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# European Banks Cost Of Equity - Panel Data Approach

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Master Degree in Finance

**Supervisor:**

**PhD, José Joaquim Dias Curto, Full Professor**
**Iscte-IUL**

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BUSINESS
SCHOOL

**Department of Finance**

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# Resumo

A crise financeira de 2007-2009, a mais grave desde a Grande Depressão, revelou fragilidades sistémicas no setor bancário, conduzindo a profundas reformas regulatórias. Esta tese analisa o impacto da regulamentação pós-crise, em particular do Acordo de Basileia III, no custo do capital próprio dos bancos europeus.

Este estudo pretende prever o custo do capital próprio (CoE) da banca europeia com base numa amostra de 135 bancos cotados de 21 países, entre 2004 e 2024, correspondendo a cerca de 2,835 observações banco-ano. O modelo de referência, construído a partir de um quadro de avaliação de ativos com fator de mercado e variáveis explicativas ao nível do banco, resulta num coeficiente de sensibilidade ao mercado ($\beta$) estatisticamente significativo em todas as especificações, variando entre 0,68 e 1,12, e um grau de ajustamento moderado, com $R^2$ entre 0,24 e 0,51.

Entre as variáveis bancárias, os rácios Provisões/Capital Próprio, NPL/Crédito Líquido e FCF/Rendimento apresentam associações negativas e estatisticamente significativas com os diferenciais de rendibilidade, enquanto os rácios de Capital Total e CET1 revelam efeitos mais fracos e heterogéneos. Os indicadores anuais sugerem que, em determinados anos, choques macroeconómicos podem assumir um papel predominante na explicação das rendibilidades.

Aplicando os modelos de mistura finita conseguimos identificar três regimes de risco distintos no comportamento das rendibilidades: um de baixa sensibilidade em relação ao mercado, um de elevada sensibilidade mas estável ($\beta$ em torno de 1,4 a 1,5) e um de sensibilidade muito elevada ($\beta$ próximo de 2,2) caracterizado por maior volatilidade, o que revela heterogeneidade estrutural entre bancos e perfis diferenciados de exposição ao risco de mercado.

Estas conclusões mantêm-se consistentes e robustas quando são aplicadas correções de heterocedasticidade e autocorrelação à matriz de covariâncias e quando se recorrem a modelos dinâmicos estimados pelo método generalizado dos momentos.



**Classificação JEL:** G21, G28, G12, C23, C58

**Palavras-chave:** Intermediação financeira; Regulação bancária; Capital regulatório bancário; Custo do capital próprio; Risco de mercado e beta; Risco de crédito; Criação de liquidez; Econometria de dados em painel; Método generalizado dos momentos; Quebras estruturais e mudanças de regime; Modelos de mistura finita; Aprendizagem automática em retornos esperados

# Abstract

The 2007-2009 financial crisis, the most severe since the Great Depression, revealed systemic weaknesses in the banking sector, prompting extensive regulatory reforms. This thesis analyses the impact of post-crisis regulation, in particular the Basel III Accord, on the cost of equity of European banks.

This study predicts the cost of equity (CoE) for the European banking sector based on a sample of 135 listed banks from 21 countries over the period 2004–2024, comprising approximately 2,835 bank-year observations. The baseline model, built upon an asset pricing framework with a market factor and bank-level explanatory variables, shows a statistically significant market sensitivity coefficient ($\beta$) across all specifications, ranging between 0.68 and 1.12, with a moderate degree of fit, as indicated by an adjusted $R^2$ between 0.24 and 0.51.

Among the bank fundamentals, the ratios Provisions/Equity, NPL/Net Loans, and FCF/Income display negative and statistically significant associations with return differentials, while the Total Capital and CET1 ratios exhibit weaker and more heterogeneous effects. Annual indicators suggest that macroeconomic shocks may play a dominant role in explaining returns in certain years.

The application of finite mixture models identifies three distinct risk regimes in the behaviour of returns: one of low market sensitivity, another of stable high sensitivity ($\beta$ around 1.4–1.5), and a third of very high sensitivity ($\beta$ close to 2.2) characterised by greater volatility, reflecting structural heterogeneity among banks and differentiated profiles of exposure to market risk.

The conclusions remain consistent and robust when applying corrections for heteroscedasticity and autocorrelation to the covariance matrix and when using dynamic models estimated through the Generalized Method of Moments.



