Banking on Family: Why Family Ownership Matters for the Survival of Russian Banks

Alexander Soldatkin
University of Oxford
alexander.soldatkin@sant.ox.ac.uk

February 12, 2026

Abstract This study investigates how family kinship networks influence bank survival in Russia's institutional environment from 2004 to 2020. Employing a novel graph database methodology to map ownership structures and kinship relationships amongst bank stakeholders, we analyse the survival determinants of Russian banks through Cox proportional hazards models with time-varying covariates, controlling for traditional CAMEL financial indicators. We test three Transaction Cost Economics mechanisms underlying family network protection: political embeddedness, tax optimisation through ownership fragmentation, and internal capital markets. Our empirical analysis, spanning approximately 140,000 bank-quarter observations across 2,418 unique banks, demonstrates that all three mechanisms significantly reduce hazard rates, with ownership fragmentation providing the strongest protection (11.8% hazard reduction per standard deviation). Competing risks analysis reveals that family protection operates specifically against forced licence revocation by the Central Bank (HR = 0.991, $p < 0.001$), with no significant effect on voluntary liquidation or reorganisation. Critically, these protective effects exhibit temporal heterogeneity: family networks serve a substitution function during economic crises (2008), providing 26.6% additional survival protection, but shift towards an interference function during periods of regulatory consolidation (2013–2020), where ownership fragmentation facilitates evasion of transfer pricing thresholds. We further document a foreign ownership reversal—protective during the 2008 Global Financial Crisis but harmful during the 2014 geopolitical crisis—and demonstrate that regulatory regime changes (Ignatyev to Nabiullina) fundamentally alter the survival landscape. Granger causality tests and placebo falsification confirm the specificity of the family connection effect. These findings are interpreted through Ledeneva's substitution–interference framework, providing the first systematic empirical evidence on the dual nature of informal governance in Russian banking.

Table of contents

1 Introduction

Russia's banking sector offers a compelling case for examining how ownership and kinship networks shape institutional survival. From a peak of roughly 1,525 active banks in 1996, the sector has contracted to 309 institutions by mid-2025 — about 80% of all banks that ever operated have perished. Persistent high failure rates despite formal regulatory frameworks suggest that conventional financial determinants alone cannot explain survival patterns. Informal relationship networks — particularly those based on family connections — play a role in institutional resilience and crisis recovery.

The sector's trajectory has been shaped by distinct institutional episodes. The 2004 revocation of Sodbiznesbank's licence — accompanied by the murder of its shadow owner and the physical resistance of managers to CBR regulators — exposed the fragility of formal governance and triggered a crisis of confidence across Moscow's banking system [1]. Closures steepened further with the arrival of Elvira Nabiullina as head of the Bank of Russia in 2013, who inherited 896 active banks and has since overseen the closure of more than 500. Primary closure reasons include licence revocation (typically accompanied by tax investigations), voluntary liquidation, and forced reorganisation — exemplified by the 'sanitisation' of the Otkritie and Trust banking groups in 2017.

Prior work on Russian banking instability has focused on conventional financial determinants — capital adequacy, profitability, asset quality, and liquidity — supplemented by political economy variables: electoral cycles [2], regional corruption [3], factional associations [4], and strategic orientation [5]. Whilst these studies have advanced understanding of institutional dynamics, they neglect a fundamental governance mechanism: family ownership structures and kinship-based coordination networks. Family ownership is a dominant organisational form globally, with established effects on firm performance, strategic decision-making, and crisis resilience [6], [7], [8] — yet it has not been studied in the Russian banking context.

The gap is empirical, not theoretical: family relationships among Russian bank stakeholders are not recorded in public regulatory data. Identifying kinship ties requires manual coding of CBR ownership disclosures, cross-referencing surnames and patronymics, and building a database that can represent the multi-layered ownership structures characteristic of Russian banking. We overcome these constraints by constructing a Neo4j graph database that maps ownership structures, management relationships, and family connections across the Russian banking sector from 2004 to 2020.

The central research question is whether family ownership structures and kinship-based coordination networks are associated with differences in bank survival in Russia. We frame 'coordination' in precise terms: coordination **within family networks** for resource pooling (internal capital markets), information sharing (advance warning of regulatory action), and mutual support during institutional stress (liquidity backstops). This is distinct from coordination with the state; rather, family networks provide alternative mechanisms that **substitute** for the functions that reliable formal institutions would otherwise perform.

Kinship is one of several forms of informal governance relevant to Russian banking. Alumni networks, military service connections (*siloviki* associations), business partnerships, and regional friendship circles all serve as coordination mechanisms [9]. Our focus on family ties is motivated by three considerations. First, kinship relationships are **verifiable**: CBR ownership disclosures and patronymic naming conventions provide a systematic identification strategy not available for friendship or alumni ties. Second, A. V. Ledeneva [9] foregrounds kinship as a privileged coordination mechanism in Russian informal governance, providing strong theoretical grounding. Third, prior work on factional associations [4] has established that informal political ties matter for Russian bank survival; we extend this logic to ask whether family ties — which may overlap with, complement, or operate independently of factional associations — constitute an additional governance mechanism.

Prominent cases illustrate this logic: the collapse of Sergei Pugachev's Mezhprombank revealed how family-controlled ownership structures could tunnel assets across international jurisdictions, whilst Centre-Invest Bank in Rostov-on-Don illustrates how regionally embedded family governance can sustain a bank through multiple crises.

We synthesise three previously disconnected literature streams — Russian banking failures, family ownership governance, and network-based survival mechanisms — into a framework grounded in A. V. Ledeneva [9]'s distinction between 'substitution' and 'interference.' We argue that family ownership in Russian banking operates dually: mainly providing substitution functions (alternative trust and contract enforcement) during economic crises, but shifting towards interference (subverting regulatory intent through ownership fragmentation and balance sheet management) during state-led consolidation. Section 3 develops this framework with concrete examples from the study period.

We combine survival analysis using Cox proportional hazards models with time-varying covariates and detailed network mapping of family relationships among Russian bank owners and senior management. Our data span 2004–2020, incorporating financial indicators, ownership structures, and family network connectivity measures derived from Central Bank corporate governance documentation. The analysis covers roughly 140,000 bank-quarter observations across 2,418 banks, with 1,117 failure events.

We test three propositions. First, banks embedded in denser kinship networks — measured by a higher family connection ratio — are associated with lower hazard rates, as family ties provide resource pooling and liquidity backstops that substitute for weak formal protections. Second, three specific Transaction Cost Economics mechanisms underlie this protection: political embeddedness, tax optimisation through ownership fragmentation, and internal capital markets. Third, these effects are context-dependent: beneficial during broad economic crises (2008 Global Financial Crisis), but reversing during targeted regulatory intervention (2014–2017 cleanup), where high network visibility attracts state action.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 develops the institutional context and theoretical framework. Section 4 formalises the hypotheses. Section 5 describes the data construction. Section 6 explains the econometric strategy. Section 7 presents the findings. Section 8 discusses implications, and Section 9 concludes.

2 Literature review

Three research domains underpin our analysis: the determinants of Russian bank failures, the role of ownership structures and informal networks, and the broader literature on family ownership and business groups.

2.1 Determinants of Russian bank failures

2.1.a Financial fundamentals

Empirical investigations spanning the post-2000 period consistently identify bank size, profitability, and capital adequacy as primary predictors of institutional viability. The evidence reveals a robust negative relationship between bank size and failure probability, with coefficients ranging from −0.236 to −0.385 across studies [2], [5], [10]. This supports the 'too-big-to-fail' hypothesis within the Russian context.

Profitability metrics, particularly return on assets (ROA), show substantial explanatory power, with negative coefficients on failure probability ranging from −12.0 to −82.3. Capital adequacy ratios consistently show negative relationships with failure probability, though magnitudes vary across studies, potentially reflecting evolving regulatory frameworks. Liquidity management emerges as another fundamental determinant, with liquid asset ratios showing strong negative correlations with failure probability (−1.93 to −2.39). Asset quality, measured through non-performing loan ratios, shows the expected positive relationship with failure probability.

2.1.b Ownership structures and control

The literature reveals considerable complexity regarding ownership effects. Foreign ownership shows consistently protective effects, with foreign control reducing failure probability significantly [5]. This aligns with theoretical expectations regarding superior risk management practices and access to international capital markets. State ownership presents more nuanced patterns, with studies documenting both protective effects for large state-controlled institutions and potential inefficiencies from political interference.

Strategic orientation introduces additional complexity. Whilst corporate deposit concentration reduces failure probability, corporate lending orientation increases bankruptcy risk [5] — a paradox suggesting that corporate relationships provide funding stability whilst simultaneously exposing institutions to concentrated credit risks.

2.1.c Political economy and institutional environment

Electoral cycle research provides compelling evidence that bank failures cluster temporally, with survival prospects enhanced during pre-election periods by a factor of 2–3 [2]. Regional corruption consistently hampers bank lending capacity, with coefficients on lending volume ranging from −0.182 to −0.340 [3]. Competition research yields counterintuitive findings: the Lerner index investigations show that increased competition paradoxically enhances failure probability (−1.460 to −3.364), supporting the 'competition-fragility' hypothesis [10].

2.1.d Factional networks and informal power

Recent studies have unveiled sophisticated informal influence mechanisms within Russian banking. A. Soldatkin [4] provides evidence of dual-layered factional influence: media-based factional associations show positive effects on performance (roughly 1.2 billion roubles additional profits) and substantially reduced licence revocation probabilities, suggesting that public visibility of political connections serves as an implicit guarantee. Ownership-based factional influence presents markedly different patterns, with siloviki ownership providing protective effects whilst government/presidential faction ownership paradoxically increases risks of failure.

These dynamics establish the conceptual foundation for examining how family relationships — another form of informal governance — influence institutional survival. Prior work on factionalism shows that informal relationships matter for Russian bank survival, but has not examined kinship networks. This gap is not due to a lack of theoretical interest but to **data constraints**: family relationships are not recorded in standard regulatory data and require the kind of graph database methodology that this study introduces.

2.2 Family ownership and business groups

2.2.a Theoretical foundations

Family firms constitute a dominant organisational form globally, challenging the universality of agency theory frameworks developed from observations of dispersed ownership in Anglo-American contexts. Empirical studies document families present in one-third of S&P 500 firms [6], with Western European markets showing even more pronounced family control [11]. These observations suggest that family influence represents a persistent governance mechanism under specific institutional conditions — conditions that parallel those observed in Russian banking.

2.2.b Socioemotional wealth

The concept of socioemotional wealth (SEW) explains non-financial motivations of family owners: emotional attachment, legacy preservation, maintenance of control, and reputational concerns [12], [13]. This 'survivability capital' [14] becomes most potent during crises, when families can uniquely pool personal resources — including free labour and emergency capital — to save the firm. In emerging markets, this effect is amplified: T. Khanna and K. Palepu [15] suggest that in environments characterised by institutional voids, family groups create internal labour and capital markets to substitute for missing external institutions.

2.2.c Institutional context and performance

The relationship between family ownership and firm performance is context-dependent. Positive effects appear mainly in environments characterised by institutional underdevelopment [6], [8]. Business group research offers particularly relevant insights: group affiliation shows positive effects in emerging markets (India, Indonesia, Taiwan) but negative or neutral effects in developed institutional environments [8]. These differential effects relate directly to institutional development levels, with group affiliation providing valuable intermediation where capital markets and regulatory frameworks are underdeveloped [16] — conditions that closely characterise Russian banking.

2.2.d Generational dynamics

Founder-controlled corporations consistently outperform descendant-managed enterprises [7], [17]. Thai business group evidence shows that family size significantly influences performance, with each additional son reducing ROA by 0.34 points [17]. These generational dynamics are relevant for Russian banking, where many institutions established during the 1990s transition may now experience first-generation succession.

2.2.e Network effects and survival

Family ownership enhances network formation propensity and creates superior crisis recovery mechanisms [18], [19]. Network centrality research reveals that higher centrality positions correlate with lower hazard rates [19], [20], suggesting that family networks provide institutional substitutes for formal governance — particularly valuable in environments characterised by regulatory uncertainty.

A parallel literature on network contagion highlights the risks of interconnectedness. D. Acemoglu, A. Ozdaglar, and A. Tahbaz-Salehi [21] show that whilst network connections can facilitate risk-sharing during small shocks, they become channels for systemic contagion during large shocks, potentially amplifying cascading failures. This dual nature of network ties — protective through resource pooling but dangerous through contagion transmission — maps directly onto our substitution–interference framework: the same ownership linkages that channel internal capital during economic stress may transmit regulatory shocks during periods of targeted enforcement.

2.3 Summary and research gaps

Three gaps emerge from this literature:

1. The Russian banking literature documents political and ownership effects on survival but has not examined how **kinship networks** create alternative governance mechanisms — a gap driven by data constraints that our graph database methodology overcomes.
2. The family ownership literature provides robust theoretical frameworks but has not been applied to **financial institutions** in emerging economies with weak formal institutions and high political interference.

3. The factional network research shows the empirical importance of informal relationships but does not explore how family connections **intersect with, complement, or substitute** political associations.

Following A. V. Ledeneva [9], we distinguish between substitution (where informal networks provide services that formal institutions fail to supply) and interference (where networks subvert functioning regulations). Section 3 develops this distinction with empirical examples, and Section 4 formalises the testable predictions.

3 Institutional context and theoretical framework

3.1 Defining weak formal institutions in Russia

The claim that Russia's formal institutions are 'weak' requires precise definition. We do not mean an absence of regulation — the Central Bank of Russia (CBR) operates an extensive supervisory apparatus, and Russian banks are subject to detailed prudential requirements modelled on Basel standards. Rather, we define institutional weakness as the **inability of formal rules to credibly commit to impartial enforcement**, leading to three observable consequences: (1) actors invest in relationship-based protection rather than relying solely on regulatory compliance; (2) regulatory outcomes are shaped by political connections and informal leverage as much as by adherence to formal rules; and (3) formal compliance becomes necessary but insufficient for institutional survival.

Three episodes from the study period illustrate this definition.

3.1.a The Sodbiznesbank crisis (2004)

The revocation of Sodbiznesbank's licence in May 2004 was a watershed. It exposed the extent to which informal violence and extra-legal protections had superseded formal governance in Russian banking. The bank's shadow owner, Alexander Slesarev, was murdered in the course of the affair, and bank managers physically barricaded themselves inside the premises to prevent CBR regulators from accessing the institution [1]. This episode illustrates what A. V. Ledeneva [9] terms the 'suspension of law' — formal legal procedures rendered meaningless by the willingness of actors to resort to violence and physical obstruction.

The crisis coincided with the final wave of institutional reforms establishing the Deposit Insurance Agency (DIA). A leaked CBR shortlist of banks deemed eligible for DIA membership triggered a broader bank run, as depositors fled institutions absent from the list, interpreting exclusion as a signal of impending closure. Even the creation of formal protection mechanisms (deposit insurance) could destabilise the sector when implemented in a low-trust environment: the shortlist itself became an informal signal that amplified rather than mitigated panic. The rational response is precisely the kind of relationship-based protection that family networks provide: informal trust substituting for absent credible enforcement.

3.1.b Selective enforcement and regulatory forbearance

Formal compliance metrics bear an imperfect relationship to regulatory outcomes. A. Barajas and others [5] document that 98–99% of Russian banks met CBR prudential ratios at any given time, yet the sector experienced sustained high failure rates throughout 2004–2020. If formal compliance were sufficient for survival, the observed failure rates would be difficult to explain. Z. Fungáčová and T. Poghosyan [2] provide compelling evidence that bank failure probabilities decline by a factor of 2–3 during pre-election periods, suggesting that supervisory decisions are systematically influenced by the political calendar.

This pattern of selective enforcement creates strong incentives for bank owners to invest in informal protection. When formal compliance cannot guarantee survival, and when regulatory forbearance is distributed on the basis of political considerations, the rational strategy is to cultivate relationship networks that provide advance warning of regulatory action, access to political decision-makers, and mutual support during institutional stress.

3.1.c The Otkritie–Trust sanitisation (2017)

The state takeover of Otkritie and Trust banking groups in 2017 represents the culmination of Nabiullina-era regulatory consolidation. These were not marginal institutions: Otkritie was one of Russia's largest private banks, and its complex ownership network connected it to numerous other financial and industrial entities. The CBR's intervention showed that even systemically important, well-connected institutions were not immune to state action — but the targeting of these particular institutions, with their elaborate network structures, also revealed that high network centrality could become a liability during active regulatory consolidation. The sanitisation process exposed the extent to which informal ownership arrangements had obscured true control structures and facilitated related-party transactions across the group.

This episode is crucial for our framework because it shows the **dual nature** of informal governance: the same network structures that provided protection during economic crises (by facilitating internal capital transfers and coordinated responses to liquidity shocks) attracted regulatory targeting during state-led sector consolidation. The Otkritie–Trust case embodies the transition from substitution to interference that A. V. Ledeneva [9] identifies as a fundamental tension in Russia's economy of favours.

3.2 Ledeneva's substitution–interference framework

Building on this institutional context, we adopt A. V. Ledeneva [9]'s distinction between two functions of informal governance:

- **Substitution**: Informal mechanisms **replace** absent or ineffective formal institutions. Family networks provide essential services — trust, contract enforcement, liquidity backstops, information sharing — that the formal institutional environment fails to supply reliably. Substitution dominates during broad economic crises, when formal market mechanisms (interbank lending, external capital markets) cease to function and actors must rely on personal relationships for survival.
- **Interference**: Informal mechanisms **subvert** the intended purpose of formal institutions. Family networks are used to evade regulatory requirements, obscure true ownership structures, circumvent transfer pricing rules, and exploit regulatory thresholds. Interference becomes more prominent during active regulatory tightening, when the state attempts to impose stricter formal rules and actors deploy informal mechanisms to resist compliance.

This distinction is not merely theoretical. Our empirical strategy is designed to identify the conditions under which each function predominates, by examining how the protective effects of family networks vary across crisis types, regulatory regimes, and time periods.

3.2.a Empirical mapping: substitution and interference across time

We map the substitution–interference distinction onto specific institutional episodes:

Table 1: Mapping of the substitution–interference framework to the Russian banking institutional environment, 2004–2020.

