the surge of the business models focused on sight assets, government securities, and SCI securities, respectively. Crucially, the substitution between the retail loans and the SCI-focused business model after

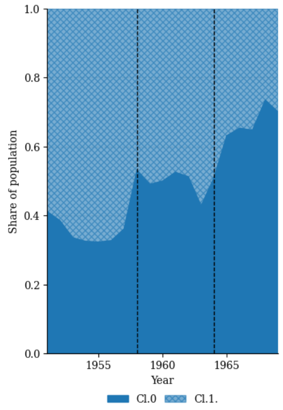
1964 is remarkably consistent with our main findings.

3. Clustering on Post-1958 Data. To ensure the pivotal post-1964 shift is not an artifact of including the distinct preceding periods in the model, we re-ran the analysis using only data from 1958 onward. This analysis yields two highly distinct clusters that align perfectly with our baseline retail-focused and securities-focused models. Crucially, the resulting dynamics (Figure D.4f and D.4g) reconfirm the key substitution event, clearly showing the sharp decline of the retail-focused model as the securities-focused model surges after 1964.

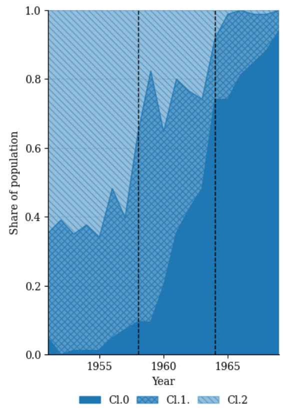
4. Clustering with Combined Securities. Finally, to ensure our baseline split is not influenced by separating the two main security types (which could overweight their cumulative signal), we re-estimated the model using a single, combined "Securities" variable. The resulting clusters are again consistent with our baseline, identifying a clear securities-focused model. The dynamics reconfirm our main finding, showing this model gaining strength after 1964 at the expense of the retail-focused model. Moreover, this specification adds nuance by also clearly capturing a second moment of shift around 1958, as suggested by the historical narrative. This proves the fundamental strategic dichotomy captured by the main model.

Taken together, these checks confirm that the identified business models are a robust feature of the data. The fundamental split between a retail-focused and a securities-focused strategy is stable across different institutional types, feature specifications, and time periods.

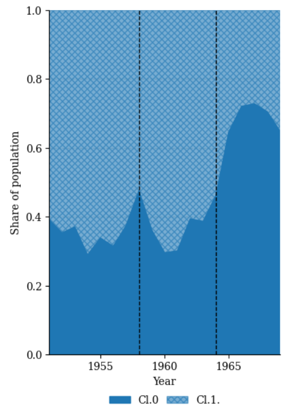
Figure D.4: Business models dynamics: alternative specifications



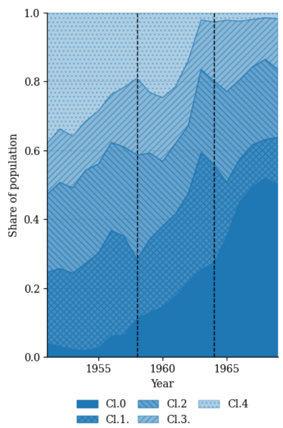
(a) SOC, DB, IDP, BIN (% P.)



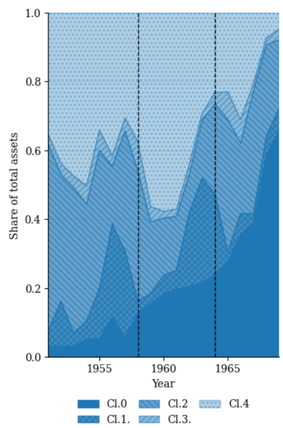
(b) CRO and MDP (% P.)



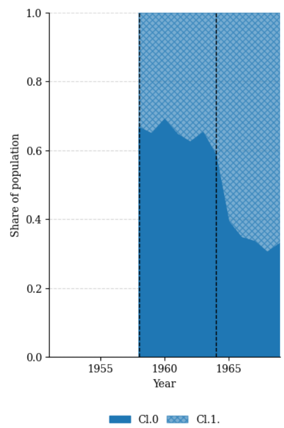
(c) BP (% P.)