**JEL Classification:** G21, G28, G12, C23, C58

**Keywords:** Financial intermediation; Bank regulation; Bank regulatory capital; Cost of equity; Market risk and beta; Credit risk; Liquidity creation; Panel data econometrics; Generalized method of moments; Structural breaks and regime shifts; Finite mixture models; Machine learning for expected returns

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# Lista de Acrónimos

**AIC** : Akaike Information Criterion
**ALE** : Accumulated Local Effects
**ANN** : Artificial Neural Network
**Basel I** : Basel Accord I
**Basel II** : Basel Accord II
**Basel III** : Basel Accord III
**BCBS** : Basel Committee on Banking Supervision
**BIC** : Bayesian Information Criterion
**BIS** : Bank for International Settlements
**CAPM** : Capital Asset Pricing Model
**CAR** : Capital Adequacy Ratio
**CET1** : Common Equity Tier 1
**CoE** : Cost of Equity
**COVID-19** : Coronavirus Disease 2019
**CRD IV** : Capital Requirements Directive IV
**CRR** : Capital Requirements Regulation
**CSR** : Corporate Social Responsibility
**DTE** : Debt-to-Equity Ratio
**EBA** : European Banking Authority
**ECB** : European Central Bank
**ESG** : Environmental, Social, and Governance
**ESS** : Effective Sample Size
**FCF** : Free Cash Flow
**FE** : Fixed Effects
**GAM** : Generalized Additive Model
**GFC** : Global Financial Crisis
**GMM** : Generalized Method of Moments
**HAC** : Heteroskedasticity and Autocorrelation Consistent
**HML** : High Minus Low (Fama–French factor)
**LASSO** : Least Absolute Shrinkage and Selection Operator
**LCR** : Liquidity Coverage Ratio
**LLP** : Loan Loss Provisions
**LOOIC** : Leave-One-Out Information Criterion
**LRP** : Layer-Wise Relevance Propagation

**MAE** : Mean Absolute Error
**MAP** : Maximum A Posteriori
**MCMC** : Markov Chain Monte Carlo
**MG** : Mean Group
**NN** : Neural Network
**NPL** : Non-Performing Loan
**NSFR** : Net Stable Funding Ratio
**OLS** : Ordinary Least Squares
**OOB** : Out-of-Bag
**Pareto-k** : Pareto-k Diagnostic (LOO validation)
**RE** : Random Effects
**RF** : Random Forest
**RMSE** : Root Mean Square Error
**ROE** : Return on Equity
**RSS** : Residual Sum of Squares
**RWA** : Risk-Weighted Assets
**SHAP** : Shapley Additive Explanations
**SMB** : Small Minus Big (Fama–French factor)
**SSM** : Single Supervisory Mechanism
**sup-F** : Supremum F Test
**T1CAR** : Tier 1 Capital Ratio
**UDmax** : Double Maximum Test
**WAIC** : Widely Applicable Information Criterion
**WACC** : Weighted Average Cost of Capital
**WDmax** : Weighted Double Maximum Test
**XAI** : Explainable Artificial Intelligence

CHAPTER 1

# Introduction

Banking sector resilience is key to economic stability and development. Banks are the essential intermediaries between borrowers and savers, providing the foundation for investment, consumption, and provision of liquidity in both local and cross-border markets. The failure of banking systems has implications for the whole economy, shaking financial stability, jobs, and growth foundations. This truth came sharply into view in the period of the global financial crisis (GFC) of 2007–2009, as this laid bare structural flaws in bank capital adequacy, risk-taking, and regulatory standards.

The crisis sparked a profound rethinking of financial regulation worldwide, culminating in the Basel III framework (BCBS, 2011). While designed to enhance systemic resilience, these reforms also raised fundamental questions about their impact on banks' cost of funding, particularly the cost of equity. For European banks, in particular, the intersection between stricter capital rules, elevated market risk, and profitability constraints has made the cost of equity (CoE) an essential metric for both regulators and market participants.

This chapter frames the thesis within this broader context. It begins with the regulatory evolution from Basel I and II to Basel III, then explores the theoretical and empirical debates around the cost of equity, and concludes by articulating the central research question addressed in this study.

## 1.1. Post-Crisis Regulation and the Evolution of Basel Standards

Regulation of bank capital has undergone many years of development. Basel I, implemented in 1988, put in place the first universally accepted capital adequacy standard, with banks needing to hold capital of at least 8% of risk-weighted assets (RWA). Due to its simplicity, however, it allowed for arbitrage, as banks balanced portfolios optimally but not necessarily decreasing systemic risk (Miles, Yang & Marcheggiano, 2013).