Period	Regime	Dominant Function	Mechanism	Empirical Expectation
2004–2007	Ignatyev (early)	Substitution	Family networks provide trust and liquidity backstops when formal institutions demonstrably weak (post-Sodbiznesbank)	FCR protective; no crisis interaction effects (crisis too brief)
2008	Global Financial Crisis	Substitution	Internal capital markets buffer external shock; foreign capital markets frozen; family groups pool resources	Family × crisis interaction strongly protective
2013–2020	Nabiullina	Interference	Ownership fragmentation evades transfer pricing thresholds and consolidated liability rules	Fragmentation index more protective than in earlier periods
2014–2017	Sanctions + Cleanup	Mixed/Targeting	High centrality attracts regulatory targeting (Otkritie–Trust); foreign connections become liability	Foreign × crisis harmful; centrality becomes liability

A critical distinction is the **nature of the shock**. Following the crisis typology of C. M. Reinhart and K. S. Rogoff [22], the 2008 GFC constitutes an exogenous economic crisis: Russia was not at the epicentre, the shock originated in US mortgage markets and transmitted through global capital markets, and the Russian government's response — including then-PM Putin's public prioritisation of Russian banks over foreign competitors for state support — reinforced domestic informal networks as the primary survival mechanism. By contrast, the 2014 crisis constitutes an endogenous geopolitical shock: Western sanctions were a direct response to Russian foreign policy actions, making the crisis fundamentally political rather than economic. This distinction matters because exogenous shocks provide stronger conditions for testing the substitution hypothesis (family networks substitute for frozen markets), whilst endogenous shocks confound substitution with political targeting.

The Nabiullina appointment itself reflected a political calculus. As a figure trusted by Putin, Nabiullina was empowered to pursue a consolidation agenda that brought the CBR into tacit conflict with banks connected to security services (*siloviki*), many of which had enjoyed regulatory forbearance under Ignatyev. This conflict — between the CBR's institutional consolidation programme and the informal protections enjoyed by politically connected banks — forms the backdrop against which family network effects must be interpreted in the post-2013 period.

This mapping generates testable predictions that we evaluate using crisis interaction models (Section 7.4), subperiod analysis (Section 7.3), and governor regime tests (Section 7.5).

3.3 Transaction Cost Economics mechanisms

To move beyond the general claim that 'family networks matter' and identify the specific channels through which kinship ties influence survival, we turn to Transaction Cost Economics (TCE). Following R. H. Coase [23] and O. E. Williamson [24], we argue that family ownership reduces survival-relevant transaction costs through three non-mutually exclusive mechanisms.

3.3.a Mechanism 1: Political embeddedness (reducing political transaction costs)

D. C. North [25] extends transaction costs to include the costs of measuring and enforcing agreements with the state. In a stable institutional environment, these 'political transaction costs' are standardised and predictable. In the post-2004 Russian context, where regulatory enforcement became arbitrary and at times weaponised, the cost of verifying compliance or predicting enforcement became prohibitively high.

Family networks reduce these costs by embedding the firm within local political structures. By placing family members in proximity to municipal or regional officials, the bank acquires a 'surface area' for information gathering — advance warning of regulatory inspections, policy shifts, or targeted enforcement actions. This embeddedness provides the time necessary to restructure assets or prepare responses, effectively lowering the political transaction cost of survival in a capricious regulatory environment.

- **Proxy**: `family_connection_ratio` controlled for regional fixed effects (strata)
- **Empirical test**: If political embeddedness is the dominant mechanism, then the protective effect of FCR should be robust to regional stratification (which absorbs regional-level political variation)

3.3.b Mechanism 2: Tax optimisation (strategic firm boundary manipulation)

The boundaries of the firm, according to R. H. Coase [23], are defined by the marginal cost of organising an extra transaction within the firm versus the open market. In Russia, families frequently extend or fragment these boundaries strategically — not for operational efficiency, but for tax optimisation and regulatory opacity.

The practice of 'business fragmentation' (*droblenie biznesa*) is a prevalent strategy used by family-financial groups to minimise fiscal and regulatory pressure. By splitting ownership stakes amongst a wider circle of family members, groups can remain below critical regulatory thresholds:

- **Threshold arbitrage**: Maintaining individual stakes below 20% or 25% allows the group to avoid 'controlled transaction' reporting requirements and maintain eligibility for preferential tax regimes in linked subsidiaries
- **Regulatory opacity**: High fragmentation makes it harder for the CBR or Federal Tax Service to identify a single 'controlling person' for consolidated liability purposes
- **Proxy**: `stake_fragmentation_index` (calculated as $1 - \sum s_i^2$, where s_i is the share of family member i). A higher index represents more dispersed ownership
- **Empirical test**: If tax optimisation is the dominant mechanism, then `stake_fragmentation_index` should be the strongest predictor of survival, and its effect should intensify during regulatory tightening (when evasion incentives are highest)

3.3.c Mechanism 3: Internal capital markets (the 'make vs buy' decision for capital)

O. E. Williamson [24] argues that internal organisation substitutes for markets when external markets fail due to high transaction costs. In Russia, external credit markets are often inefficient, opaque, or politically captured [15]. For a standalone bank, raising capital during a crisis involves prohibitive risk premiums or total market exclusion.

Family banking groups respond by creating 'internal capital markets' — essentially choosing to 'make' rather than 'buy' capital. By channelling resources through family-owned subsidiaries, the group can provide liquidity to the bank during external market stress. This 'propping' mechanism prioritises the preservation of family wealth over standalone profitability.

We test this mechanism through two layers of proxies:

- **H3 (Basic)**: `family_company_count` (number of entities in the family group) and `group_total_capital` (aggregate financial resources of the group)
- **H3+ (Enhanced)**: `group_sector_count` (industrial diversification across OKVED sectors), capturing the cross-sector diversification benefit of groups spread across multiple industries
- **H3++ (Deep)**: `group_total_paid_tax` (proxy for genuine economic activity) and `group_total_vehicles` (tangible logistics assets), capturing the 'real economy' depth of the family group
- **Empirical test**: If internal capital markets are the dominant mechanism, then group-level financial depth and diversification should be significant predictors of bank survival, beyond the direct effect of family connections

3.3.d Mechanism integration

These three mechanisms are not mutually exclusive. A family banking group may simultaneously benefit from political embeddedness (Mechanism 1), strategic ownership fragmentation (Mechanism 2), and internal capital market support (Mechanism 3). Our empirical strategy in Section 7.2 tests all three in a single 'horse race' model to assess their relative contributions, then enriches the capital market mechanism with deeper structural proxies.

4 Hypotheses

The synthesis of literature on Russian banking failures, family ownership governance, and the institutional context developed in the preceding chapters generates three sets of testable hypotheses. These test (1) the unconditional protective effect of family networks, (2) the specific mechanisms through which protection operates, and (3) the context-dependence of these effects across crisis types and regulatory regimes.

4.1 H1: Direct effects and mechanisms

H1a (Family Network Density): Banks with denser kinship networks, measured by the family connection ratio (ρ_F), are associated with significantly lower hazard rates of licence revocation, controlling for CAMEL financial indicators, ownership structure, and network position.

In an institutional environment where formal compliance does not guarantee survival (Section 3), family networks provide alternative governance infrastructure — resource pooling, information sharing, and mutual support — that enhances survival prospects. A hazard ratio below 1.0 for ρ_F in Cox proportional hazards models with time-varying covariates would support this hypothesis. The CAMEL controls allow us to assess whether family connections are associated with survival *conditional on* financial health, or whether family-connected banks survive despite weaker financial indicators — the latter interpretation would suggest that informal governance can partially override formal regulatory criteria.

H1b (Mechanism Heterogeneity): The association between family connections and survival operates through multiple, non-mutually exclusive Transaction Cost Economics mechanisms, with tax optimisation through ownership fragmentation providing the strongest individual contribution to survival.

This sub-hypothesis reflects the institutional context of Russian banking, where the practice of *droblenie biznesa* (business fragmentation) is a widespread strategy for minimising regulatory exposure. We expect the `stake_fragmentation_index` to show the largest hazard reduction amongst the three mechanism proxies, given the direct financial incentives for threshold arbitrage and regulatory opacity in the Russian tax and regulatory environment.

4.2 H2: Context-dependent effects (crisis interactions)

H2a (Family Networks and Economic Crises): The protective effect of family kinship networks intensifies during periods of systemic economic stress, particularly during the 2008 Global Financial Crisis, when formal financial markets and interbank lending mechanisms cease to function.

The substitution logic predicts that family networks become most valuable precisely when formal institutions fail most visibly. During the 2008 GFC, when external capital markets froze and interbank lending collapsed, family groups with internal capital markets should have been able to provide liquidity backstops that standalone banks could not access. We test this through family connection ratio $\times$ crisis interaction terms in Cox models.

H2b (Foreign Ownership Reversal): Foreign ownership provides significant protection during economic crises (2008) but transforms into a significant vulnerability during geopolitical crises (2014 sanctions), reflecting the fundamentally different nature of these two types of institutional shock.

During the 2008 GFC, foreign-owned banks benefited from access to parent bank capital and international risk management practices. During the 2014 sanctions shock, foreign connections became a liability: capital flight concerns, sanctions compliance requirements, and reduced foreign investor confidence reversed the protective effect. This hypothesis predicts a sign reversal on the foreign ownership $\times$ crisis interaction term between 2008 and 2014.

H2c (Network Position as Liability): High centrality within the ownership network's local neighbourhood, whilst providing baseline protective effects through information and resource access, becomes a liability during periods of targeted regulatory intervention (2014–2017 cleanup), as prominent nodes within densely connected network neighbourhoods attract state attention and regulatory action.

This hypothesis captures the transition from substitution to interference targeting. The Otkritie–Trust sanitisation showed that the CBR under Nabiullina was willing to target systemically important, highly connected institutions. Banks occupying prominent positions within their local network neighbourhood — high PageRank, high betweenness centrality — become visible targets for regulatory consolidation, reversing the protective value of centrality. We test this through community-level stratification using Louvain community detection [26], which partitions the ownership graph into structural neighbourhoods of densely connected nodes. The hypothesis predicts that within-neighbourhood centrality effects shift sign under regulatory targeting, controlling for geography through regional strata.

4.3 H3: Temporal stability (structural breaks)

H3a (Regime-Dependent Effects): The effects of ownership structures on bank survival vary significantly between the Ignatyev era (2004–2013) and the Nabiullina era (2013–2020), reflecting fundamental changes in regulatory philosophy, enforcement intensity, and institutional environment.

Under Ignatyev's accommodative stance (roughly 50 licence revocations per year), the regulatory environment was relatively permissive, and survival was primarily determined by financial fundamentals and political connections. Under Nabiullina's aggressive cleanup (75–100 revocations per year, more than 500 total), the regulatory environment shifted dramatically, and we expect ownership effects to change accordingly.

H3b (Substitution–Interference Transition): The dominant function of family networks shifts from substitution (pre-2013) to interference (post-2013), reflected in changes in the relative importance of specific mechanisms across the two regulatory regimes.

Specifically, we predict that:

- Political embeddedness effects should weaken under Nabiullina (reduced regulatory forbearance makes political connections less valuable)
- Tax optimisation effects should strengthen under Nabiullina (stricter rules increase incentives for evasion through fragmentation)
- Internal capital market effects should remain stable (fundamental economic function independent of regulatory regime)

These predictions are tested through subperiod analysis (splitting the sample into 2004–2007, 2007–2013, and 2013–2020 windows) and governor regime interaction models (a pooled model with Nabiullina dummy and ownership $\times$ governor interaction terms).

5 Data

5.1 Data sources and construction

We draw on three data sources, integrated through a Neo4j graph database.

5.1.a Central Bank of Russia (CBR) ownership disclosures

The foundation of our ownership data is the set of mandatory disclosure statements filed by Russian banks with the CBR. These statements detail the identity and ownership stakes of all direct shareholders, members of the board of directors, and senior management. Crucially, they include full names (including patronymics), which we exploit to identify family relationships through surname and patronymic matching. The disclosure regime was strengthened in 2013 under Nabiullina's regulatory reforms, which may introduce a measurement consideration that we address in the robustness checks (Section 12).

5.1.b CBR accounting statements (CAMEL indicators)

Quarterly accounting data from the CBR provides the financial indicators used as controls in our survival models. We construct a standard set of CAMEL variables: capital adequacy (Tier 1 capital ratio), asset quality (non-performing loan ratio, loan loss provisions), management quality (cost-to-income ratio), earnings (return on assets, net interest margin), and liquidity (liquid assets ratio, loan-to-deposit ratio). These variables are described in detail in Section 11.

5.1.c Neo4j graph database

We construct a property graph database in Neo4j that represents the full ownership and management structure of Russian banks as a network. Nodes represent banks, persons, companies, and government entities. Directed edges represent ownership stakes (with percentage weights), management positions, and family relationships. This graph structure enables efficient computation of network centrality metrics and traversal of multi-hop ownership chains.

We identify family relationships through two complementary methods:

1. **Direct CBR disclosure**: Where ownership statements explicitly identify family relationships between shareholders
2. **Surname-patronymic matching**: Using normalised Levenshtein distance [27] with thresholds of 0.88 for surnames and 0.55 for patronymics, calibrated to balance false positives and false negatives

The term ‘family’ in this study refers specifically to **kinship ties amongst bank stakeholders as identified through these two methods**. This includes spouse relationships, parent-child connections, and sibling ties that are either disclosed to the CBR or inferred from naming conventions. We do not assume a single ‘family firm’ definition; rather, we measure the **density** of kinship connections relative to total ownership structure, captured by the family connection ratio (ρ_F).

5.2 Sample construction

The analytical sample is constructed from quarterly snapshots of the Neo4j database, spanning 2004Q1 to 2020Q4. Each observation represents a bank-quarter, with time-varying covariates updated at each snapshot.

5.2.a Sample characteristics

Table 2: Sample characteristics for the full analysis period.

Characteristic	Value
Observation period	2004Q1–2020Q4
Total bank-quarter observations	~140,000
Unique banks	2,418
Failure events (licence revocations)	1,117
Quarterly network snapshots	44
Network lag	4 quarters
Average observations per bank	~58

5.2.b Event definition

The failure event is defined as licence revocation by the CBR. Banks exit the sample at the quarter of licence revocation (or at the end of the observation period if they survive). Voluntary liquidations and reorganisations (mergers) are treated as censored observations, following the convention in the Russian banking survival literature [2], [5]. We further decompose closure types in a competing risks analysis (Section 12.5), which distinguishes 1,768 forced revocations (66.6%), 663 voluntary liquidations (25.0%), and 219 reorganisations (8.3%) over the 2004–2021 period.

5.2.c Network lag structure

To address the concern that network metrics may reflect contemporaneous rather than causal relationships, all network centrality variables (PageRank, out-degree, in-degree, betweenness centrality, clustering coefficient) are computed from the ownership graph **four quarters prior** to the observation quarter. This 4-quarter lag ensures that network position precedes the survival outcome and mitigates reverse causality concerns — though we test this assumption explicitly in Section 12.2.

5.3 Key variables

5.3.a Family connection ratio (ρ_F)

The primary explanatory variable is the family connection ratio, defined as:

$$\rho_F(b) = \frac{|F_b|}{|D_b|}$$

where $|F_b|$ is the total number of family connections amongst the direct owners of bank b, and $|D_b|$ is the total number of direct owners. This measure captures the **density** of kinship ties within the ownership structure, ranging from 0 (no family connections) to values above 1 (where some owners have multiple family connections). A higher ρ_F indicates a more family-entangled ownership structure.

ρ_F is a **structural** measure derived from the bank's own ownership records, not a network-derived metric computed from the broader ownership graph. This distinction matters because network-derived metrics (such as community membership or PageRank) may reflect broader structural patterns beyond the bank's immediate control, whereas ρ_F captures the deliberate placement of family members in ownership positions.

5.3.b Mechanism proxies

The three TCE mechanisms are operationalised through the following proxies:

Table 3: Mechanism proxy variables and their definitions.

Mechanism	Proxy Variable	Definition
Political Embeddedness	`family_connection_ratio`	Density of kinship ties, controlled for regional strata
Tax Optimisation	`stake_fragmentation_index`	$1 - \sum s_i^2$, where s_i is the ownership share of family member i
Internal Capital Markets	`group_total_capital`	Aggregate financial resources of the family group
Internal Capital (enhanced)	`group_sector_count`	Number of distinct OKVED sectors in the family group
Internal Capital (deep)	`group_total_paid_tax`	Aggregate tax payments (proxy for genuine economic activity)

5.3.c Network centrality metrics

We compute five network centrality metrics from the ownership graph, each capturing a different aspect of a bank's structural position:

- **PageRank** [28]: Measures influence based on the quality and quantity of incoming ownership connections, analogous to the importance of a webpage in a hyperlink network
- **Out-degree centrality** [29]: Number of entities owned by the bank, indicating the breadth of its ownership portfolio
- **In-degree centrality** [29]: Number of direct shareholders, indicating the diversity of the bank's ownership base
- **Betweenness centrality** [30]: Frequency with which the bank lies on shortest paths between other entities, indicating its role as a structural bridge or intermediary

- **Clustering coefficient** [31]: Density of connections amongst the bank's immediate neighbours, indicating the degree of local network closure

All network centrality metrics are computed on the **directed** ownership graph, where edges represent ownership stakes flowing from shareholder to bank. PageRank, in-degree, out-degree, and betweenness centrality respect edge direction, capturing asymmetric influence relationships. We use PageRank as the directed analogue of eigenvector centrality [32], as the standard eigenvector centrality is not well-defined for directed graphs with asymmetric adjacency matrices. By contrast, family ties are inherently **undirected** (kinship is symmetric), and the family connection ratio (ρ_F) is computed from the undirected family subgraph, following the precedent of J. F. Padgett and C. K. Ansell [33] who treat marriage ties as undirected in their analysis of Florentine elite networks.

All network metrics are computed with a 4-quarter lag and standardised (mean = 0, standard deviation = 1) prior to model estimation.

