TEMPORAL INEFFICIENCIES IN RISK RECOGNITION: A CAUSAL ANALYSIS OF RISK PERCEPTION LAG IN GLOBAL BANKING SYSTEMS

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ABSTRACT

This paper develops a theoretical and empirical framework to measure Risk Perception Lag (RPL), the temporal distance between the objective realization of an economic shock and its subsequent incorporation into internal bank risk measurement and provisioning systems. Utilizing a comprehensive global panel of 320 commercial banks from 2011 to 2024, the author decomposes RPL into three structural dimensions: informational frictions, model inertia, and institutional delay. Methodologically, the study employs a two-step System GMM estimator to address the dynamic persistence and endogeneity inherent in risk recognition, alongside a Difference-in-Differences (DiD) design centered on the mandatory adoption of IFRS 9 and CECL. The results indicate that while the transition to forward-looking accounting has reduced average lag, structural inefficiencies, particularly rigid model recalibration cycles and governance complexity, continue to drive significant temporal gaps. Furthermore, the author finds evidence of an asymmetric "stigma effect" and forbearance incentives: banks are quick to recognize severe credit deteriorations to signal "kitchen-sinking" but delay the recognition of marginal deteriorations to prevent capital depletion. These findings provide critical insights for macroprudential surveillance, the calibration of countercyclical capital buffers, and the ongoing refinement of Basel IV and IFRS 9 frameworks.

Keywords: risk perception lag, System GMM, IFRS 9, loan loss provisions, bank governance, procyclicality, forbearance.

JEL Classifications: G21, G28, G32, M41, C23.

1. INTRODUCTION

The resilience of the global financial system is contingent not only on the magnitude of regulatory capital but also on the temporal efficiency with which institutions recognize emerging risks. Historically, banking research has focused predominantly on the precision of risk models and the volume of loan loss provisions (LLP). Yet, the 2008 global financial crisis and subsequent localized banking stresses revealed that the timing of risk recognition is often as critical as the accuracy of the final estimate (Hull, 2018; Bhattacharya et al., 2024). This paper formalizes the concept of Risk Perception Lag (RPL), representing the delay between the realization of an exogenous economic shock and its formal inclusion in a bank's internal reporting, provisioning, and capital planning systems.

The motivation for this study stems from the fundamental shift from the incurred loss" model of IAS 39 to the "expected credit loss" (ECL) frameworks under IFRS 9 and US GAAP CECL (IFRS Foundation, 2014; Basel Committee, 2019). While these reforms were explicitly intended to solve the "too little, too late" problem of risk recognition (Ryan, 2011; Beatty and Liao, 2014), recent empirical evidence suggests that implementation is far from frictionless (Behn and Couaillier, 2023). Heterogeneity in data pipelines, internal rating-based (IRB) model architecture, and corporate governance routines implies that banks face varied speeds in risk transmission, allowing discretionary delays to persist under the guise of model complexity (Huizinga and Laeven, 2012).

This paper argues that delayed risk recognition is not merely a technical artifact but an endogenous choice driven by capital constraints, governance friction, and managerial incentives to engage in supervisory forbearance or "zombie lending" (Caballero, 2008; Acharya et al., 2019). When banks delay the recognition of non-performing loans (NPLs), they artificially inflate their equity capital, staving off regulatory intervention but simultaneously freezing credit allocation to productive sectors (Diamond and Rajan, 2011).

This study contributes to the literature in three distinct ways. First, the author mathematically formalizes RPL, decomposing it into informational friction, model inertia, and institutional delay. Second, a robust causal identification strategy is introduced using a dynamic twostep System GMM estimator (Arellano and Bond, 1991; Blundell and Bond, 1998) to isolate structural delays from contemporaneous measurement error. Third, a Difference-in-Differences (DiD) is applied setting to test the exogenous shock of IFRS 9 implementation on RPL using a carefully trimmed dataset of 320 global banks spanning 2011-2024.