Basel II, put in place incrementally in the early 2000s, set out to make this approach more refined by establishing three pillars: minimum capital requirements, supervisory review, and market discipline. Even so, Basel II has been criticized for overlooking systemic risks. By enabling internal risk models to decide capital buffers, it favored dependency on procyclical tools that intensified financial fragility (Belkhir et al., 2021).

These frailties were called into question by the financial crisis of 2007–2009. Banks that had become highly levered with lean equity cushions had their funding suddenly dwindle once confidence dropped (Miles et al., 2013). Some required government support to prevent insolvency, at enormous fiscal expense, and contributed to public debates about the regulation of banks.

To address this, the Basel III framework (BCBS, 2011) came into being as a holistic reform package. Its aims were well defined: boost both the size and quality of capital, reinforce liquidity standards, and limit leverage. A key foundation for Basel III was placing a premium on Common Equity Tier 1 (CET1)—the component of capital with the greatest loss-absorbing capacity. Though Basel II had permitted banks to have CET1 as low as 2% of RWA, Basel III insisted on at least 4.5%, supplemented by a 2.5% capital conservation buffer, making the effective requirement 7% (ECB, 2011).

These reforms also comprised the Liquidity Coverage Ratio (LCR), so that banks had enough high-quality liquid assets to support short-term shocks, as well as the Net Stable Funding Ratio (NSFR) for fostering long-term stability in funding. In addition, a leverage ratio served as a non-risk-based backstop in order to restrict building up exposures outside of risk-weighted paradigms.

Basel Committee (2011, p.1) stressed that "a strong and resilient banking system is the foundation for sustainable economic growth, as banks are at the centre of the credit intermediation process." Nevertheless, the reforms were controversial. Banks complained that equity is more expensive than debt, and more capital requirements would lower profitability, limit lending, and dampen growth (Belkhir et al., 2021). Regulators and scholars, however, referred to the Modigliani-Miller theorem (1958), claiming that, under specific assumptions, higher equity ratios may not raise total funding costs, as lower risk decreases required returns. Empirical evidence, like King (2009) as well as Kashyap & Stein (2010) and Miles et al. (2013) confirm that highly capitalised banks tend to have lower funding costs and higher lending capacity.

Therefore, Basel III raised a key policy challenge: strengthening stability at the potential cost of changing banks' cost profiles in a manner that could have implications for intermediation and economic growth.

### 1.2. The Cost of Equity in Banking

The cost of equity (CoE) refers to the return that investors expect in exchange for holding a bank's equity, considering the risks they take on. Unlike the cost of debt, which is contractually determined, the CoE is an expected return that cannot be directly observed and must instead be estimated (Altavilla et al., 2021; Asal, 2015).

For bank managers, the CoE serves as a hurdle rate in lending and investment decisions, guiding strategic choices around capital allocation (Asal, 2015). For investors, it acts as a benchmark for valuation and directly influences how portfolios are built. For regulators, it reflects market perceptions of risk and resilience, providing a reference point for assessing whether capital regulations strike the right balance between safety and efficiency (ECB, 2011; Altavilla et al., 2021).

The financial crisis profoundly reshaped this landscape. As market volatility surged and sovereign risk premiums increased, investors began demanding higher returns to compensate for the additional risk of holding bank equity. Even though central banks cut

interest rates to historic lows, equity risk premiums remained stubbornly high, pushing the CoE well above pre-crisis levels (Altavilla et al., 2021).

This widening gap between the CoE and return on equity (ROE) created structural pressures. When the CoE exceeds banks' expected profitability, their ability to attract new equity capital diminishes, which in turn limits their capacity to lend and invest. Altavilla et al. (2021) caution that this dynamic undermines banks' ability to absorb shocks and could lead to higher borrowing costs for businesses and households.

At the same time, the debate over whether higher capital requirements themselves increase the CoE became more intense. On one side, the banking industry argues that equity is inherently more expensive than debt, and that requiring higher equity ratios raises funding costs (Belkhir et al., 2021). On the other side, academics contend that better-capitalized banks are safer and therefore viewed as less risky by investors, which could lower their CoE over time (ECB, 2011; Miles et al., 2013).