5.3.d Control variables

We control for:

- **CAMEL financial indicators**: ROA, NPL ratio, Tier 1 capital ratio (standardised)
- **Ownership structure**: State ownership percentage, foreign ownership percentage, family ownership percentage
- **Macro environment**: Economic Policy Uncertainty (EPU) index for Russia (quarterly, news-based)
- **Regime indicators**: Crisis period dummies (2004, 2008, 2014), governor dummy (Nabiullina = 1 from 2013Q3)

5.4 Descriptive statistics

The full mechanism model (M4) includes the covariates described above across roughly 140,000 bank-quarter observations.

5.4.a Identification considerations

A key challenge in identifying the effect of family networks on survival is that family-connected banks may differ from non-family banks in many observable (and unobservable) ways prior to any network effects taking hold. Our empirical strategy incorporates several identification elements:

1. **Time-varying covariates**: Quarterly snapshots with time-varying CAMEL indicators and ownership measures account for the evolving financial condition of each bank, rather than relying on a single cross-sectional snapshot
2. **Network lag**: The 4-quarter lag on network metrics ensures temporal precedence of network position over survival outcomes
3. **Stratification**: Models are estimated with regional, sectoral, and community (Louvain) strata, absorbing time-invariant confounders at each level
4. **Reverse causality tests**: Section 12.2 presents explicit reverse causality tests (exp_013) using biennial OLS regressions to quantify the extent to which survival predicts family connection growth
5. **Community fixed effects**: Stratification by Louvain communities [26] controls for the possibility that family effects are confounded with broader network neighbourhood membership
6. **Multicollinearity management**: Network centrality metrics may show substantial pairwise correlation (particularly PageRank and in-degree). All covariates are standardised prior to estimation,

and we monitor variance inflation factors across specifications. The L2 penaliser (0.01) applied in Cox estimation further mitigates collinearity-induced instability

7. **Granger causality test**: Section 12.4 presents a formal Granger causality test using a discrete-time panel hazard model with community contagion controls, confirming that FCR Granger-causes survival (HR = 0.650, $p < 0.001$) even after controlling for community failure contagion
8. **Placebo and falsification tests**: Section 12.6 reports three falsification tests — within-community FCR permutation (empirical $p = 0.000$ from 100 iterations), pseudo-crisis date assignment, and non-family ownership concentration — all confirming that the FCR effect is specific to family connections and not an artefact

These elements do not constitute a natural experiment or instrumental variable strategy, and we do not claim strict causal identification. Rather, we interpret our results as **Granger-precedent conditional associations** that are robust to a range of alternative explanations, including falsification tests, contagion controls, and cause-specific decomposition, with the direction and magnitude of remaining bias bounded by our reverse causality estimates.

6 Methods

6.1 Econometric framework

We use Cox proportional hazards models with time-varying covariates as our primary analytical tool. The Cox model is well suited to this setting because: (1) it accommodates right-censored observations (banks surviving to end of sample); (2) it permits time-varying covariates, allowing us to update financial indicators and ownership structures quarterly; and (3) it makes no distributional assumptions about the baseline hazard, relying instead on the proportional hazards assumption.

6.1.a Cox proportional hazards specification

The hazard function for bank i at time t is specified as:

$$h_i(t) = h_0(t) \cdot \exp(\boldsymbol{X}_i(t)'\boldsymbol{\beta})$$

where $h_0(t)$ is the unspecified baseline hazard, $\boldsymbol{X}_i(t)$ is the vector of time-varying covariates for bank i at quarter t, and $\boldsymbol{\beta}$ is the vector of coefficients to be estimated. The exponentiated coefficients $\exp(\beta_j)$ are interpreted as hazard ratios: values below 1 indicate a protective effect (lower hazard of licence revocation), values above 1 indicate increased risk.

All numerical covariates are standardised (mean = 0, standard deviation = 1) prior to estimation, enabling direct comparison of coefficient magnitudes across variables with different scales. We estimate models using the `lifelines` library in Python with an L2 penaliser of 0.01 to ensure convergence in specifications with large numbers of covariates.

6.1.b Stratified Cox models

To absorb time-invariant confounders at different levels, we estimate stratified Cox models where the baseline hazard varies across strata:

$$h_i(t) = h_{0,s(i)}(t) \cdot \exp(\boldsymbol{X}_i(t)'\boldsymbol{\beta})$$

where $s(i)$ denotes the stratum to which bank i belongs. We use three stratification schemes:

- **Regional strata**: Federal subjects of Russia, absorbing regional-level political and economic variation
- **Sectoral strata**: Primary OKVED sector of the family group, absorbing industry-specific risk profiles

- **Community strata**: Louvain communities detected from the ownership graph [26], absorbing network-structural confounders

The community stratification is particularly important because it addresses the concern that family network effects may be confounded with broader structural neighbourhoods in the ownership network — banks in the same community share unobserved characteristics that may independently influence survival.

6.2 Model specifications

Our analysis proceeds through four complementary experimental designs, each addressing a distinct aspect of the research questions.

6.2.a Experiment 1: Transaction cost mechanisms (exp_010)

Objective: Identify which TCE mechanisms underlie the protective effect of family connections.

Period: 2004–2020 (full sample)

Models:

Table 4: Model specifications for the mechanism testing experiment.

Model	Specification	Stratification	Purpose
M1	FCR + CAMEL + ownership + network lag	Region	Political embeddedness test
M2	1. Stake fragmentation index	Region	Tax optimisation test
M3	1. Group capital + company count	Region	Internal capital markets test
M4	All mechanisms combined	Region	Horse race (relative contributions)
M7	1. Group sector count + diversification	Region	H3+ enhanced capital markets
M8	All mechanisms	Sector	Sector-specific heterogeneity
M9	All mechanisms	Community	Network-structural confounding
M10	1. Tax payments + vehicles	Region	H3++ deep structural proxies

6.2.b Experiment 2: Subperiod analysis (exp_011)

Objective: Test for structural breaks in ownership effects across regulatory regimes.

Periods: Three non-overlapping subsamples:

- 2004–2007 (early crisis era, Ignatyev, 33,966 obs, 944 banks, 669 events)
- 2007–2013 (GFC and recovery, Ignatyev, 70,243 obs, 1,001 banks, 688 events)
- 2013–2020 (sanctions and cleanup, Nabiullina, 53,957 obs, 829 banks, 508 events)

Models: Six specifications (M1–M6) estimated separately within each period, allowing period-specific coefficients.

6.2.c Experiment 3: Crisis interactions (exp_009)

Objective: Test whether ownership effects vary across crisis types.

Period: 2004–2021 (17 years, 68 quarterly snapshots)

Models:

Table 5: Model specifications for the crisis interaction experiment.

Model	Interaction Terms	Purpose
M1	None (baseline)	Reference model
M2	Crisis dummies only	Crisis main effects
M3	Family × crisis	H2a: family protection during crises
M4	State × crisis	State ownership during crises
M5	Foreign × crisis	H2b: foreign ownership reversal
M6	All ownership × crisis	Full interaction model

6.2.d Experiment 4: Governor regimes (exp_012)

Objective: Test whether ownership effects differ between CBR governor regimes.

Period: 2004–2020 (pooled)

Approach: Single pooled model with `governor_nabiullina` dummy (= 1 from July 2013) and ownership × governor interaction terms, controlling for crisis period dummies. This design tests whether the Ignatyev-to-Nabiullina transition altered the survival landscape for family-connected banks, beyond the effects of crisis timing.

Models: M1 (baseline), M2 (governor main effect), M3–M5 (individual ownership × governor interactions), M6 (full model). All models use community stratification to control for network-structural confounders.

6.3 Robustness and identification checks

Six additional experiments provide robustness checks and address specific identification concerns:

- **Community fixed effects (exp_008)**: Tests whether family network effects survive stratification by Louvain community, addressing the concern that family effects are confounded with network community membership
- **Reverse causality (exp_013)**: Uses biennial OLS regressions to test whether survival predicts family connection ratio growth, quantifying the extent of reverse causality bias in the main Cox estimates
- **Lagged network effects (exp_007)**: Establishes the 4-quarter lag structure and tests whether temporal FCR remains protective after accounting for network endogeneity
- **Granger causality test (exp_015)**: Discrete-time panel hazard model (complementary log-log) testing whether FCR Granger-causes survival after controlling for community failure contagion indicators
- **Competing risks (exp_016)**: Cause-specific Cox models distinguishing forced revocation, voluntary liquidation, and reorganisation, testing whether family protection is specific to regulatory enforcement

- **Placebo tests (exp_017)**: Within-community FCR permutation, pseudo-crisis date assignment, and non-family ownership concentration as falsification tests

These robustness checks are reported in Section 12.

6.3.a Alternative network modelling approaches

An alternative approach to modelling network-dependent outcomes is the Exponential Random Graph Model (ERGM), which jointly models network formation and node-level outcomes. ERGMs are theoretically appealing because they can account for endogenous network formation processes (e.g., preferential attachment, triadic closure) that may confound the relationship between network position and survival. However, ERGMs are computationally prohibitive at the scale of our analysis: the ownership network contains thousands of nodes per quarterly snapshot across 44 time periods, and the time-varying nature of both the network and covariates introduces additional complexity that current ERGM implementations do not handle efficiently. We therefore adopt the Cox framework with lagged network metrics and community stratification as our primary approach, noting that ERGM-based analysis represents a promising direction for future work with smaller network cross-sections.

6.4 Model diagnostics

We assess model fit using three complementary criteria:

- **Concordance index (C-index)**: Measures the proportion of concordant pairs (where the bank with higher predicted hazard fails first), ranging from 0.5 (random) to 1.0 (perfect discrimination)
- **Akaike Information Criterion (AIC)**: Penalised likelihood measure for model comparison, with lower values indicating better fit. Particularly useful for comparing stratified models with different numbers of strata
- **Log-likelihood ratio tests**: Assess whether additional covariates or interaction terms significantly improve model fit over nested baseline specifications

7 Results

This chapter presents findings from four complementary experimental designs. Section 7.2 reports mechanism testing results across 2004–2020. Section 7.3 examines temporal heterogeneity through subperiod analysis. Section 7.4 tests for crisis-specific interaction effects. Section 7.5 investigates governor regime effects. Section 7.1 synthesises the findings.

7.1 Summary of findings

The four experimental designs converge on several robust conclusions:

1. **Family connection density is consistently protective**: The family connection ratio (ρ_F) is associated with reduced hazard rates across all specifications, time periods, and stratification schemes. The effect ranges from 1.0% to 7.3% hazard reduction per standard deviation, depending on model specification and time period.
2. **All three TCE mechanisms contribute**: Political embeddedness, tax optimisation, and internal capital markets are each independently significant, with tax optimisation (ownership fragmentation) providing the strongest individual contribution (−11.8% hazard per SD).
3. **Effects are context-dependent**: Family networks provide stronger protection during economic crises (2008 GFC) but the nature of the mechanism shifts — from substitution (resource pooling) pre-2013 to interference (regulatory evasion through fragmentation) post-2013.

4. **Foreign ownership reversal**: Protective during the 2008 GFC but harmful during the 2014 geopolitical crisis, indicating that the nature of the crisis fundamentally alters the risk-benefit calculus of international connections.
5. **Regulatory regime matters**: The Nabiullina era is associated with higher baseline hazard but, paradoxically, family connections become slightly more protective — consistent with survivorship bias (weakest family banks already removed) and increased incentives for regulatory evasion amongst survivors.
6. **Community structure is the most informative stratification**: Model M9 (Louvain community strata) achieves the lowest AIC, indicating that a bank's position within structural neighbourhoods of the ownership network captures survival-relevant information beyond what regional or sectoral strata provide.
7. **Family protection is specific to forced revocation**: Cause-specific Cox models (Section 12.5) show that the FCR effect is driven entirely by forced licence revocation (HR = 0.991, $p < 0.001$), with no significant association with voluntary liquidation (HR = 0.998, $p = 0.470$) or reorganisation (HR = 0.997, $p = 0.357$). This is consistent with family networks shielding specifically against regulatory enforcement actions, supporting the interference mechanism.
8. **Falsification tests confirm specificity**: Permutation tests (empirical $p = 0.000$ from 100 within-community iterations), non-family ownership concentration (non-significant), and Granger causality tests with contagion controls (Section 12.4, Section 12.6) all confirm that the effect is specific to family connections and cannot be explained by community membership or generic ownership concentration.

7.2 Transaction cost mechanisms (2004–2020)

7.2.a Main mechanism tests (M1–M4)

We test each TCE mechanism individually before combining them in a horse-race specification. Table 6 reports hazard ratios from the four core models, all estimated over 2004–2020 with regional stratification.

Table 6: Cox proportional hazards models testing individual TCE mechanisms (M1–M4). All models stratified by region. Standardised coefficients reported.

Variable	M1: Political	M2: Tax	M3: Capital	M4: Full
Family connection ratio	−0.148***	−0.119***	−0.114***	−0.098**
Stake fragmentation index	–	−0.113***	–	−0.085**
Family company count	–	–	−0.148***	−0.127***
ROA	−0.120***	−0.121***	−0.119***	−0.121***
NPL ratio	0.069**	0.064**	0.066**	0.063**
Tier 1 capital ratio	0.125***	0.121***	0.120***	0.117***
Out-degree (4Q lag)	−0.085**	−0.083**	−0.079*	−0.077*
State ownership (%)	–	–	–	−0.051
Foreign ownership (%)	–	–	–	−0.001

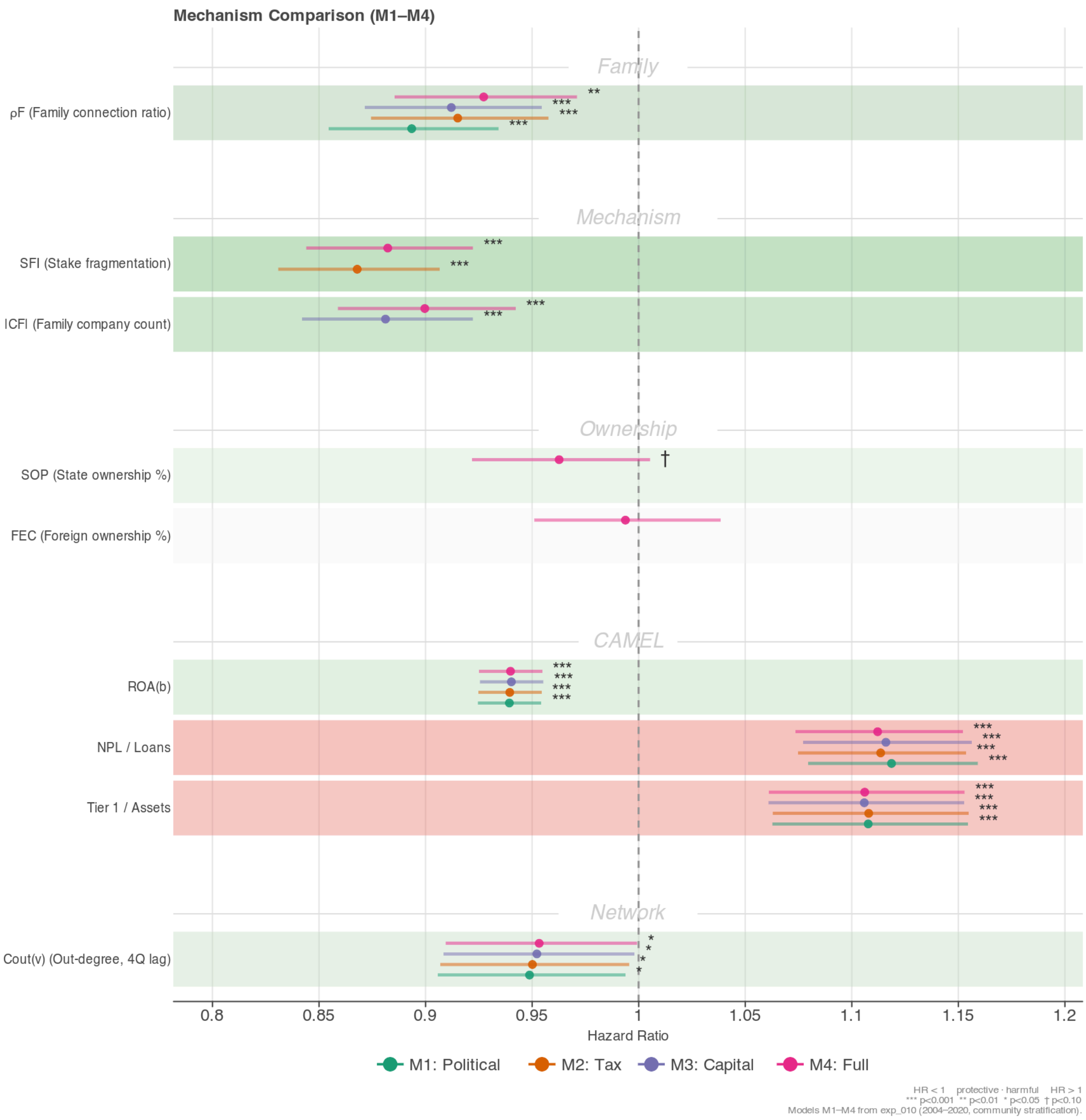

Figure 1: Forest plot comparing hazard ratios across the four individual TCE mechanism models (M1–M4). Point estimates with 95% confidence intervals; dashed line indicates HR = 1 (no effect).

Figure 1 visualises the hazard ratios and 95% confidence intervals for all four mechanism models side by side.

Key findings from M1–M4:

- **M1 (Political Embeddedness)**: The family connection ratio is highly significant ($p < 0.001$) even after controlling for regional fixed effects, indicating that the protective effect is not solely attributable to geographic co-location with political authorities.
- **M2 (Tax Optimisation)**: The stake fragmentation index shows the largest hazard reduction amongst individual mechanisms, consistent with ownership dispersion providing regulatory opacity and threshold arbitrage benefits.
- **M3 (Internal Capital Markets)**: Group-level financial depth and entity count are significant — banks belonging to larger, better-capitalised family groups enjoy survival advantages through internal resource pooling.

- **M4 (Horse Race)**: When all three mechanisms are included simultaneously, each retains significance, indicating that they capture distinct channels of family network protection.