2. COMPREHENSIVE LITERATURE REVIEW

2.1. Accounting Regimes and Provisioning Discretion

The foundational literature on banking risk heavily scrutinizes the role of accounting regimes in shaping managerial behavior. Beatty and Liao (Beatty and Liao, 2014) and Bushman and Williams (Bushman and Williams, 2012) establish that managers utilize loan loss provisions not only to reflect credit risk but to manage earnings and regulatory capital. Under the incurred loss model, provisions were backward-looking, exacerbating procyclicality (Gaston and Song, 2014). The introduction of IFRS 9 and CECL was designed to front-load provisions (Abad and Suarez, 2017). However, Guenther et al. [2021] and Behn and Couaillier (2023) show that ECL models rely heavily on macroeconomic forecasts, injecting a new vector of subjectivity. If banks possess the discretion to select optimistic macroeconomic scenarios, the ”too little, too late” problem morphs into a “model inertia” problem.

2.2. Bank Governance, Information Processing, and Delay

Institutional design dictates how efficiently information flows from loan officers to the board of directors. Jiang et al. (2019) demonstrate that hierarchical complexity within banks slows down information processing, particularly for soft information. Furthermore, Laeven and Levine (2009) and Berger et al. (2016) highlight that bank governance – specifically the risk appetite of the board—significantly dictates the timeliness of loss recognition. Banks with weaker governance or entrenchment issues tend to exhibit higher opacity and longer delays in downgrading borrower credit ratings (Flannery, 2013; Naburgi, 2025).

2.3. Procyclicality, Forbearance, and Real Economic Effects

Delayed risk perception has real macroeconomic consequences. When banks fail to recognize losses promptly, they are incentivized to roll over bad debt – “zombie lending” – to avoid depleting capital (Caballero, 2008; Acharya, 2019). Diamond and Rajan (2011) argue that the fear of fire sales causes banks to hold onto illiquid, impaired assets longer than optimal. This regulatory forbearance (Gaston and Song, 2014; Becker and Ivashina, 2024) traps capital in unproductive sectors. Moreover, banks dynamically adjust their risk standards based on competition and the macroeconomic cycle (Ruckes, 2004; Begenau, 2018), meaning RPL is likely countercyclical: lengthening during the onset of a crisis as banks delay bad news, and shortening during recoveries.

3. THEORETICAL FRAMEWORK AND HYPOTHESES

3.1. Mathematical Formalization of RPL

Let tshockit be the exact moment an exogenous risk event occurs (e.g., a borrower defaults or an industry-wide macroeconomic shock hits). Let tresponseit be the moment the bank officially adjusts its capital provisions. RPL for bank i at time t is:

$$RPL_{it} = t_{response_{it}} - t_{shock_{it}} \quad (1)$$

The author models the bank’s decision to recognize risk as a dynamic optimization problem. The bank aims to maximize the expected utility of its reported capital C_τ at recognition time τ, subject to a regulatory and market penalty for delayed recognition $\Phi(\tau - t_{shock})$.

$$\max_{\tau \geq t_{shock}} E\,[U\,(C_\tau)] - \Phi\,(\tau - t_{shock}) - \Omega\,(IF,MI,ID) \quad (2)$$

Here, Ω represents the structural friction costs comprising:

1. **Informational Friction (IF):** Cost of verifying soft information (Stiglitz and Weiss, 1981).
2. **Model Inertia (MI):** The cost of out-of-cycle IRB recalibration.
3. **Institutional Delay (ID):** Governance bottlenecks requiring board approval for massive LLP shifts.

3.2. Hypotheses Development

Based on the theoretical friction parameters, the author formalizes the following hypotheses:

- **H1 (Informational Distance):** Banks with higher monitoring costs and greater geographic dispersion of asset portfolios exhibit a significantly larger RPL due to elevated IF.
- **H2 (Model Rigidity):** Banks utilizing through-the-cycle (TTC) rating models rather than point-in-time (PIT) models exhibit higher model inertia (MI), thereby increasing RPL.
- **H3 (Governance Efficiency):** An increased proportion of board members with dedicated risk management expertise reduces institutional delay (ID), accelerating risk recognition.

- **H4 (Capital Constraint / Forbearance):** Weakly capitalized banks exhibit an extended RPL during macroeconomic shocks, delaying recognition to prevent breaches of Basel minimum capital requirements (Gropp, 2014; Thakor, 2014).
- **H5 (IFRS 9 Shock):** The transition to IFRS 9 ECL models significantly reduced average RPL, but generated an asymmetric "stigma effect" where positive rating migrations are recognized much slower than negative ones.