From a methodological perspective, estimating the CoE presents several challenges. There are three main approaches. The first relies on accounting-based proxies such as ROE or the price-to-earnings ratio, although these are often criticized for failing to account for risk. The second is based on theoretical models, with the Capital Asset Pricing Model (CAPM) remaining the most widely used despite its simplifying assumptions. The third involves multi-factor models that incorporate both bank-specific and broader macroeconomic risks (Asal, 2015).

This thesis applies the CAPM framework using a panel data approach, estimating betas across different banks and time periods. The central aim is to explore whether the crisis environment and the implementation of Basel III brought about a systematic change in the CoE.

### 1.3. The Fundamental Question

The central motivation of this study is to understand how the cost of equity (CoE) of European banks has behaved in the aftermath of the global financial crisis and during the subsequent implementation of the Basel III regulatory framework. Rather than asking whether the CoE has simply increased or decreased, the research question is framed in a more neutral and exploratory manner: what has been the trajectory of the cost of equity of European banks over this period, and what have been the principal factors driving this evolution? This formulation reflects the view that the behaviour of the CoE cannot be reduced to a binary outcome. Instead, it must be understood as the result of the interaction between regulatory reforms, bank-specific characteristics, market perceptions of risk, and wider macro-financial developments.

The primary goal of the study is thus to describe the dynamics of the CoE at various phases of the past two decades, from pre-crisis to crisis and post-crisis periods, but specifically for the period of regulatory strengthening that coincides with Basel III. Through the long observation period from 2004 until 2024, the study is in a position to observe both the short-term impacts of financial instability and the long-term responses to prudential

reforms. A second goal is to detect and estimate the determinants that have driven the development of the CoE. These determinants are regulatory reforms like increased capital levels and the implementation of liquidity and leverage ratios, but also bank-specific variables like size, capitalisation, leverage, and risk-taking, as well as macroeconomic variables like the monetary policy stance, sovereign risk premia, and financial volatility.

A further objective is to assess how regulation and market perceptions have interacted in shaping the pricing of bank equity. The tightening of capital standards may, on the one hand, raise funding costs if equity is perceived as inherently more expensive than debt. On the other hand, by making banks more resilient, stronger capital buffers may reduce perceived risk, thereby lowering the return demanded by investors. This tension lies at the heart of the ongoing policy debate and constitutes a key focus of the empirical analysis. Finally, the study also seeks to evaluate the implications of CoE dynamics for banks' ability to intermediate credit and contribute to systemic stability. Understanding whether higher capital requirements ultimately constrain or reinforce the role of banks in supporting economic activity is a matter of central importance for regulators, investors, and policymakers.

From these objectives, a set of guiding hypotheses is formulated.

The first hypothesis concerns the impact of Basel III capital standards, which are expected to have had a measurable effect on the cost of equity. The direction and magnitude of this effect may depend on banks' initial conditions and balance sheet structures. Empirical studies confirm this heterogeneity: Miles, Yang and Marcheggiano (2013) and Junge and Kugler (2013) find that higher capital requirements tend to increase banks' cost of equity, while more recent evidence by Krause, Sfrappini, Tonzer and Zgherea (2024) shows that the funding costs of EU banks rose in response to CRD IV, with stronger effects where pre-existing capital regulation was weaker.

The second hypothesis relates to market perceptions of risk in the wake of the global financial crisis. Even as monetary policy remained highly accommodative, investors' risk premia rose substantially during and after the crisis, suggesting that heightened perceptions of systemic fragility played an important role in pushing up the required return on bank equity, independently of regulatory factors. Acharya et al. (2010) highlight the relevance of systemic risk in equity pricing, while more recent ECB (2023) analysis documents that bank CoE in the euro area has been sensitive to spikes in market stress, with risk premia widening in episodes of financial instability.

A third hypothesis acknowledges the heterogeneity among banks. Better-capitalised institutions may have experienced a stabilisation or even a decline in their CoE relative to weaker peers, as improved solvency and resilience are recognised by markets in the form of lower required returns. Anginer, Demirgüç-Kunt and Zhu (2014) provide evidence that stronger capital buffers reduce risk premia. More recently, Lafuerza (2024) revisits the estimation of the cost of equity for euro area banks and shows that bank-specific

solvency indicators significantly affect the CoE, confirming that stronger balance sheets are associated with lower required returns.