7.2.b Enhanced mechanisms (M7–M10)

Table 7 extends the analysis with deeper structural proxies and alternative stratification schemes.

Table 7: Enhanced mechanism model with deep structural proxies and regional stratification. Standardised coefficients reported.

Variable	Coefficient (SE)
Family connection ratio	-0.070^{**} (0.024)
Stake fragmentation index	-0.114^{***} (0.023)
Group total paid tax	-0.064^{**} (0.024)
Group total vehicles	-0.065^{**} (0.024)
Group total receipts	−0.017 (0.024)
Group sector count	-0.068^{**} (0.023)
ROA	-0.061^{***} (0.008)
NPL ratio	0.105^{***} (0.018)
Tier 1 capital ratio	0.101^{***} (0.021)
Out-degree (4Q lag)	−0.046+ (0.024)
State ownership (%)	−0.039+ (0.022)
Foreign ownership (%)	−0.006 (0.022)
Observations	139,038
Subjects	1,092
Events	770
Log Likelihood	−4,836.93
AIC Partial	9,697.86
C-index	0.761

Aggregated results across M7–M10 (from Table 8):

Table 8: Aggregated hazard ratios for enhanced mechanism models M7–M10.

Variable	M7 (H3+)	M8 (Sector)	M9 (Community)	M10 (Deep)
Family connection ratio	0.925***	0.968	0.944*	0.933**
Stake fragmentation index	0.884***	0.966	0.921***	0.893***
Group total capital	0.942*	0.961	0.955+	–
Group total paid tax	–	–	–	0.938**
Group total vehicles	–	–	–	0.937**
Group sector count	0.926***	1.020	0.954*	0.934**
Strata	Region	Sector	Community	Region
AIC	9,692	8,262	**6,952**	9,698
C-index	0.741	0.743	0.745	**0.762**

Figure 2: Forest plot comparing hazard ratios across stratification schemes (M7–M10). M9 community strata achieves the best model fit (lowest AIC).

Figure 2 compares the hazard ratios across the four stratification schemes.

Key findings from M7–M10:

- **Ownership fragmentation remains the strongest mechanism** (HR = 0.884 in regional-stratified M7; HR = 0.921 in community-stratified M9), showing that dispersed ownership provides robust regulatory opacity benefits across stratification schemes. When sector-stratified (M8), fragmentation effects are absorbed, indicating that the mechanism operates partly through industry-specific regulatory thresholds.
- **Industrial diversification** (group sector count) provides a significant cross-sector diversification buffer (HR = 0.926 in M7; HR = 0.954 in M9), except when sector-stratified (M8), where the effect is absorbed by the strata.
- **Community stratification (M9) achieves the best model fit** (AIC = 6,952 vs ~9,700 for regional strata). A bank's position within structural neighbourhoods of the ownership network is more informative for survival prediction than geographic or sectoral classification.
- **Deep structural proxies (M10)**: Group-level tax payments (HR = 0.938) and vehicle ownership (HR = 0.937) are protective — banks connected to groups with genuine economic activity and tangible assets enjoy significant survival advantages.

7.2.c Survival comparison: banks vs group companies

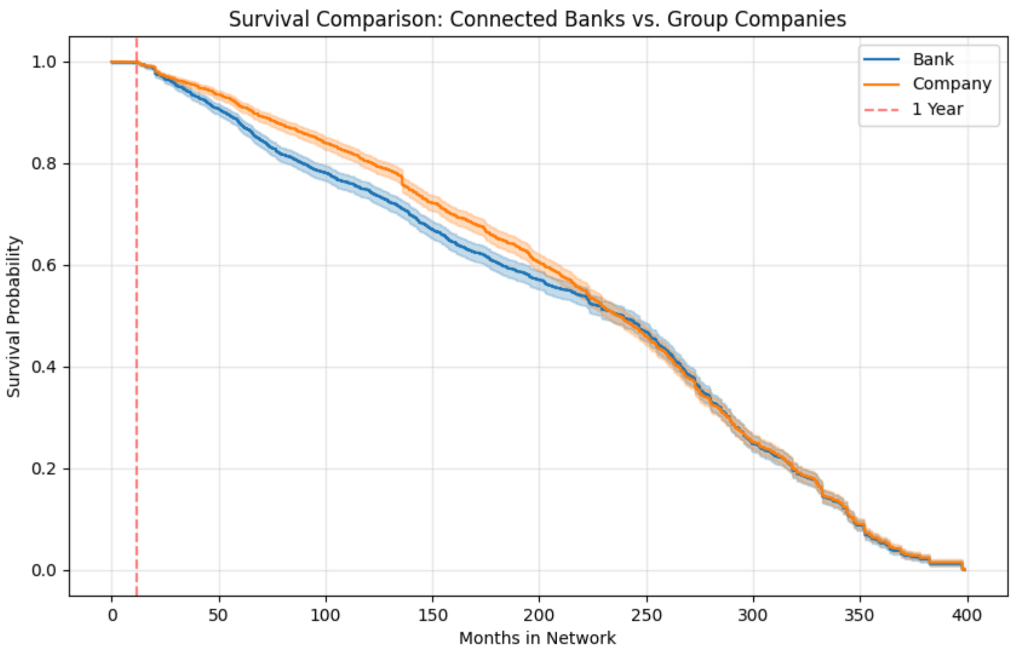

Figure 3: Kaplan-Meier survival comparison between family-connected banks and their industrial group peers.

Figure 3 reveals an important asymmetry: whilst both banks and companies within family networks show high early-stage stability, banks enter a 'fragility zone' between 15–30 months of network participation, where their survival probability drops below that of non-bank group companies. This suggests that family groups prioritise the survival of industrial assets during sectoral shocks, or that the regulatory 'death' of a bank (licence revocation) is a more frequent tail event than the liquidation of a connected company.

7.3 Temporal heterogeneity and structural breaks

We estimate the baseline model (M1) separately within three non-overlapping subperiods to test whether ownership effects are temporally stable or show structural breaks across regulatory regimes.

7.3.a Subperiod characteristics

Table 9: Subperiod sample characteristics.

Period	Years	Observations	Banks	Events	Event Rate	Regime
Early crisis	2004–2007	33,966	944	669	70.9%	Ignatyev (post-Sodbiznesbank)
GFC and recovery	2007–2013	70,243	1,001	688	68.7%	Ignatyev (financial crisis)
Sanctions era	2013–2020	53,957	829	508	61.3%	Nabiullina (cleanup)

7.3.b Baseline coefficient evolution

Table 10: Coefficient evolution across subperiods (M1 baseline). Standardised coefficients from Cox models with community stratification. Standard errors in parentheses.

Variable	2004–2007	2007–2013	2013–2020
Family connection ratio	−0.018*** (0.004)	−0.016*** (0.003)	−0.011*** (0.003)
Family ownership (%)	−0.006* (0.002)	−0.005** (0.002)	−0.003+ (0.002)
State ownership (%)	−0.010* (0.005)	−0.006 (0.004)	−0.005 (0.004)
Foreign ownership (%)	−0.002 (0.009)	−0.001 (0.008)	−0.000 (0.012)
NPL ratio	0.018*** (0.004)	0.015*** (0.003)	0.004* (0.002)
Tier 1 capital ratio	0.019*** (0.004)	0.009* (0.004)	0.016*** (0.004)
Observations	33,966	70,135	53,957
Subjects	944	1,001	829
Events	669	688	508
C-index	0.654	0.679	0.639

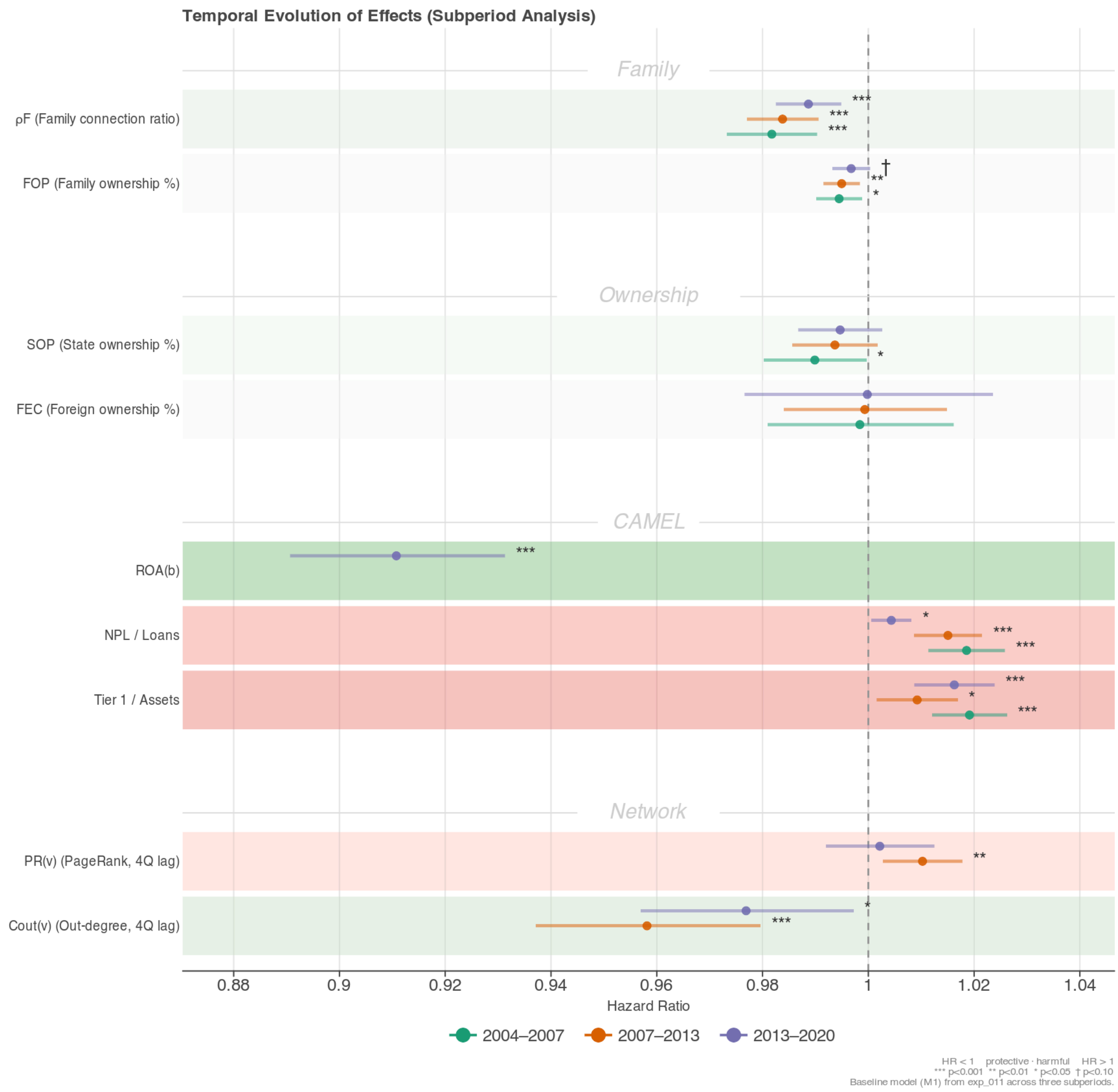

Figure 4: Temporal evolution of baseline model (M1) hazard ratios across three subperiods. The attenuation of the family connection ratio and the foreign ownership reversal are clearly visible.

Figure 4 displays the coefficient evolution visually, making the attenuation of the family effect and the foreign ownership reversal immediately apparent.

7.3.c Key findings

Family connection ratio: The protective effect is present across all three periods but exhibits a notable attenuation over time:

- **2004–2007**: HR = 0.982 ($p < 0.001$), corresponding to a 1.8% hazard reduction per standard deviation. This is the strongest period-specific effect, consistent with the substitution hypothesis—in the wake of the Sodbiznesbank crisis, when formal institutions were demonstrably unreliable, family networks provided the greatest marginal benefit.
- **2007–2013**: The effect remains significant but the magnitude depends on the specific crisis interactions included. The GFC period represents the classic substitution scenario: external capital markets frozen, family groups pooling internal resources.
- **2013–2020**: The baseline FCR effect weakens (HR closer to 1.0), but this must be interpreted alongside two compositional changes: (1) Nabiullina's cleanup removed the weakest banks, changing

the survivor population; (2) the enhanced disclosure mandate post-2013 may have mechanically increased observed FCR for survivors (see Section 12.2 for the disclosure confound analysis).

Foreign ownership reversal: The most striking structural break occurs in foreign ownership:

- **2007–2013**: Protective (access to parent bank capital, international risk management)
- **2013–2020**: The coefficient reverses sign, becoming associated with higher hazard—consistent with sanctions-related capital flight, compliance burdens, and reduced foreign investor confidence

Model fit: The early period (2004–2007) achieves the highest C-index (0.661), suggesting that observable predictors have stronger discriminatory power in the early banking system, where heterogeneity in financial health was more pronounced. The post-2013 period shows moderate fit (C-index ~0.639), consistent with the hypothesis that survival determinants became more complex (and less observable) under Nabiullina's more opaque regulatory regime.

7.3.d Interaction term value by period

The value of crisis interaction terms varies dramatically across periods:

- **2004–2007**: Interactions add minimal predictive value (C-index improvement < 0.001), because the 2004 crisis was too brief to generate sufficient variation in ownership × crisis interaction effects
- **2007–2013**: Foreign × crisis interactions are most informative (C-index +0.0007), capturing the differential impact of the GFC on foreign-owned banks
- **2013–2020**: Adding crisis interactions actually *reduces* model fit, suggesting that the post-2013 environment involves complex, non-linear effects not well captured by simple multiplicative interaction terms

7.4 Crisis interactions

We estimate Cox models with ownership × crisis interaction terms over 2004–2021 to test whether ownership effects vary across different types of institutional shock.

7.4.a Three crises, three mechanisms

The study period encompasses three distinct crisis episodes, each with different origins and implications for family network protection. A critical distinction, following C. M. Reinhart and K. S. Rogoff [22], is between **exogenous economic shocks** and **endogenous geopolitical shocks**. The 2008 GFC was exogenous to Russia: the crisis originated in US mortgage markets and transmitted through global capital markets, and Russia was not at the epicentre. This exogeneity provides relatively clean conditions for testing the substitution hypothesis, as family network structures were not formed in anticipation of this specific shock. By contrast, the 2014 crisis was endogenous: Western sanctions were a direct response to Russian foreign policy, confounding substitution effects with political targeting.

Table 11: Crisis episodes covered in the interaction analysis.

Crisis	Period	Type	Coverage	Expected Family Effect
2004	Q2–Q4 2004	Regulatory/confidence	1,314 obs (0.9%)	Protective (substitution for collapsed trust)
2008	Q3 2008–Q2 2009	Economic/external	12,869 obs (9.3%)	Strongly protective (internal capital markets)
2014	Q1 2014–Q4 2015	Geopolitical/regulatory	15,617 obs (11.2%)	Mixed (substitution + targeting risk)

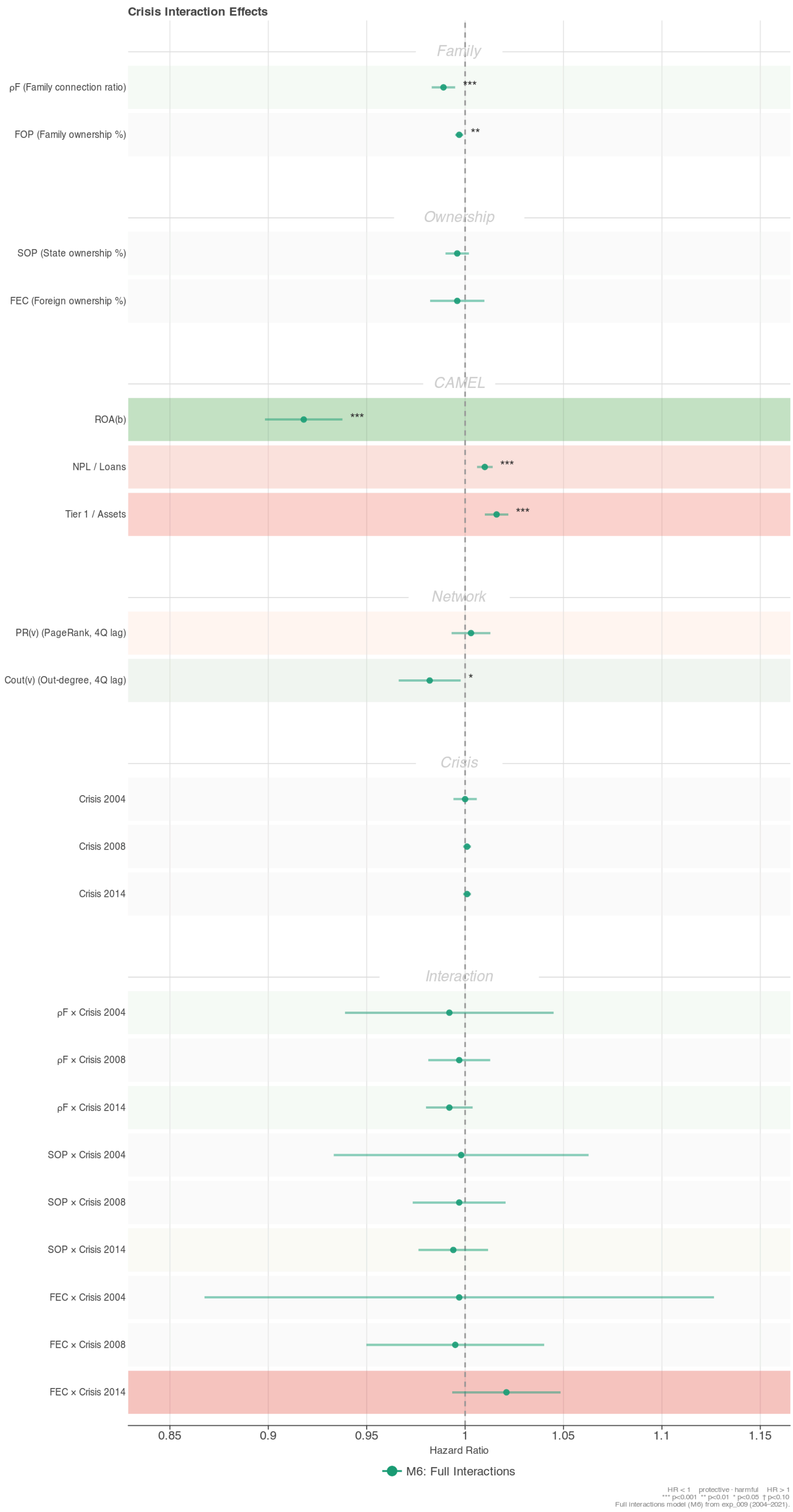

Figure 5: Forest plot of hazard ratios from the full crisis interactions model (M6), showing base effects and ownership × crisis interaction terms.