4. DATA AND METHODOLOGICAL RIGOR

4.1. Sample Selection and Trimming

The dataset consists of an unbalanced panel of 320 commercial banks from 20 OECD countries over the period 2011–2024. Data is extracted from Orbis Bank Focus, matched with market data from Bloomberg and macroeconomic data from the World Bank.

Due Diligence Criteria: To ensure the validity of dynamic panel estimators, banks with fewer than four consecutive years of observations (Roodman, 2009) are excluded. To mitigate the effect of extreme outliers caused by mergers and acquisitions, all continuous bank-level variables are winsorized at the 1st and 99th percentiles.

Table 1.

Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	P25	Median	P75
RPL (Days)	3,840	142.5	45.3	110.0	138.5	165.0
IF Cost (OpEx/Loans %)	3,840	2.45	0.88	1.80	2.30	2.95
MI Freq (Recalibrations/Yr)	3,840	1.75	0.95	1.00	2.00	4.00
Gov Exp (% Risk Experts)	3,840	18.5	8.2	12.0	18.0	25.0
ETA (Equity/Assets %)	3,840	8.55	2.15	7.10	8.40	9.80
NPL Ratio (%)	3,840	3.12	2.45	1.50	2.60	4.10
Size (Ln Total Assets)	3,840	16.5	1.8	15.2	16.4	17.8

4.2. Econometric Identification: System GMM

Bank governance, model calibration, and risk perception are highly endogenous; unobserved managerial quality simultaneously affects profitability and RPL. Furthermore, RPL exhibits path dependence (a bank that is slow to update this quarter is likely to be slow next quarter). Therefore, static OLS or Fixed Effects models will yield biased, inconsistent estimates (Nickell bias).

The author employs the two-step System GMM estimator proposed by Blundell and Bond [12]. The specification is:

$$RPL_{it} = \alpha RPL_{it-1} + \beta_1 IF_{it} + \beta_2 MI_{it} + \beta_3 ID_{it} + \beta_4 Shock_t + \gamma' X_{it} + \eta_i + \delta_t + \epsilon_{it} \quad (3)$$

where η_i captures unobserved time-invariant bank heterogeneity and δ_t controls for global macroeconomic shocks. Internal variables (IF, MI, ID, ETA) are treated as endogenous and instrumented with their own lagged levels in the differenced equation, and lagged differences in the level's equation (Roodman, 2009).

4.3. Difference-in-Differences (DiD) Specification

To isolate the regulatory shock (H5), the author leverages the staggered global rollout of ECL models (IFRS 9 in 2018 for Europe; CECL in 2020 for the US).

$$RPL_{it} = \theta_0+\theta_1(Treat_i\times Post_t)+\theta_2(Treat_i\times Post_t\times LowCap_i)+\gamma' X_{it}+\eta_i+\delta_t+\epsilon_{it} \quad (4)$$

Treat equals 1 for banks adopting IFRS 9 in 2018. LowCap is a dummy for banks in the bottom quartile of capitalization, testing the forbearance hypothesis.

5. EMPIRICAL RESULTS AND DISCUSSION

5.1. Baseline GMM Results: The Anatomy of Delay

Table 2 presents the core System GMM estimations. The coefficient on the lagged dependent variable (RPL_{t-1}) is robustly positive (∼ 0.58), confirming severe persistence in risk reporting delays.

Table 2.

System GMM Regression Results: Determinants of RPL

Dependent: RPL_{it}	(1) Baseline	(2) Gov & Model			(3) Capital	(4) Full Model
		0.598***	0.602***	0.585***		
		(0.042)	(0.048)	(0.051)		
		–	–	0.132**		
				(0.058)		
		-2.10***	–	-1.95***		
		(0.55)		(0.62)		
		-0.455**	–	-0.442**		
MI Freq		(0.172)		(0.168)		
Gov Exp			(0.85)	(0.91)		
		1.20*	1.05	1.12*		
ETA (Capital)	–	(0.61)	(0.65)	(0.60)	-3.12***	-2.85***
AR(1) *p*-value	0.012	0.014			0.011	0.015
AR(2) *p*-value	0.245	0.312			0.285	0.355
Hansen J *p*-value	0.412	0.485			0.455	0.512
Observations	3,840	3,840			3,840	3,840
Instruments	24	28			26	34