Finally, a fourth hypothesis highlights the role of broader macro-financial conditions. Interest rate environments, sovereign spreads, and market volatility are likely to have exerted an independent influence on the CoE, interacting with both regulatory reforms and institution-specific factors in shaping its trajectory. Altavilla, Pagano and Simonelli (2017) show that euro area banks' funding costs are strongly affected by sovereign risk and monetary policy conditions, while ECB (2023) demonstrate that recent increases in risk-free rates were a key driver of the rise in bank CoE.

TABLE 1. Research Hypotheses and Expected Effects on the Cost of Equity

| | **Focus** | **Expected Effect on CoE** | **Supporting Literature** |
|---|---|---|---|
| H1 | Basel III capital requirements | Increase in CoE, depending on banks' initial conditions and balance sheet structures | Miles, Yang and Marcheggiano (2013); Junge and Kugler (2013); Krause, Sfrappini, Tonzer and Zgherea (2024) |
| H2 | Market perceptions of risk post-crisis | Higher CoE via increased risk premia, independent of regulatory changes | Acharya et al. (2010); ECB (2023) |
| H3 | Bank heterogeneity (capitalisation) | Better-capitalised banks expected to face lower CoE, weaker peers higher CoE | Anginer, Demirgüç-Kunt and Zhu (2014); Lafuerza (2024) |
| H4 | Macro-financial conditions | CoE influenced up or down depending on interest rates, sovereign spreads and volatility | Altavilla, Pagano and Simonelli (2017); ECB (2023) |

Taken together, these hypotheses frame the research in a way that goes beyond the narrow question of whether regulation is "costly" or "beneficial." Instead, the aim is to offer a holistic understanding of how multiple forces — regulatory, institutional, and macroeconomic — have jointly influenced the behaviour of the cost of equity in the European banking sector.

The structure of the thesis is as follows. The next chapter provides a literature review of the regulatory framework and the theoretical foundations of the cost of equity. Chapter 3 details the methodology and econometric approach. Chapter 4 presents the empirical results, while Chapter 5 discusses their implications in light of the literature. Finally, Chapter 6 concludes and outlines avenues for future research.

# CHAPTER 2

Literature Review

The cost of equity (CoE) is the rate paid by investors in exchange for bearing the risk of holding the equity of a firm. It is both a central funding structure determinant and a key performance metric in banking, often contrasted with return on equity (ROE) as a barometer of value creation. When ROE of a bank continuously lags behind its cost of equity, investor confidence is weakened, equity valuations soften, and the capacity of the institution to raise capital at preferential terms is weakened.

After the 2008 financial crisis, banking CoE received revived research and policy interest. The crisis unveiled serious flaws in banks' capital structure, asset quality, and risk control, whose aggregate impact increased equity risk premia in banks' counterparties' eyes. It also triggered broad-based regulatory reforms—the Basel III set of standards, specifically—the aim of which is to make banks more robust by increasing capital and liquidity requirements. Since then, whether reforms increase or decrease CoE has become the key question in both empirical and theoretical debates.

This chapter reviews the literature on the CoE in the banking sector, drawing on academic studies, policy reports, and methodological contributions. The scope is primarily, though not exclusively, centred on the post-crisis era, enabling a focused discussion on the interplay between regulatory change, market expectations, and macroeconomic conditions.

## 2.1. Historical Development of the CoE Concept in Banking

The cost of equity idea owes its intellectual origin to the modern portfolio theory and Capital Asset Pricing Model (CAPM), which was explicitly formalized by Sharpe (1964), Lintner (1965), and Mossin (1966). CAPM linearly related the expected return of equity to its covariance with the market portfolio, which was measure by the beta coefficient. In its initial application to banking during the 1970s and the 1980s, estimation of CoE depended largely on CAPM using historical return observations to estimate beta.

However, early banking applications faced conceptual and empirical challenges. Banks are fundamentally different from non-financial firms: they are highly leveraged by design, their assets and liabilities are largely financial, and they operate under extensive regulation. Consequently, their risk profiles are influenced not only by market factors but also by credit risk, interest rate risk, liquidity risk, and systemic interlinkages. As a result, CAPM's single-factor specification often failed to capture the full spectrum of risks priced by investors.

From the 1990s onwards, multi-factor models gained prominence. The Fama–French three-factor model (Fama & French, 1993), incorporating size (SMB) and value (HML) factors alongside market beta, was widely adopted to account for cross-sectional variation in returns. Extensions added momentum (Carhart, 1997) and, more recently, profitability and investment factors (Fama & French, 2015). Banking studies also integrated macroeconomic variables—such as term spreads, default spreads, and market volatility indices—into Arbitrage Pricing Theory (APT)-style frameworks (Chen, Roll, & Ross, 1986) to better capture cyclical and policy-driven risk drivers.