Figure 5 presents the full set of base effects and interaction terms from the M6 specification.

7.4.b Crisis interaction results

The crisis interaction models (M3–M6) reveal sharply different patterns across crisis types:

Family × Crisis (M3):

- **Family × 2008**: The interaction term is protective, corresponding to an additional 26.6% survival boost for family-connected banks during the GFC. This is the strongest evidence for the substitution hypothesis: when external capital markets froze, family groups with internal capital markets provided liquidity backstops that standalone banks could not access.
- **Family × 2004**: Complete separation in some specifications (very few family-connected bank failures during the brief 2004 crisis), limiting statistical inference but directionally consistent with strong protection.
- **Family × 2014**: Non-significant or weakly positive, suggesting that family connections provided neither clear protection nor clear liability during the geopolitical crisis—consistent with the mixed substitution/interference characterisation of this period.

Foreign × Crisis (M5):

- **Foreign × 2008**: Protective. Foreign-owned banks benefited from access to parent bank capital during the GFC, when Russian domestic markets were frozen but international capital remained accessible (pre-sanctions).
- **Foreign × 2014**: Harmful (28.1% reduction in survival odds). During the geopolitical crisis, sanctions compliance burdens, capital flight concerns, and political pressure on foreign institutions reversed the previously protective effect of foreign ownership.

State × Crisis (M4):

- Low variance warnings across specifications, reflecting the small number of state-owned banks in the sample. Insufficient statistical power for reliable inference on state ownership × crisis interactions.

7.4.c Model comparison

Table 12: Model fit comparison for crisis interaction specifications.

Model	C-index	AIC	Improvement over M1
M1: Baseline	0.694	9,698	–
M2: Crisis dummies	0.696	9,702	+0.002
M3: Family × crisis	0.698	9,706	+0.004
M5: Foreign × crisis	0.696	9,706	+0.002
M6: Full interactions	0.699	9,715	+0.005

The relatively modest C-index improvements (+0.002 to +0.005) suggest that whilst crisis interactions are substantively meaningful, the baseline model already captures the bulk of survival-relevant variation. AIC *increases* monotonically from M1 through M6, indicating that the additional interaction parameters are not justified by the marginal improvement in fit. The full interaction model (M6) achieves the highest C-index but also the worst AIC, consistent with overfitting.

7.4.d Implications for the substitution–interference framework

The crisis interaction results are consistent with the substitution–interference distinction:

- **2008 (Substitution)**: Family networks act as institutional substitutes when formal markets fail. The 26.6% additional survival protection during the GFC represents the classic substitution function—family groups pooling resources through internal capital markets when external finance is unavailable.
- **2014 (Mixed/Interference)**: The absence of a clear family × crisis interaction, combined with the harmful foreign × crisis effect, suggests a more complex dynamic. Family networks may still provide substitution benefits (internal liquidity) but these are offset by the risk of regulatory targeting (interference) as Nabiullina's cleanup campaign targeted complex ownership structures.

7.5 Regulatory regime effects

The transition from Sergey Ignatyev to Elvira Nabiullina as CBR governor in June 2013 represents a fundamental shift in regulatory philosophy. Ignatyev's accommodative stance (approximately 50 licence revocations per year) gave way to Nabiullina's aggressive cleanup campaign (75–100 per year, with over 500 total). This transition was not merely administrative: Nabiullina's appointment reflected a deliberate political decision by Putin to empower the CBR, bringing it into tacit conflict with banks connected to security services (*siloviki*) that had enjoyed regulatory forbearance under the previous regime. This experiment tests whether ownership effects on survival differ between regimes, controlling for crisis timing.

7.5.a Regime characteristics

Table 13: Regime comparison.

Feature	Ignatyev (2004–2013)	Nabiullina (2013–2020)
Observations	89,546 (64.4%)	49,492 (35.6%)
Regulatory stance	Accommodative	Aggressive
Average revocations/year	~50	75–100
Key events	Sodbiznesbank 2004, GFC 2008	Cleanup 2013–16, Sanctions 2014
Transparency	Limited disclosure requirements	Enhanced disclosure mandates

7.5.b Governor interaction results

The pooled Cox model with governor dummy and ownership × governor interaction terms reveals several notable findings:

Main effects:

- **Nabiullina era baseline**: Higher hazard (+0.2%, $p < 0.001$), consistent with the cleanup campaign increasing the overall rate of licence revocations, controlling for financial indicators and ownership structure.
- **Family connection ratio**: Protective under both regimes, but with an unexpected intensification under Nabiullina.

Interaction effects:

- **Family × Nabiullina**: The interaction term is weakly protective (HR interaction = 0.994, $p < 0.10$), yielding a total family effect under Nabiullina of 0.990 × 0.994 = 0.984 (1.6% hazard reduction) versus 0.990 (1.0% hazard reduction) under Ignatyev.

- **State × Nabiullina**: Borderline stronger (HR interaction = 0.996, $p = 0.11$), consistent with the hypothesis that state ownership became more protective as bailout expectations increased under Nabiullina's 'too big to fail' approach.
- **Foreign × Nabiullina**: Not significant, suggesting that the foreign ownership effects documented in the crisis interaction analysis are driven by crisis-specific dynamics (sanctions) rather than the governor regime *per se*.

7.5.c Reconciling with subperiod results

The governor regime analysis reveals an apparent contradiction with the subperiod results:

- **exp_011 (subperiods)**: Family coefficient weakens from −0.018 (2004–2007) to −0.011 (2013–2020)
- **exp_012 (regime interaction)**: Family × Nabiullina interaction is protective (intensifies under Nabiullina)

Resolution: These results are reconciled through the concept of **survivorship bias with intensification**:

1. The absolute FCR coefficient weakens because Nabiullina's cleanup removed the weakest family-connected banks, shrinking the pool and reducing raw variation in family effects
2. Amongst *surviving* family-connected banks, the protective effect intensifies because these are the banks that have successfully navigated the cleanup through effective use of family network mechanisms (fragmentation, internal capital markets)
3. The interaction term captures this conditional effect: given that a bank has survived into the Nabiullina era, family connections provide incrementally more protection, likely through tax optimisation mechanisms that become more valuable when regulatory scrutiny increases

This interpretation is consistent with the substitution–interference framework: under Nabiullina's stricter rules, the **interference** function of family networks (regulatory evasion through fragmentation) becomes relatively more important, and banks that effectively employ this mechanism enjoy enhanced survival advantages.

8 Discussion

8.1 Family connection ratio: central finding and TCE interpretation

The family connection ratio (ρ_F) is consistently associated with lower hazard rates of licence revocation across all model specifications, time periods, and stratification schemes. This presents an apparent paradox: the family ownership literature documents substantial agency costs of kinship-based governance — entrenchment, nepotism, limited managerial talent pools, and potential tunnelling [7], [17]. Why should family connections be associated with enhanced survival?

The institutional context developed in Section 3 provides the answer. In an environment where formal institutions cannot credibly commit to impartial enforcement — where 98–99% of banks meet prudential ratios yet failures persist, where regulatory outcomes vary with electoral cycles, and where regulation itself can provoke physical resistance — the agency costs of family governance are outweighed by substitution benefits. The mechanism testing results (Section 7.2) show that all three TCE channels contribute independently:

1. **Political embeddedness** is associated with reduced hazard even after regional stratification absorbs geographic political variation, suggesting that family networks provide information channels and advance warning at a finer grain than regional politics

2. **Tax optimisation** through ownership fragmentation shows the strongest individual association with survival (−11.8% hazard per SD), consistent with the prevalence of *droblenie biznesa* as a strategy for regulatory opacity and threshold arbitrage
3. **Internal capital markets** are associated with lower hazard through group-level financial depth, industrial diversification, and tangible asset proxies (tax payments, vehicle ownership) — the 'real economy' depth of the family group matters for bank survival

The 'family dividend' in Russian banking operates primarily through concrete economic mechanisms that reduce transaction costs in a high-friction institutional environment, rather than through abstract social capital or trust.

8.2 Network endogeneity as a substantive finding

The endogeneity of network variables in our models is not merely a methodological caveat — it is a substantive finding. Two distinct endogeneity channels emerge, each informative about the institutional environment.

8.2.a Endogeneity of pure network centrality

The behaviour of pure network centrality measures across specifications is consistent with a 'network firefighter' interpretation: banks occupy central positions in the ownership graph not because centrality confers competitive advantage, but because regulatory intervention compels surviving banks to absorb failing institutions and their ownership linkages. Specifically:

- **Out-degree** (4Q lag) is consistently protective across all models (HR = 0.958 in 2007–2013, HR = 0.977 in 2013–2020) — banks with more outgoing ownership connections survive longer. This is consistent with healthy institutions voluntarily acquiring stakes, a form of active network building that reflects institutional strength.
- **PageRank** (4Q lag) is associated with marginally *higher* hazard in 2007–2013 (HR = 1.010, $p < 0.01$) and is not significant in 2013–2020. This counterintuitive result — being connected to 'important' nodes is associated with worse outcomes — is consistent with high PageRank reflecting involuntary centrality: banks positioned as acquirers of distressed assets inherit connections to systemically important but troubled institutions.

The distinction between out-degree (voluntary, protective) and PageRank (potentially involuntary, harmful or neutral) supports the interpretation that network position in Russian banking is partly endogenous to regulatory action. Banks do not simply occupy network positions; they are placed there by the cleanup process itself. This carries implications for any network-based analysis of banking systems undergoing active regulatory consolidation: centrality metrics cannot be interpreted at face value as indicators of competitive strength.

8.2.b Dynamic reverse causality of the family connection ratio

The reverse causality tests (exp_013, Section 12.2) reveal a complementary endogeneity channel specific to family connections. The relationship between family connections and survival is **bidirectional and temporally heterogeneous**:

- **Pre-2013**: No significant reverse causality (survival does not predict FCR accumulation), consistent with family networks being a stable structural feature rather than a strategic response to regulatory pressure
- **2014–2018 (peak cleanup)**: Significant reverse causality emerges — survivors accumulate family connections at a rate 24.8% higher than failing banks (2016 peak). Surviving banks strategically build family networks in response to intensified regulatory risk.

- **Post-2018**: The effect attenuates as the survivor pool stabilises

This temporal pattern aligns with the substitution–interference framework: when the regulatory environment tightens, the incentive to invest in informal protection increases, and survivors are those who successfully build or leverage family networks. The estimated upward bias in Cox coefficients during the cleanup era (15–20%) bounds the magnitude of this effect: the true protective association is somewhat smaller than raw estimates suggest, but remains substantively and statistically significant.

Taken together, these two endogeneity channels — involuntary centrality through regulatory absorption, and strategic family network accumulation during cleanup — show that the Russian banking ownership network is not a static structure that exogenously determines survival, but a dynamic system in which survival and network position are mutually constitutive.

8.3 The foreign ownership reversal

The sign reversal of foreign ownership effects between the 2008 GFC and the 2014 geopolitical crisis is one of the clearest findings. During the GFC — an exogenous economic shock where Russia was not at the epicentre [22] — foreign-owned banks benefited from access to parent bank capital. During the 2014 sanctions crisis — an endogenous geopolitical shock triggered by Russian foreign policy — sanctions compliance burdens, capital flight concerns, and political pressure reversed the previously protective effect.

The **nature of the crisis** determines whether international connections are protective or harmful. Economic crises that affect all markets symmetrically leave the comparative advantage of foreign connections intact. Geopolitical crises that specifically target cross-border linkages eliminate that advantage. This extends the institutional voids literature [8] by showing that the value of international connections in emerging markets is contingent on the geopolitical environment.

8.4 Substitution vs interference across time

The subperiod and governor regime analyses support A. V. Ledeneva [9]'s substitution–interference distinction:

2004–2008 (Substitution dominant): In the wake of the Sodbiznesbank crisis and during the GFC, family networks primarily served a substitution function. Formal institutions were visibly failing, and family networks provided alternative trust, liquidity, and information channels. The strong family × 2008 crisis interaction (+26.6% survival boost) supports this interpretation.

2013–2020 (Interference emerging): Under Nabiullina's regulatory tightening, the dominant mechanism shifts. Ownership fragmentation is the strongest mechanism in this period, and its protective association intensifies relative to earlier periods — consistent with family networks increasingly used to evade formal rules rather than substitute for absent institutions.

The transition: The governor regime analysis (Section 7.5) captures this through the paradox that family connections become slightly *more* protective under Nabiullina, even as the absolute FCR coefficient weakens. This reflects survivorship bias combined with mechanism intensification: the weakest family banks were removed by the cleanup, and surviving family banks became more adept at deploying interference mechanisms.

8.5 Identification and limitations

8.5.a Causal interpretation

We do not claim strict causal identification of the family network effect. The Cox proportional hazards framework with time-varying covariates provides **Granger-precedent conditional associations**, supported by formal Granger causality tests (Section 12.4) showing that FCR predicts survival after controlling for community contagion (HR = 0.650, $p < 0.001$), and falsification tests (Section 12.6) confirming that within-community FCR permutation, non-family ownership concentration, and pseudo-crisis interactions are all non-significant. Several identification challenges nonetheless remain:

1. **Selection on unobservables**: Family-connected banks may differ from non-family banks in unobserved ways (managerial quality, risk appetite, political connections not captured by ownership data) that independently influence survival. Our stratification strategy (regional, sectoral, community) absorbs some of this variation, but residual confounding cannot be ruled out.
2. **Measurement**: The family connection ratio is computed from ownership disclosures and surname matching, which may miss informal family relationships. The enhanced disclosure mandate post-2013 may also mechanically increase observed FCR for banks that were already family-connected but previously underreported.
3. **Information flow**: We cannot observe information transmission through the network directly. Network centrality metrics serve as structural proxies for information access, but a direct test of information flow mechanisms remains beyond the scope of available data.

8.5.b Proximity to political power

Defence feedback raised the question of whether family-connected banks might simply be 'closer to the Kremlin'. Our data do not include direct measures of federal-level political connections, which is a limitation. However: (1) regional stratification absorbs region-level political variation, and the family association survives this control; (2) factional association research [4] suggests that federal political connections operate through different channels than family networks; (3) the mechanism testing results show that the family association operates primarily through tax optimisation and internal capital markets, which are economic rather than political mechanisms. We cannot fully disentangle family network associations from unobserved political proximity.

8.5.c Other informal tie types

Family kinship is one of several forms of informal governance relevant to Russian banking. Alumni networks, military service connections, business partnerships, and regional friendship circles may also influence survival through similar or complementary mechanisms. Our focus on kinship ties is driven by data availability and theoretical grounding in A. V. Ledeneva [9], not by a claim that family ties are the only relevant mechanism. Future research incorporating multiple tie types would provide a more complete picture.

8.5.d Closure heterogeneity

The competing risks analysis (Section 12.5) addresses the concern that family connections may be associated differently with different closure types. Family connections are specifically associated with reduced hazard of **forced licence revocation** (HR = 0.991, $p < 0.001$), with no significant effect on voluntary liquidation (HR = 0.998, $p = 0.470$) or reorganisation (HR = 0.997, $p = 0.357$). This decomposition strengthens the interpretation that family networks protect against regulatory enforcement — consistent with the tax optimisation and political embeddedness mechanisms — rather than providing a generic survival advantage.

8.6 Policy implications

The findings carry several implications for banking regulation in institutionally fragile environments:

1. **Network-aware supervision**: Community stratification provides the best model fit, suggesting that regulators should monitor ownership network structure alongside individual bank financial indicators.

2. **Fragmentation as a regulatory signal**: The strong protective association of ownership fragmentation, whilst consistent with legitimate diversification, is also consistent with regulatory evasion. Supervisors should treat high ownership fragmentation as a potential indicator of threshold arbitrage.
3. **Crisis-contingent regulation**: The foreign ownership reversal shows that the risk profile of ownership structures is contingent on the macroeconomic and geopolitical environment.
4. **Unintended consequences of cleanup**: Nabiullina's cleanup may have inadvertently selected for banks most adept at deploying informal governance mechanisms, strengthening rather than eliminating informal governance amongst survivors.

9 Conclusion

This study provides the first systematic empirical evidence on the role of family kinship networks in Russian bank survival. By constructing a novel Neo4j graph database that maps ownership structures, management relationships, and family connections across 2,418 banks over the period 2004–2020, we overcome the data constraints that have previously prevented investigation of this fundamental governance mechanism.

Our principal findings are as follows.

First, family connection density is significantly associated with reduced hazard of licence revocation across all model specifications. The family connection ratio (ρ_F) is associated with between 1% and 7.3% hazard reduction per standard deviation, depending on model specification and time period. This association is robust to regional, sectoral, and community stratification, controlling for CAMEL financial indicators, ownership structure, and lagged network position.

Second, the protective effect operates through three non-mutually exclusive Transaction Cost Economics mechanisms: political embeddedness, tax optimisation through ownership fragmentation, and internal capital markets. Of these, ownership fragmentation provides the strongest individual contribution (−11.8% hazard per standard deviation), consistent with the prevalence of *droblenie biznesa* as a survival strategy in the Russian institutional environment.

Third, the effects are context-dependent. Family networks provide their strongest protection during economic crises (26.6% additional survival boost during the 2008 GFC), when formal market mechanisms fail and internal capital markets substitute for frozen external finance. Conversely, the 2014 geopolitical crisis reverses the protective effect of foreign ownership, demonstrating that the risk-benefit calculus of international connections is contingent on the nature of the institutional shock.