Notes*: Standard errors in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. AR(2) confirms no second-order serial correlation. Hansen J confirms instrument validity (avoiding instrument proliferation, keeping instruments ¡ groups).*

Supporting H1 and H2, high information friction (IF_Cost) increases the lag, while frequent model recalibration (MI_Freq) sharply decreases it. A 1 standard deviation increase in recalibration frequency reduces RPL by approximately 2 days. Supporting H3, risk expertise on the board accelerates recognition significantly. Crucially, supporting H4, higher capitalization (ETA) reduces RPL; conversely, weakly capitalized banks delay recognition by nearly 3 additional days per unit drop in capital, strongly validating the "forbearance" and capital preservation theories established by Diamond and Rajan (2011) and Kagerer et al. (2025).

5.2. IFRS 9 Exogenous Shock and Forbearance Incentives

Table 3 evaluates the DiD specification surrounding IFRS 9.

Table 3.
Difference-in-Differences: IFRS 9 Adoption and Strategic Delay

Outcome: RPL_{it}	Coefficient	Std. Error	*t*-stat
Treat×Post (Base IFRS 9 effect)	-14.45***	4.12	-3.50
Treat×Post×WeakGov	8.32*	4.45	1.87
Treat×Post×LowCap	11.15***	3.80	2.93
Bank Fixed Effects	Yes		
Time Fixed Effects	Yes		
Adj. R-squared	0.45		

Note. *IFRS 9 reduced average lag by 14.45 days. However, this efficiency gain is almost entirely offset (by +11.15 days) in banks with low capital buffers, indicating that ECL frameworks do not eliminate strategic managerial delay when survival is at stake.*

The baseline adoption of IFRS 9 successfully reduced RPL by roughly two weeks (14.45 days), corroborating the intended forward-looking nature of the regulation (Abad and Suarez, 2017). However, the triple interaction term (*Treat* × *Post* × *LowCap*) is highly significant and positive (11.15). This implies that vulnerable banks utilize the subjective macroeconomic forecasting inherent in IFRS 9 to “hide” behind optimistic scenarios, effectively neutralizing the regulatory intent and continuing to exhibit substantial risk perception lags.

6. ROBUSTNESS AND DIAGNOSTIC CHECKS

To ensure the credibility of the findings, several due diligence checks were conducted:

1. **Instrument Validity:** Following Roodman (2009), the author collapses the instrument matrix in the System GMM to prevent instrument proliferation, which can overfit endogenous variables and weaken the Hansen J-test. The instrument count remains strictly below the number of bank groups (N = 320).
2. **Parallel Trends Assumption:** For the DiD analysis, a pre-trend analysis was conducted by interacting the Treat dummy with time indicators for $t-3$, $t-2$, and $t-1$. None of the pre-treatment coefficients were statistically significant, confirming that treated and control banks were on parallel RPL trajectories prior to IFRS 9.
3. **Too-Big-To-Fail (G-SIB) Placebo:** The author interacted the main variables with a Global Systemically Important Bank (G-SIB) dummy. Interestingly, G-SIBs exhibit longer institutional delay (ID), suggesting that extreme hierarchical complexity in mega-banks offsets their superior IT and data infrastructures (Jiang, 2019).

7. CONCLUSION AND POLICY IMPLICATIONS

This paper introduces Risk Perception Lag as a vital empirical metric, arguing that in financial risk management, delayed truth is functionally equivalent to error. By rigorously mapping the structural transmission mechanisms of risk shocks into bank provisions, it is demonstrated that informational friction, rigid models, and complex governance inherently slow down risk recognition.

While forward-looking accounting standards like IFRS 9 have structurally reduced the average time-to-recognition, they have not eliminated the agency problems underlying banking. Specifically, the author finds robust causal evidence of capital forbearance: weakly capitalized banks exploit the subjective nature of ECL macroeconomic scenarios to delay the recognition of credit deterioration, engaging in stealth capital preservation.

For policymakers and supervisors, the implication is clear. Macroprudential stress tests and asset quality reviews (AQRs) must evaluate banks not just on the static level of their provisions, but on the dynamic velocity of their risk updating pipelines. Regulators should scrutinize out-of-cycle IRB recalibrations and board-level overrides, particularly during the onset of macroeconomic downturns, to prevent the crystallization of zombie lending.

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