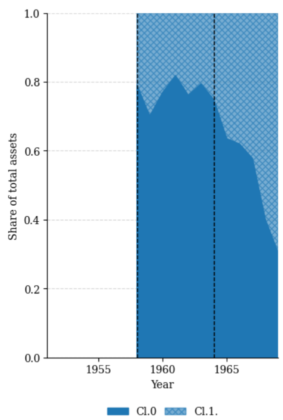
(d) Only assets (% P.)



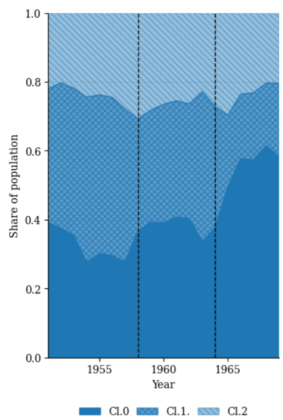
(e) Only assets (% A.)



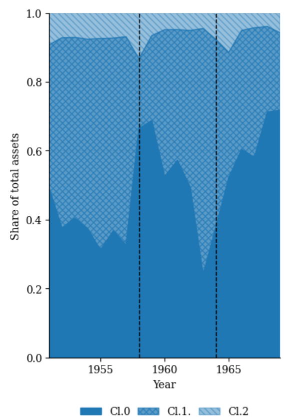
(f) Post-1958 (% P.)



(g) Post-1958 (% A.)



(h) Combined Sec. (% P.)



(i) Combined Sec. (% A.)

The figures show the business model dynamics for the selected robustness checks. Note: %P. and %A. indicates the unit of measurement: share of the total bank population and of the total assets, respectively. Black dashed lines mark 1958 and 1964.

Table D.2: Robustness Checks: Cluster Centroids

	Clustering by Bank Category								
	SOC, DB, IDP, BIN			*CRO, MDP*			*BP*		
	C0	*C1*	*C2*	*C0*	*C1*	*C2*	*C0*	*C1*	*C2*
Sight assets	0.17	0.18	-	0.13	0.23	0.14	0.20	0.15	-
Bank loans	0.18	0.07	-	0.08	0.09	0.08	0.13	0.08	-
Retail loans	0.43	0.54	-	0.42	0.40	0.53	0.41	0.55	-
Government securities	0.09	0.10	-	0.05	0.08	0.12	0.13	0.13	-
SCI securities	0.05	0.03	-	0.25	0.13	0.06	0.08	0.03	-
Equity	0.06	0.06	-	0.03	0.03	0.03	0.04	0.05	-
Bank deposits	0.04	0.07	-	0.03	0.06	0.06	0.04	0.06	-
Retail deposits	0.85	0.80	-	0.87	0.82	0.83	0.86	0.83	-

	Assets Only					*Post-1958*		*Combined Securities*		
	C0	*C1*	*C2*	*C3*	*C4*	*C0*	*C1*	*C0*	*C1*	*C2*
Sight assets	0.16	0.14	0.25	0.16	0.13	0.16	0.18	0.17	0.16	0.18
Bank loans	0.09	0.09	0.08	0.23	0.07	0.10	0.13	0.09	0.07	0.20
Retail loans	0.40	0.60	0.46	0.42	0.48	0.53	0.39	0.41	0.57	0.45
Government securities	0.07	0.08	0.09	0.07	0.23	0.09	0.07	-	-	-
SCI securities	0.21	0.04	0.05	0.03	0.03	0.05	0.15	-	-	-
Securities	-	-	-	-	-	-	-	0.27	0.14	0.11
Equity	-	-	-	-	-	0.05	0.04	0.04	0.05	0.06
Bank deposits	-	-	-	-	-	0.05	0.04	0.04	0.06	0.05
Retail deposits	-	-	-	-	-	0.83	0.86	0.85	0.81	0.84

The table shows the business models identified in the four robustness checks: (i) running the algorithm separately for different bank groups (SOC, DB, IDP, and BIN; CRO and MDP; BP). Note: IDP and BIN are combined with SOC and DB because limited observation prevents the algorithm from being fitted separately. (ii) considering only the asset mix; (iii) considering only the post-1958 period; (iv) combining government securities and SCI securities into the same item. Note: the number of clusters can vary across the exercises—and can be different from the main exercises—because for each application, the number of clusters is optimized by maximizing the silhouette score.