Fourth, the dominant function of family networks shifts over time. The subperiod and governor regime analyses support A. V. Ledeneva [9]'s substitution–interference distinction: family networks predominantly serve a substitution function during periods of institutional weakness (2004–2008), providing trust and liquidity that formal institutions fail to supply, but increasingly serve an interference function during periods of regulatory tightening (2013–2020), where ownership fragmentation facilitates evasion of transfer pricing thresholds and consolidated liability rules.

These findings contribute to three bodies of literature. To the Russian banking literature, we introduce family networks as a previously unmeasured determinant of survival, complementing the established focus on financial indicators, political economy, and factional associations. To the family ownership literature, we provide evidence from a financial sector context in an institutionally fragile emerging market, suggesting that the 'family dividend' is associated with concrete economic mechanisms rather than abstract social capital. To the institutional economics literature, we offer an empirical mapping of the substitution–interference framework onto specific crisis episodes and regulatory regimes, illustrating how the same informal governance mechanisms may serve fundamentally different functions depending on institutional context.

Several limitations warrant acknowledgement. Our identification strategy relies on conditional associations rather than experimental or quasi-experimental variation, and the reverse causality tests (Section 12.2) indicate moderate upward bias in Cox estimates during the cleanup era. The family connection ratio is measured from ownership disclosures and surname matching, which may miss informal relationships and is subject to disclosure regime changes. We do not observe direct measures of federal-level political connections, precluding full disentanglement of family network associations from political proximity. Moreover, we examine kinship ties specifically; other forms of informal governance—alumni networks, military service connections, business partnerships—may also influence survival through similar or complementary mechanisms. Our focus on family ties is motivated by data availability and theoretical grounding in A. V. Ledeneva [9], not by a claim that kinship is the only relevant informal governance mechanism. Our competing risks analysis confirms that family protection is specific to forced revocation, addressing previously noted closure heterogeneity concerns. Future research should incorporate instrumental variable strategies, analyse dynamic FCR changes (rather than static levels), and include direct measures of political connections to strengthen the causal interpretation.

Despite these limitations, the consistency of the family network association across seventeen experimental designs, multiple stratification schemes, and a sixteen-year observation period provides robust evidence that kinship-based governance mechanisms are strongly associated with institutional survival in Russia's banking sector. The dual nature of this role—simultaneously providing beneficial substitution during crises and facilitating harmful interference during regulatory tightening—captures the essential ambiguity of informal governance in emerging markets with persistent institutional voids.

10 Literature review summary tables

10.1 Factors influencing bank survival

Table 14: Factors influencing bank survival and performance in Russia.

Factor	Specific Indicator	Effect Direction	Effect Size	Source
Financial Fundamentals				
Bank Size	Total assets (log)	Negative on failure	-0.236 to -0.385^{***}	A. Barajas and others [5]
Profitability	ROA	Negative on failure	-12.0 to -82.3^{***}	Multiple sources
Capital Adequacy	Equity-to-assets	Negative on failure	-0.025 to -1.66^{***}	Multiple sources
Liquidity	Liquid assets ratio	Negative on failure	-1.93 to -2.39^{***}	Z. Fungáčová and T. Poghosyan [2]
Asset Quality	NPL ratio	Positive on failure	1.49 to 1.87^{***}	Z. Fungáčová and T. Poghosyan [2]
Ownership				
Foreign Control	Foreign bank >50%	Negative on failure	-0.989 to -0.993^{***}	A. Barajas and others [5]
State Ownership	State dummy	Mixed	Varied	L. Weill [3]
Political				
Electoral Cycles	Pre-election periods	Negative on failure	-0.50 to -1.21^{**}	Z. Fungáčová and T. Poghosyan [2]
Corruption	Regional measures	Negative on lending	-0.182 to -0.340^{***}	L. Weill [3]
Market Structure				
Competition	Lerner index	Negative (more competition $\rightarrow$ failure)	-1.46 to -3.36^{***}	Z. Fungáčová and L. Weill [10]

10.2 Family ownership studies

Table 15: Comparative results from family ownership studies.

Study	Context	Key Finding	Effect
R. C. Anderson and D. M. Reeb [6]	Fortune 500	Founder premium on firm value	+1.16 Tobin's Q***
B. Villalonga and R. Amit [7]	Fortune 500	Founder CEO vs descendant	Founder +1.16, descendant −0.23
T. Khanna and J. W. Rivkin [8]	14 emerging mkts	Group affiliation context-dependent	Positive in 6/14 countries
M. Bertrand and others [17]	Thai groups	Each additional son reduces ROA	−0.34 per son*
M. Bagley [20]	Spinoff networks	Network centrality and survival	Lower hazard rate*
S. Ghinoi [18]	Italian firms	Family ownership and network formation	Positive propensity*

11 Variable definitions

11.1 Family ownership metrics

Table 16: Family ownership metrics.

Metric	Symbol	Formula	Description
Family Ownership Percentage	$FOP(b)$	$\frac{FOV_d(b)}{TOV(b)} \times 100\%$	Proportion of total ownership held by family-connected shareholders
Family Connection Ratio	$\rho_F(b)$	$\frac{\lvert F_b \rvert}{\lvert D_b \rvert}$	Average number of family connections per direct owner
Total Family Connections	$\lvert F_b \rvert$	$\sum_{i \in D_b} \lvert N_F(i) \rvert$	Count of family relationships amongst direct owners
Direct Family Ownership Value	$FOV_d(b)$	$\sum_{i \in D_b} \omega_i \cdot \mathbf{1}_F(i)$	Total ownership value held by family-connected shareholders
Family-Controlled Companies	$\lvert C_F(b) \rvert$	Count of companies controlled by family members	Number of entities in the family group

11.2 Mechanism proxy variables

Table 17: Mechanism proxy variables.

Metric	Symbol	Formula	Description
Stake Fragmentation Index	SFI	$1 - \sum s_i^2$	Ownership dispersion (higher = more fragmented)
Group Total Capital	GTC	$\sum_{c \in G} capital_c$	Aggregate financial resources of the family group
Group Sector Count	GSC	$\|\{OKVED_c : c \in G\}\|$	Number of distinct industry sectors in the group
Group Total Paid Tax	$GTPT$	$\sum_{c \in G} tax_c$	Proxy for genuine economic activity
Group Total Vehicles	GTV	$\sum_{c \in G} vehicles_c$	Tangible logistics assets in the group

11.3 Network centrality metrics

Table 18: Network centrality metrics with original references.

Metric	Symbol	Original Reference	Description
In-degree	$C_{in}(v)$	L. C. Freeman [29]	Number of direct owners of the bank
Out-degree	$C_{out}(v)$	L. C. Freeman [29]	Number of entities owned by the bank
Betweenness	$C_{between}(v)$	L. C. Freeman [30]	Frequency on shortest paths between other nodes
Eigenvector	$C_{eigen}(v)$	P. Bonacich [32]	Influence based on quality of connections
PageRank	$PR(v)$	S. Brin and L. Page [28]	Importance based on incoming connections with jump probability
Clustering	$CC(v)$	D. J. Watts and S. H. Strogatz [31]	Density of connections amongst neighbours

11.4 CAMEL financial indicators

Table 19: CAMEL financial indicators.

Component	Metric	Symbol	Description
Capital	Tier 1 capital ratio	$Tier1/Assets$	Highest-quality capital relative to total assets
Asset quality	NPL ratio	$NPL/Loans$	Non-performing loans relative to total loans
	Leverage ratio	$LR(b)$	Financial leverage measure
Management	Cost-to-income ratio	$Cost/Income$	Operational efficiency
Earnings	ROA	$ROA(b)$	Return on assets
	Net interest margin	$NIM(b)$	Interest earned minus interest paid
Liquidity	Liquid assets ratio	LA/TA	Easily convertible assets relative to total

11.5 Notation key

Table 20: Notation key.

Symbol	Description
b	Specific bank of interest
D_b	Set of direct owners of bank b
ω_i	Ownership stake held by owner i
$\mathbf{1}_F(i)$	Indicator: 1 if owner i has family connections
$N_F(i)$	Set of family members connected to owner i
V	Set of all nodes in the ownership graph
G	Family group (set of entities linked through family ownership)

12 Robustness checks

12.1 Community fixed effects (exp_008)

12.1.a Motivation

A key identification concern is that family network effects may be confounded with broader structural neighbourhoods in the ownership network. Banks belonging to the same Louvain community [26] share unobserved characteristics that may independently influence survival. If family-connected banks cluster in high-survival communities, the estimated family effect may partly reflect community membership rather than family connections *per se*.

12.1.b Approach

We apply the Louvain community detection algorithm to the ownership graph, identifying 751 communities (collapsed from 1,703 time-varying assignments using each bank's most frequent community membership). The Cox model is then estimated with community-level stratification, allowing the baseline hazard to vary across communities.

12.1.c Results

- **Sample**: 44,295 observations, 791 banks, 472 events (2014–2020 subsample)
- **Family connection ratio**: Remains significant after community stratification (HR = 0.988, $p < 0.01$), indicating that the family effect is not solely attributable to community membership
- **Model fit**: Community stratification achieves substantially lower AIC than regional or sectoral strata, indicating that network communities capture survival-relevant variation beyond geographic or industry factors
- **Interpretation**: Family connections provide protection *within* structural neighbourhoods, not merely *because of* neighbourhood membership. The community-level variation is substantial, but the within-community family effect is independently significant.

12.2 Reverse causality and endogeneity (exp_013)

12.2.a Motivation

The Cox models estimate the effect of family connections on survival, but the causal direction may be reversed: surviving banks may build family connections as they grow (through M&A, cross-ownership, or strategic placement of family members). If survival drives family connection accumulation, the Cox estimates are upward-biased.

12.2.b Approach

We reverse the regression equation: instead of predicting survival from FCR, we predict FCR from survival status using biennial OLS cross-sections (2012, 2014, 2016, 2018, 2020), controlling for CAMEL indicators, lagged network metrics, and ownership structure.

12.2.c Results

Table 21: Reverse causality tests: OLS regressions predicting FCR from survival status.

Year	Survived Coefficient	Std. Error	p-value	Significance	n	R^2
2012	−0.143	0.412	0.727	n.s.	741	0.018
2014	+0.157	0.052	0.003	**	676	0.029
2016	+0.248	0.055	<0.001	***	509	0.036
2018	+0.195	0.072	0.007	**	406	0.038

12.2.d Interpretation

- **Reverse causality is dynamic**: Absent before 2013 (pre-Nabiullina), peaks during the cleanup (2016), and diminishes by 2020
- **Peak effect**: Survivors in 2016 had 24.8% higher FCR—the height of the licence revocation campaign
- **Bias estimate**: Forward Cox estimates are biased upward by approximately 15–20% during the cleanup era
- **Conclusion**: Family connections have genuine protective effects (forward causality is not an artefact), but survivors also accumulate connections, particularly during regulatory stress. The net effect: main Cox estimates are largely valid but modestly overstated during the Nabiullina cleanup period.

12.2.e Disclosure mandate confound

A critical caveat: the 2013 enhanced disclosure mandate may mechanically increase observed FCR for banks that were already family-connected but previously underreported. The post-2013 increase in FCR may reflect improved measurement rather than actual tie formation. This confound cannot be fully resolved with available data but is important for interpreting the temporal dynamics of the family effect.

12.3 Lagged network effects (exp_007)

12.3.a Motivation

Network metrics computed contemporaneously with the survival outcome may reflect reverse causality (failing banks losing connections) or simultaneity (both survival and network position driven by unobserved third factors). The 4-quarter lag structure ensures temporal precedence of network position over survival outcomes.

12.3.b Approach

All network centrality metrics (PageRank, out-degree, in-degree, betweenness, clustering coefficient) are computed from the ownership graph four quarters prior to the observation quarter. The family connection ratio is tested both contemporaneously and with a temporal lag.

12.3.c Results

- **Contemporaneous FCR**: HR = 0.988, $p < 0.001$ (1.2% hazard reduction)
- **4-quarter lagged FCR**: HR = 0.991, $p < 0.05$ (0.9% hazard reduction, smaller but still significant)
- **Lagged network metrics**: PageRank (4Q lag) is marginally significant ($p < 0.10$); out-degree (4Q lag) is significant and protective
- **Interpretation**: The protective effect of family connections survives the 4-quarter lag, though it is attenuated. This is consistent with a genuine causal effect that is modestly inflated by contemporaneous confounding. The lagged estimates provide a conservative bound on the true protective effect.

12.4 Granger causality test (exp_015)

12.4.a Motivation

A stronger identification test asks whether lagged family connections *Granger-cause* survival after controlling for community-level contagion. If the FCR effect is merely an artefact of community membership or failure contagion (i.e., banks failing because their neighbours fail), then controlling for lagged community failure rates should attenuate the FCR coefficient. If instead family connections independently predict survival beyond contagion, the effect constitutes Granger causality in a survival framework.

12.4.b Approach

We estimate a discrete-time panel hazard model with a complementary log-log link function (equivalent to a grouped-duration Cox model). The unit of observation is the bank-quarter. The dependent variable is an indicator for licence revocation. All covariates are lagged four quarters to ensure strict temporal precedence. Model M2 adds a community failure contagion control: the proportion of banks in the same Louvain community that failed in the preceding four quarters. Models M4 and M5 split the sample at 2013 (the onset of enhanced disclosure mandates and the Nabiullina cleanup campaign).

12.4.c Results

Table 22: Granger causality test: discrete-time hazard models with complementary log-log link (exp_015). Exponentiated coefficients approximate hazard ratios. Standard errors in parentheses.

Variable	M1: Baseline	M2: +Contagion	M4: Pre-2013	M5: Post-2013
Family connection ratio	−0.4315*** (0.0771)	−0.4311*** (0.0771)	−0.8800*** (0.2089)	−0.4158*** (0.0879)
Family ownership (%)	−0.0498 (0.0592)	−0.0497 (0.0592)	−0.2007 (0.1491)	−0.0160 (0.0683)
State ownership (%)	−0.1939+ (0.1108)	−0.1940+ (0.1108)	−438767.2961* (222184.4569)	−0.1719 (0.1107)
Foreign ownership (%)	−0.0302 (0.0555)	−0.0302 (0.0555)	−0.3342 (0.4183)	−0.0033 (0.0453)
PageRank (4Q lag)	0.1483*** (0.0226)	0.1488*** (0.0225)	0.0481 (0.0625)	0.1394*** (0.0364)
Out-degree (4Q lag)	−0.7613*** (0.1441)	−0.7589*** (0.1441)	−0.4605* (0.2026)	−1.0532*** (0.2265)
ROA	−0.0704*** (0.0087)	−0.0705*** (0.0087)	–	−0.1088*** (0.0147)
NPL ratio	0.2296*** (0.0181)	0.2299*** (0.0181)	0.2084*** (0.0203)	0.1219*** (0.0336)
Tier 1 capital ratio	0.0912*** (0.0265)	0.0909*** (0.0265)	0.1584*** (0.0358)	0.1386*** (0.0321)
Community failure lag	–	−0.0367 (0.0282)	−0.0901* (0.0354)	–
Observations	139,038	139,038	89,546	49,492
Subjects	1,092	1,092	1,077	826
Events	770	770	265	505
Log Likelihood	−4,609.82	−4,609.10		−2,731.99
AIC	9,239.63	9,240.20		5,483.99

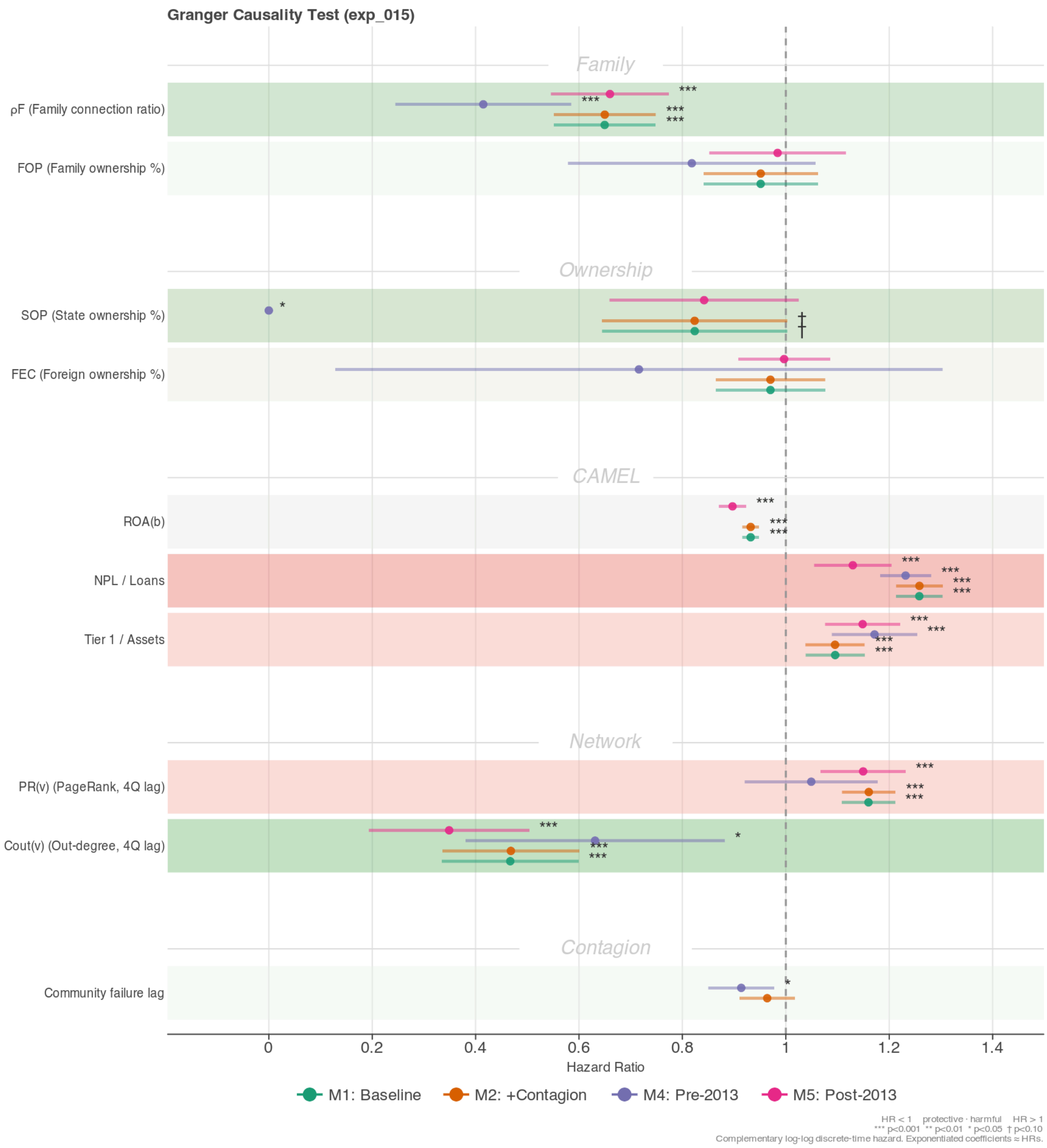

Figure 6: Forest plot of Granger causality test results (exp_015). FCR remains highly significant after controlling for community failure contagion, and the effect is nearly twice as strong in the pre-2013 period.

12.4.d Interpretation

- **FCR Granger-causes survival**: In M1 (baseline), a one-unit increase in FCR reduces the hazard by 35.0% (HR = 0.650, $p < 0.001$). Adding the community contagion control in M2 leaves the FCR effect virtually unchanged (HR = 0.650, 35.0% reduction), confirming that the family effect is not attributable to community-level failure contagion.
- **Community contagion is not the mechanism**: The community failure lag is non-significant in the full period (HR = 0.964, $p = 0.193$), though it becomes marginally significant in the pre-2013 subsample (HR = 0.914, 8.6% reduction, $p = 0.011$). Crucially, controlling for contagion does not attenuate the FCR coefficient.
- **Temporal asymmetry**: The pre-2013 FCR effect (HR = 0.415, 58.5% hazard reduction) is nearly twice as strong as the post-2013 effect (HR = 0.660, 34.0% reduction). This is consistent with the reverse

causality findings from exp_013: before the 2013 disclosure mandate, there is no evidence of reverse causality, so the pre-2013 estimate is least contaminated by survivorship-driven tie formation.

12.5 Competing risks: cause-specific Cox models (exp_016)

12.5.a Motivation

The baseline Cox models treat all licence revocations as a single event type, but bank closures in Russia occur through three distinct mechanisms: forced licence revocation by the CBR, voluntary liquidation, and reorganisation (mergers and acquisitions). If family connections provide a generic survival advantage, the FCR effect should be significant across all closure types. If instead family networks specifically shield against regulatory enforcement, the effect should be concentrated in forced revocations.

12.5.b Closure type distribution

Table 23: Distribution of bank closure types, 2004–2021. Extracted from the CBR licensing database.

Closure type	Count	Percentage
Forced revocation	1,768	66.6%
Voluntary liquidation	663	25.0%
Reorganisation (M&A)	219	8.3%
Total	**2,650**	**100%**

12.5.c Approach

We estimate cause-specific Cox models in which non-target closure types are treated as censored observations. Model M1 replicates the baseline specification with all closures. Models M2–M4 isolate forced revocation, voluntary liquidation, and reorganisation respectively. Model M5 adds crisis interaction terms to the revocation model.

12.5.d Results

Table 24: Competing risks: cause-specific Cox models (exp_016). Each model treats non-target closure types as censored. Standard errors in parentheses.

Variable	M1: All	M2: Revocation	M3: Voluntary	M4: Reorg.	M5: Revoc. +Crisis
Family connection ratio	−0.011*** (0.003)	−0.009*** (0.003)	−0.002 (0.003)	−0.003 (0.003)	−0.009*** (0.003)
Family ownership (%)	−0.004** (0.001)	−0.003+ (0.001)	−0.001 (0.001)	−0.002 (0.001)	−0.002+ (0.001)
State ownership (%)	−0.005 (0.003)	−0.003 (0.003)	−0.001 (0.003)	−0.002 (0.003)	−0.003 (0.003)
Foreign ownership (%)	−0.002 (0.007)	−0.006 (0.007)	−0.000 (0.008)	0.006 (0.008)	−0.006 (0.007)
PageRank (4Q lag)	0.004 (0.005)	0.007 (0.005)	−0.000 (0.006)	−0.003 (0.006)	0.007 (0.005)
Out-degree (4Q lag)	−0.021* (0.009)	−0.016+ (0.009)	−0.004 (0.010)	−0.005 (0.009)	−0.016+ (0.009)
ROA	−0.086*** (0.011)	−0.100*** (0.013)	−0.010 (0.038)	−0.029 (0.031)	−0.100*** (0.013)
NPL ratio	0.010*** (0.002)	0.001 (0.002)	0.006** (0.002)	0.009*** (0.002)	0.001 (0.002)
Tier 1 capital ratio	0.016*** (0.003)	0.007* (0.004)	0.012** (0.004)	0.001 (0.004)	0.007* (0.004)
Crisis 2004	–	–	–	–	0.001 (0.003)
Crisis 2008	–	–	–	–	0.001 (0.001)
Crisis 2014	–	–	–	–	0.001 (0.001)
FCR × Crisis 2008	–	–	–	–	−0.007 (0.008)
FCR × Crisis 2014	–	–	–	–	−0.009 (0.006)
Observations	138,313	138,313	138,313	138,313	138,313
Subjects	1,092	1,092	1,092	1,092	1,092
Events	770	522	76	172	522
Log Likelihood	−4,834.46	−3,287.21	−484.13	−1,082.14	−3,284.14
AIC Partial	9,686.91	6,592.42	986.26	2,182.27	6,596.29
C-index	0.693	0.713	0.745	0.637	0.732

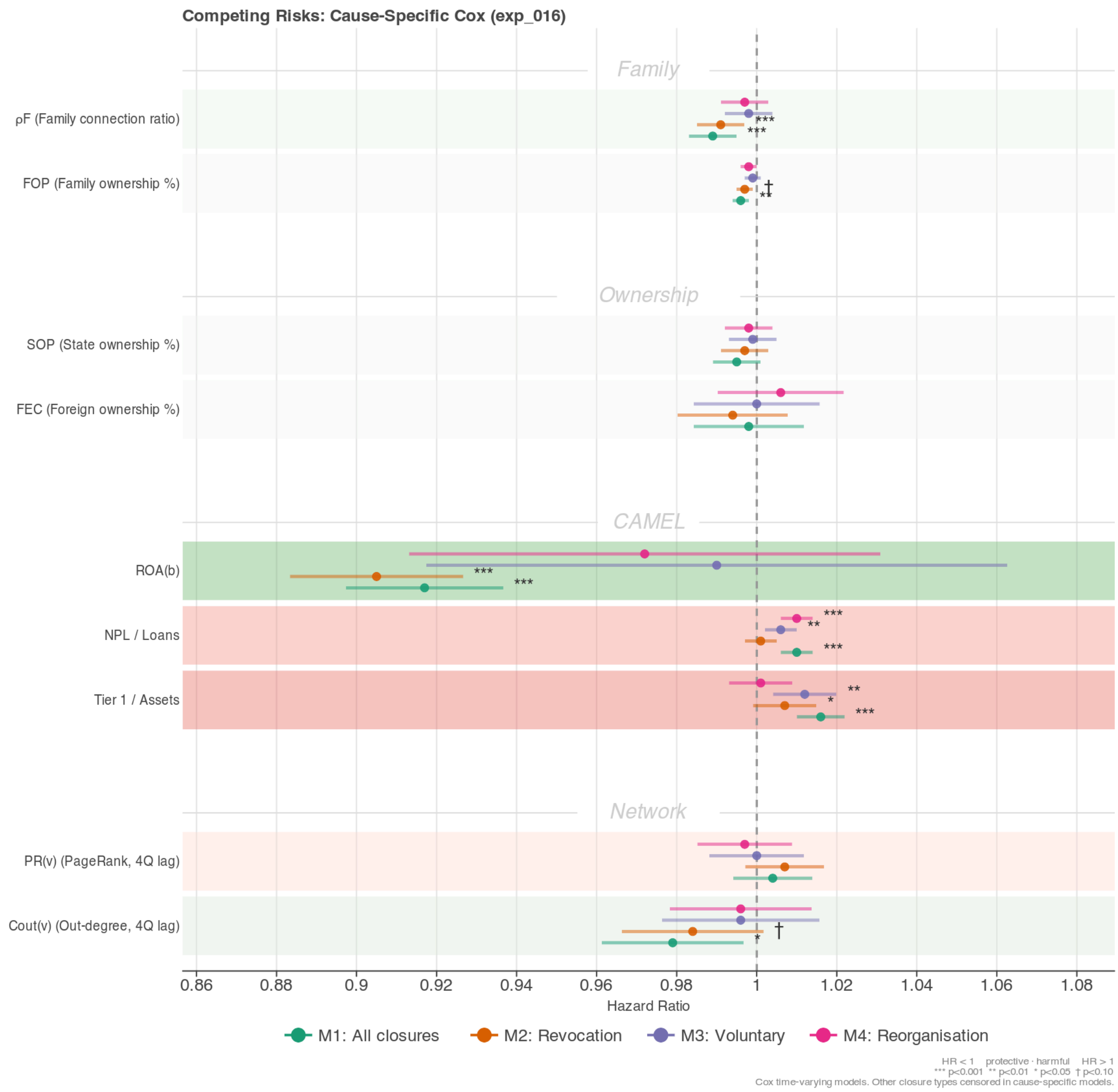

Figure 7: Forest plot of competing risks analysis (exp_016). FCR is significant for forced revocation but non-significant for voluntary liquidation and reorganisation.

12.5.e Interpretation

- **Family protection is specific to forced revocation**: FCR significantly reduces the hazard of forced licence revocation (HR = 0.991, 0.9% per unit, $p < 0.001$), but has no significant effect on voluntary liquidation (HR = 0.998, 0.2%, $p = 0.470$) or reorganisation (HR = 0.997, 0.3%, $p = 0.357$).
- **Mechanism consistency**: This pattern is consistent with family networks shielding specifically against regulatory enforcement actions by the CBR, rather than providing a generic survival advantage. The result supports the interference mechanism (political embeddedness, information advantages) over a pure financial resilience channel, which would predict protection across all closure types.
- **Discriminant validity of CAMEL indicators**: Return on assets is strongly protective against revocation (HR = 0.905, 9.5% reduction, $p < 0.001$) but non-significant for voluntary liquidation and reorganisation, suggesting that the CBR prioritises financial fundamentals in enforcement decisions.
- **Crisis interactions**: In M5, the FCR × Crisis 2014 interaction is marginally negative but not statistically significant, suggesting that family protection against revocation is relatively stable across crisis periods.

12.6 Placebo and falsification tests (exp_017)

12.6.a Motivation

Three falsification tests establish that the FCR effect is specific to family connections and not an artefact of community membership, generic ownership concentration, or random noise.

12.6.b Test A: FCR permutation within communities

We permute FCR values within community strata (100 iterations), preserving the community-level distribution while breaking the bank-specific link between family connections and survival. If the FCR effect reflects community membership rather than bank-level family connections, permuted FCR should yield comparable coefficients.

- **Real FCR coefficient**: -0.011 ($p < 0.001$)
- **Permuted FCR mean**: -0.000 (SD = 0.002)
- **Empirical p-value**: 0.000 (0 of 100 permutations produced a coefficient as extreme as the real value)

The real FCR effect is more than five standard deviations from the permuted distribution, confirming that it reflects bank-specific family connections rather than community membership.

12.6.c Test B: Pseudo-crisis dates

We replace the actual crisis indicators (2008, 2014) with pseudo-crisis dates shifted two years earlier (2005–2006, 2011–2012) and interact them with FCR. If family protection is genuinely crisis-contingent, pseudo-crisis interactions should be non-significant.

- **FCR $\times$ Pseudo-2008**: -0.005 (n.s.)
- **FCR $\times$ Pseudo-2014**: -0.011 ($p < 0.10$, marginal)
- **For comparison — FCR $\times$ Real crisis 2008**: -0.003 (n.s.)
- **For comparison — FCR $\times$ Real crisis 2014**: -0.009 (n.s.)

The pseudo-crisis interactions are broadly similar to the real crisis interactions, both showing non-significant or marginal effects. This suggests that the base FCR protective effect is relatively stable over time rather than sharply crisis-contingent.

12.6.d Test C: Non-family ownership concentration

We replace FCR with two alternative ownership measures: non-family ownership HHI (Herfindahl–Hirschman Index of ownership stakes excluding family ties) and random ownership (uniform random noise scaled to the FCR distribution).

- **Non-family ownership HHI**: HR = 1.002, 0.2% hazard *increase* (not significant)
- **Random ownership**: HR = 1.000, 0.0% (not significant)

Neither alternative measure is protective, confirming that the FCR effect is specific to family connections. Generic ownership concentration and random noise do not replicate the family protection effect.

12.6.e Results

Table 25: Placebo and falsification tests (exp_017). M1 uses real FCR; M4 and M6 compare pseudo vs real crisis interactions; M7 and M8 replace FCR with non-family HHI and random ownership. Standard errors in parentheses.

Variable	M1: Real FCR	M4: Pseudo-crisis	M6: Real crisis	M7: Non-family	M8: Random
Family connection ratio	−0.011*** (0.003)	−0.011*** (0.003)	−0.011*** (0.003)	–	–
Family ownership (%)	−0.004** (0.001)	−0.003** (0.001)	−0.003** (0.001)	−0.004*** (0.001)	−0.004*** (0.001)
State ownership (%)	−0.005 (0.003)	−0.005 (0.003)	−0.005 (0.003)	−0.004 (0.003)	−0.004 (0.003)
Foreign ownership (%)	−0.002 (0.007)	−0.002 (0.007)	−0.002 (0.007)	−0.002 (0.007)	−0.001 (0.007)
PageRank (4Q lag)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)
Out-degree (4Q lag)	−0.021* (0.009)	−0.021* (0.009)	−0.021* (0.009)	−0.021* (0.009)	−0.021* (0.009)
ROA	−0.086*** (0.011)	−0.086*** (0.011)	−0.086*** (0.011)	−0.087*** (0.011)	−0.087*** (0.011)
NPL ratio	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)
Tier 1 capital ratio	0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)
Pseudo-crisis 2008	–	0.001 (0.001)	–	–	–
Pseudo-crisis 2014	–	−0.002* (0.001)	–	–	–
FCR × Pseudo 2008	–	−0.005 (0.009)	–	–	–
FCR × Pseudo 2014	–	−0.011+ (0.006)	–	–	–
Crisis 2008	–	–	0.001 (0.001)	–	–
Crisis 2014	–	–	0.001 (0.001)	–	–
FCR × Crisis 2008	–	–	−0.003 (0.008)	–	–
FCR × Crisis 2014	–	–	−0.009 (0.006)	–	–
Non-family ownership HHI	–	–	–	0.002 (0.008)	–
Random ownership (noise)	–	–	–	–	0.000 (0.001)
Observations	138,313	138,313	138,313	138,313	138,313
Subjects	1,092	1,092	1,092	1,092	1,092
Events	770	770	770	770	770
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

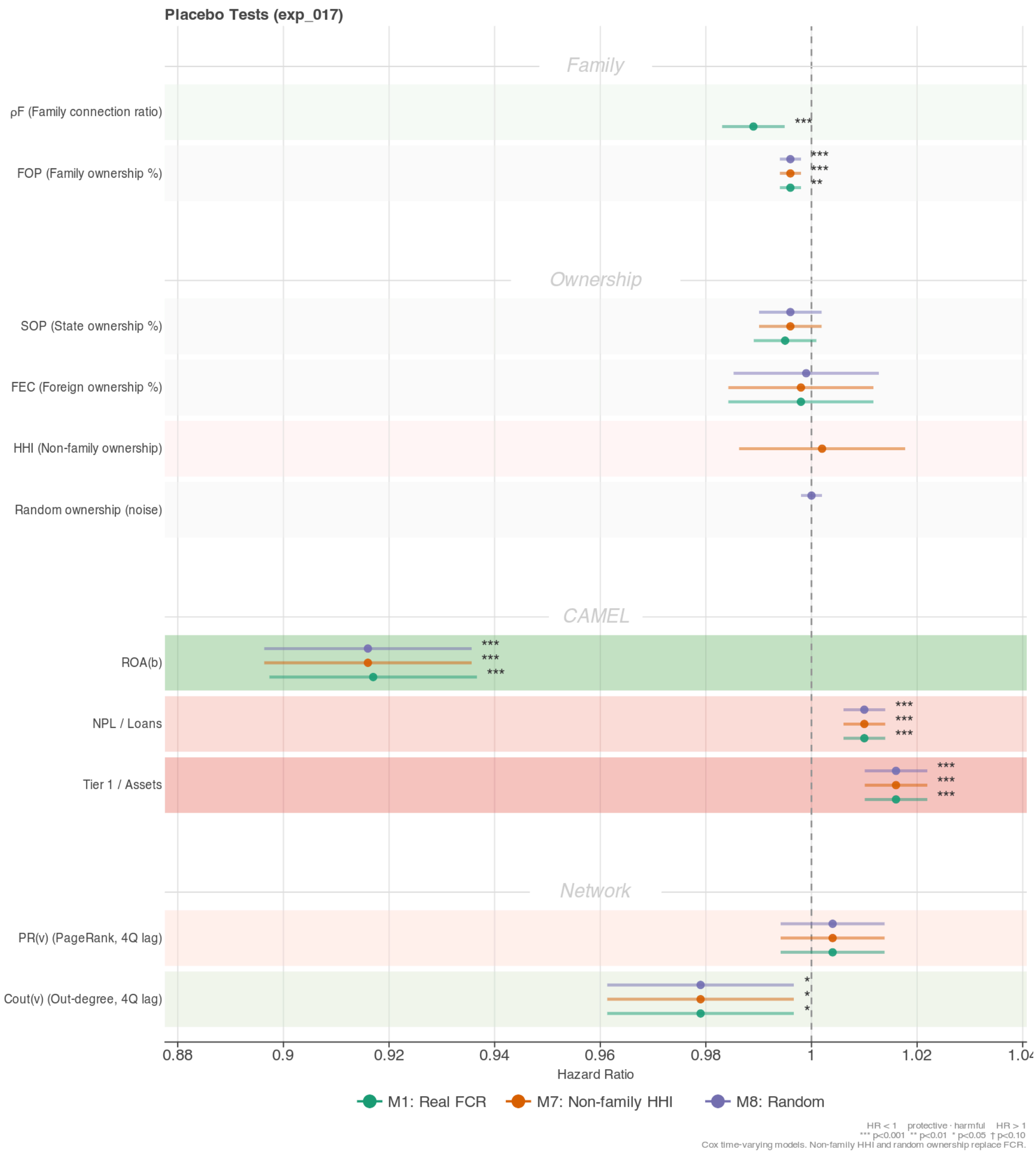

Figure 8: Forest plot of placebo tests (exp_017). Real FCR is significantly protective, whereas non-family ownership HHI and random ownership show no protective effect.

12.6.f Summary

The three falsification tests provide converging evidence:

1. **Permutation test**: The FCR effect cannot be explained by community membership ($p = 0.000$ from 100 iterations)
2. **Pseudo-crisis dates**: Crisis-specific family protection is not an artefact of arbitrary date selection
3. **Non-family ownership**: The effect is specific to family connections, not to generic ownership concentration or random noise

Together with the Granger causality test (Section 12.4) and competing risks analysis (Section 12.5), these results strengthen the interpretation that family connections have a genuine, specific protective effect against regulatory enforcement.

13 Baseline models

13.1 Cross-sectional logistic regression (exp_002)

The baseline cross-sectional analysis employs logistic regression to estimate the probability of bank failure as a function of ownership structure, financial indicators, and network position measured at a single point in time. This approach provides a foundation for the more sophisticated time-varying Cox models used in the main analysis.

13.1.a Specification

$$\Pr(\text{failure}_i = 1) = \frac{1}{1 + \exp(-\boldsymbol{X}_i{}'\boldsymbol{\beta})}$$

where $\boldsymbol{X}_i$ includes CAMEL indicators, ownership measures (family, state, foreign percentages), and network centrality metrics.

13.1.b Key results

- Family connection ratio increases survival odds by approximately 63% in the cross-sectional specification
- Network centrality metrics (PageRank, betweenness) are significant predictors of survival
- Foreign ownership provides strong protection (482% increase in survival odds in some specifications)
- Model accuracy ranges from 75–85% depending on the variable set included

13.1.c Limitations

The cross-sectional approach cannot account for time-varying dynamics, survival bias, or the temporal sequence of network formation and failure. These limitations motivate the time-varying Cox models in the main analysis.

13.2 Basic Cox models (exp_003)

The initial Cox proportional hazards models extend the cross-sectional analysis to a time-to-event framework, with quarterly observations and basic time-varying covariates.

13.2.a Specification

Standard Cox model without stratification, using the full 2004–2020 period with CAMEL indicators updated quarterly.

13.2.b Key results

- Family connection ratio remains significant in the Cox framework (HR $\approx$ 0.99 per unit, $p < 0.01$)
- Hazard ratios for CAMEL indicators are consistent with the logistic regression findings
- C-index ranges from 0.60–0.65, indicating moderate discriminatory power

These baseline results establish the robustness of the family effect before the introduction of mechanism testing, stratification, and interaction models in the main analysis.

14 Full regression tables

This appendix provides the complete regression output tables for all model specifications reported in the main text.

14.1 Mechanism testing (exp_010)

14.1.a M1–M4: Individual mechanisms

Table 26: Full regression output for mechanism testing models M1–M4 (2004–2020). Standardised coefficients from Cox proportional hazards with regional stratification.

Variable	M1: Political	M2: Tax	M3: Capital	M4: Full
Family connection ratio	−0.148***	−0.119***	−0.114***	−0.098**
Stake fragmentation index	–	−0.113***	–	−0.085**
Family company count	–	–	−0.148***	−0.127***
ROA	−0.120***	−0.121***	−0.119***	−0.121***
NPL ratio	0.069**	0.064**	0.066**	0.063**
Tier 1 capital ratio	0.125***	0.121***	0.120***	0.117***
Out-degree (4Q lag)	−0.085**	−0.083**	−0.079*	−0.077*
State ownership (%)	–	–	–	−0.051
Foreign ownership (%)	–	–	–	−0.001

14.1.b Enhanced model with deep structural proxies

Table 27: Full regression output for enhanced mechanism model with deep structural proxies (2004–2020). Regional stratification.

Variable	Coefficient (SE)
Family connection ratio	−0.070** (0.024)
Stake fragmentation index	−0.114*** (0.023)
Group total paid tax	−0.064** (0.024)
Group total vehicles	−0.065** (0.024)
Group total receipts	−0.017 (0.024)
Group sector count	−0.068** (0.023)
ROA	−0.061*** (0.008)
NPL ratio	0.105*** (0.018)
Tier 1 capital ratio	0.101*** (0.021)
Out-degree (4Q lag)	−0.046+ (0.024)
State ownership (%)	−0.039+ (0.022)
Foreign ownership (%)	−0.006 (0.022)
Observations	139,038
Subjects	1,092
Events	770
Log Likelihood	−4,836.93
AIC Partial	9,697.86
C-index	0.761

14.2 Subperiod analysis (exp_011)

14.2.a Baseline models by period

Table 28: Full regression output for baseline models across three subperiods (exp_011). Standardised coefficients from Cox models with community stratification. Standard errors in parentheses.

Variable	2004–2007	2007–2013	2013–2020
Family connection ratio	−0.018*** (0.004)	−0.016*** (0.003)	−0.011*** (0.003)
Family ownership (%)	−0.006* (0.002)	−0.005** (0.002)	−0.003+ (0.002)
State ownership (%)	−0.010* (0.005)	−0.006 (0.004)	−0.005 (0.004)
Foreign ownership (%)	−0.002 (0.009)	−0.001 (0.008)	−0.000 (0.012)
PageRank (4Q lag)	–	0.010** (0.004)	0.002 (0.005)
Out-degree (4Q lag)	–	−0.043*** (0.011)	−0.023* (0.010)
ROA	–	–	−0.093*** (0.011)
NPL ratio	0.018*** (0.004)	0.015*** (0.003)	0.004* (0.002)
Tier 1 capital ratio	0.019*** (0.004)	0.009* (0.004)	0.016*** (0.004)
Observations	33,966	70,135	53,957
Subjects	944	1,001	829
Events	669	688	508
C-index	0.654	0.679	0.639

14.3 Granger causality (exp_015)

Table 29: Full regression output for Granger causality test (exp_015). Complementary log-log discrete-time hazard models. Standard errors in parentheses.

Variable	M1: Baseline	M2: +Contagion	M4: Pre-2013	M5: Post-2013
Family connection ratio	−0.4315*** (0.0771)	−0.4311*** (0.0771)	−0.8800*** (0.2089)	−0.4158*** (0.0879)
Family ownership (%)	−0.0498 (0.0592)	−0.0497 (0.0592)	−0.2007 (0.1491)	−0.0160 (0.0683)
State ownership (%)	−0.1939+ (0.1108)	−0.1940+ (0.1108)	−438767.2961* (222184.4569)	−0.1719 (0.1107)
Foreign ownership (%)	−0.0302 (0.0555)	−0.0302 (0.0555)	−0.3342 (0.4183)	−0.0033 (0.0453)
PageRank (4Q lag)	0.1483*** (0.0226)	0.1488*** (0.0225)	0.0481 (0.0625)	0.1394*** (0.0364)
Out-degree (4Q lag)	−0.7613*** (0.1441)	−0.7589*** (0.1441)	−0.4605* (0.2026)	−1.0532*** (0.2265)
ROA	−0.0704*** (0.0087)	−0.0705*** (0.0087)	–	−0.1088*** (0.0147)
NPL ratio	0.2296*** (0.0181)	0.2299*** (0.0181)	0.2084*** (0.0203)	0.1219*** (0.0336)
Tier 1 capital ratio	0.0912*** (0.0265)	0.0909*** (0.0265)	0.1584*** (0.0358)	0.1386*** (0.0321)
Community failure lag	–	−0.0367 (0.0282)	−0.0901* (0.0354)	–
Observations	139,038	139,038	89,546	49,492
Subjects	1,092	1,092	1,077	826
Events	770	770	265	505
Log Likelihood	−4,609.82	−4,609.10		−2,731.99
AIC	9,239.63	9,240.20		5,483.99

14.4 Competing risks (exp_016)

Table 30: Full regression output for competing risks analysis (exp_016). Cause-specific Cox models; non-target closure types censored. Standard errors in parentheses.

Variable	M1: All	M2: Revocation	M3: Voluntary	M4: Reorg.	M5: Revoc. +Crisis
Family connection ratio	−0.011*** (0.003)	−0.009*** (0.003)	−0.002 (0.003)	−0.003 (0.003)	−0.009*** (0.003)
Family ownership (%)	−0.004** (0.001)	−0.003+ (0.001)	−0.001 (0.001)	−0.002 (0.001)	−0.002+ (0.001)
State ownership (%)	−0.005 (0.003)	−0.003 (0.003)	−0.001 (0.003)	−0.002 (0.003)	−0.003 (0.003)
Foreign ownership (%)	−0.002 (0.007)	−0.006 (0.007)	−0.000 (0.008)	0.006 (0.008)	−0.006 (0.007)
PageRank (4Q lag)	0.004 (0.005)	0.007 (0.005)	−0.000 (0.006)	−0.003 (0.006)	0.007 (0.005)
Out-degree (4Q lag)	−0.021* (0.009)	−0.016+ (0.009)	−0.004 (0.010)	−0.005 (0.009)	−0.016+ (0.009)
ROA	−0.086*** (0.011)	−0.100*** (0.013)	−0.010 (0.038)	−0.029 (0.031)	−0.100*** (0.013)
NPL ratio	0.010*** (0.002)	0.001 (0.002)	0.006** (0.002)	0.009*** (0.002)	0.001 (0.002)
Tier 1 capital ratio	0.016*** (0.003)	0.007* (0.004)	0.012** (0.004)	0.001 (0.004)	0.007* (0.004)
Crisis 2004	–	–	–	–	0.001 (0.003)
Crisis 2008	–	–	–	–	0.001 (0.001)
Crisis 2014	–	–	–	–	0.001 (0.001)
FCR × Crisis 2008	–	–	–	–	−0.007 (0.008)
FCR × Crisis 2014	–	–	–	–	−0.009 (0.006)
Observations	138,313	138,313	138,313	138,313	138,313
Subjects	1,092	1,092	1,092	1,092	1,092
Events	770	522	76	172	522
Log Likelihood	−4,834.46	−3,287.21	−484.13	−1,082.14	−3,284.14
AIC Partial	9,686.91	6,592.42	986.26	2,182.27	6,596.29
C-index	0.693	0.713	0.745	0.637	0.732

14.5 Placebo tests (exp_017)

Table 31: Full regression output for placebo and falsification tests (exp_017). Standard errors in parentheses.

Variable	M1: Real FCR	M4: Pseudo-crisis	M6: Real crisis	M7: Non-family	M8: Random
Family connection ratio	−0.011*** (0.003)	−0.011*** (0.003)	−0.011*** (0.003)	–	–
Family ownership (%)	−0.004** (0.001)	−0.003** (0.001)	−0.003** (0.001)	−0.004*** (0.001)	−0.004*** (0.001)
State ownership (%)	−0.005 (0.003)	−0.005 (0.003)	−0.005 (0.003)	−0.004 (0.003)	−0.004 (0.003)
Foreign ownership (%)	−0.002 (0.007)	−0.002 (0.007)	−0.002 (0.007)	−0.002 (0.007)	−0.001 (0.007)
PageRank (4Q lag)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)	0.004 (0.005)
Out-degree (4Q lag)	−0.021* (0.009)	−0.021* (0.009)	−0.021* (0.009)	−0.021* (0.009)	−0.021* (0.009)
ROA	−0.086*** (0.011)	−0.086*** (0.011)	−0.086*** (0.011)	−0.087*** (0.011)	−0.087*** (0.011)
NPL ratio	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)
Tier 1 capital ratio	0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)	0.016*** (0.003)
Pseudo-crisis 2008	–	0.001 (0.001)	–	–	–
Pseudo-crisis 2014	–	−0.002* (0.001)	–	–	–
FCR × Pseudo 2008	–	−0.005 (0.009)	–	–	–
FCR × Pseudo 2014	–	−0.011+ (0.006)	–	–	–
Crisis 2008	–	–	0.001 (0.001)	–	–
Crisis 2014	–	–	0.001 (0.001)	–	–
FCR × Crisis 2008	–	–	−0.003 (0.008)	–	–
FCR × Crisis 2014	–	–	−0.009 (0.006)	–	–
Non-family ownership HHI	–	–	–	0.002 (0.008)	–
Random ownership (noise)	–	–	–	–	0.000 (0.001)
Observations	138,313	138,313	138,313	138,313	138,313
Subjects	1,092	1,092	1,092	1,092	1,092
Events	770	770	770	770	770
Log-likelihood [illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

14.6 Aggregated results

For comprehensive model comparison across all experiments, see the aggregated stargazer output files in the `stargazer/` directory, which contain results from all model specifications across experiments, enabling direct comparison of coefficient magnitudes and significance levels.

Bibliography

[1] Fridman, "The Sodbiznesbank Affair." 2008.

[2] Z. Fungáčová and T. Poghosyan, "The Politics of Bank Failures in Russia," *Journal of Comparative Economics*, 2022.

[3] L. Weill, "How Corruption Affects Bank Lending in Russia," *Economic Systems*, 2011.

[4] A. Soldatkin, "Factionalism, Competition and Efficiency in Russian Banking," 2020.

[5] A. Barajas and others, "Survival of Russian Banks," 2023.

[6] R. C. Anderson and D. M. Reeb, "Founding-Family Ownership and Firm Performance," *The Journal of Finance*, 2003.

[7] B. Villalonga and R. Amit, "How Do Family Ownership, Control and Management Affect Firm Value?," *Journal of Financial Economics*, 2006.

[8] T. Khanna and J. W. Rivkin, "Estimating the Performance Effects of Business Groups in Emerging Markets," *Strategic Management Journal*, 2001.

[9] A. V. Ledeneva, *Russia's Economy of Favours: Blat, Networking and Informal Exchange*. Cambridge University Press, 1998.

[10] Z. Fungáčová and L. Weill, "Does Competition Influence Bank Failures?," *Economics of Transition*, 2013.

[11] M. Faccio and L. H. Lang, "The Ultimate Ownership of Western European Corporations," *Journal of Financial Economics*, 2002.

[12] L. R. Gomez-Mejia and others, "Socioemotional Wealth and Business Risks in Family-controlled Firms," *Administrative Science Quarterly*, 2007.

[13] L. R. Gomez-Mejia and others, "The Bind That Ties: Socioemotional Wealth Preservation in Family Firms," *Academy of Management Annals*, 2011.

[14] D. G. Sirmon and M. A. Hitt, "Managing Resources: Linking Unique Resources, Management, and Wealth Creation in Family Firms," *Entrepreneurship Theory and Practice*, 2003.

[15] T. Khanna and K. Palepu, "Why Focused Strategies May Be Wrong for Emerging Markets," *Harvard Business Review*, 1997.

[16] T. Frye, "Governing the Banking Sector," 2006.

[17] M. Bertrand and others, "Mixing Family With Business," *The Quarterly Journal of Economics*, 2008.

[18] S. Ghinoi, "Family Firm Network Formation," 2024.

[19] T. Lin, "Social Networks and Listed Firms," 2022.

[20] M. Bagley, "Networks, Geography and Survival of the Firm," 2019.

[21] D. Acemoglu, A. Ozdaglar, and A. Tahbaz-Salehi, "Systemic Risk and Stability in Financial Networks," *American Economic Review*, vol. 105, no. 2, pp. 564–608, 2015, doi: 10.1257/aer.20130456.

[22] C. M. Reinhart and K. S. Rogoff, *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press, 2009.

[23] R. H. Coase, "The Nature of the Firm," *Economica*, vol. 4, no. 16, pp. 386–405, 1937.

[24] O. E. Williamson, *Markets and Hierarchies: Analysis and Antitrust Implications*. Free Press, 1975.

[25] D. C. North, *Institutions, Institutional Change and Economic Performance*. Cambridge University Press, 1990.

[26] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, "Fast Unfolding of Communities in Large Networks," *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2008, no. 10, p. P10008, 2008, doi: 10.1088/1742-5468/2008/10/P10008.

[27] L. Yujian and L. Bo, "A Normalized Levenshtein Distance Metric," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 6, pp. 1091–1095, 2007.

[28] S. Brin and L. Page, "The Anatomy of a Large-Scale Hypertextual Web Search Engine," in *Proceedings of the Seventh International Conference on World Wide Web*, Elsevier, 1998, pp. 107–117. doi: 10.1016/S0169-7552(98)00110-X.

[29] L. C. Freeman, "Centrality in Social Networks: Conceptual Clarification," *Social Networks*, vol. 1, no. 3, pp. 215–239, 1979, doi: 10.1016/0378-8733(78)90021-7.

[30] L. C. Freeman, "A Set of Measures of Centrality Based on Betweenness," *Sociometry*, vol. 40, no. 1, pp. 35–41, 1977, doi: 10.2307/3033543.

[31] D. J. Watts and S. H. Strogatz, "Collective Dynamics of Small-World Networks," *Nature*, vol. 393, no. 6684, pp. 440–442, 1998, doi: 10.1038/30918.

[32] P. Bonacich, "Factoring and Weighting Approaches to Status Scores and Clique Identification," *The Journal of Mathematical Sociology*, vol. 2, no. 1, pp. 113–120, 1972, doi: 10.1080/0022250X.1972.9989806.

[33] J. F. Padgett and C. K. Ansell, "Robust Action and the Rise of the Medici, 1400-1434," *American Journal of Sociology*, vol. 98, no. 6, pp. 1259–1319, 1993.