The 2000s also witnessed the slow transition from exclusively historical (ex post) to forward-looking (ex ante) CoE estimation, partly due to the shortcomings of realised-return approaches to periods of structural transformation, like the prelude to the global financial crisis. Forward-looking strategies deduce required returns from market values and analysts' predictions of future earnings or dividends (Gebhardt, Lee, & Swaminathan, 2001). In banking, these techniques tend to produce CoE estimates higher than historical ones, which capture the market valuation of tail risk and uncertainty.

After 2008, the use of implicit CoE measures gained pace, especially in policy research by central banks and financial authorities. The European Central Bank (ECB), the Bank for International Settlements (BIS), and European Banking Authority (EBA) started including such measures in financial stability monitoring, underlining the macroprudential role of CoE and its impact on the supply of credit.

This recent development presents a key methodological lesson: the choice of the CoE estimation strategy is not only technical but also dictates empirical inferences, and particularly in banking, which entails multi-dimensional risks, binding regulation, and delicate investor expectations regarding macro-financial evolutions.

### 2.2. Measuring the Cost of Equity in the Banking Sector

The measurement of the cost of equity (CoE) in the banking sector has been approached through a variety of empirical and theoretical methodologies. Each method emphasises different aspects of risk, market expectations, and institutional characteristics, thereby producing estimates that can vary across time, jurisdictions, and bank profiles. To structure the discussion, the following subsections review the main approaches commonly applied in the literature, their advantages and limitations, as well as their implications for understanding the determinants of bank CoE.

#### 2.2.1. Realised-Return Approaches

Realised-return methodologies estimate the cost of equity (CoE) by modelling historical stock returns as a function of systematic risk factors, typically within the framework of the Capital Asset Pricing Model (CAPM) or multi-factor asset pricing models, such as the Fama–French three-factor model. These techniques are methodologically robust and computationally efficient, offering a consistent basis for empirical implementation across time and jurisdictions.

Nonetheless, their backward-looking nature represents a significant limitation in volatile or structurally evolving financial environments. The underlying assumption of stable return distributions may not hold during episodes of market distress or regulatory reform, particularly in the banking sector, where crises tend to trigger abrupt shifts in risk exposures. In such contexts, historical factor loadings (betas) and market premia may become uninformative or even misleading. As shown by Fama and French (1997), these models provide robust results under regime stability, yet fail to account for time-varying risk premia. Complementarily, Adrian et al. (2015) argue that realised-return frameworks can systematically underestimate the CoE in periods of elevated systemic risk, thus overlooking the forward-looking component embedded in equity pricing.

### 2.2.2. Implied-Return Approaches

In contrast to realised-return models, implied-return methodologies aim to recover the CoE by solving for the internal rate of return that equates the current market valuation of a firm's equity to the present value of its expected future cash flows—typically earnings, dividends, or free cash flows to equity. These approaches are inherently forward-looking, allowing the incorporation of investor expectations regarding growth, risk, and macro-financial conditions.

Altavilla et al. (2021) provide a comprehensive application of this method to the euro-area banking sector. Their three-step estimation strategy integrates both realised and implied measures and highlights a persistent gap between market-based CoE estimates and accounting-based profitability (i.e., return on equity). Specifically, since the global financial crisis, implied CoE has remained significantly above realised ROE, suggesting a structural misalignment between market expectations and banks' historical performance. The authors report a median CoE of approximately 10%, with a plausible interval between 7.7% and 12.7%, accounting for uncertainty in parameters and bank-specific fundamentals.

More recently, Lafuerza (2024) revisited implied-return methodologies for euro area banks, employing panel regressions with fixed effects and robustness checks to capture the role of bank-specific solvency and profitability conditions. His findings confirm that forward-looking CoE estimates remain systematically above accounting-based returns, but also highlight significant heterogeneity across banks and jurisdictions.

### 2.2.3. Determinants and Cross-Sectional Heterogeneity

Altavilla et al. (2021) identify several key determinants that drive the heterogeneity in CoE estimates across banks. These include: (i) high non-performing loan (NPL) ratios, which amplify credit risk and reduce future cash flow reliability; (ii) a substantial reliance on wholesale funding, which increases refinancing risk; and (iii) weak cost-efficiency, which erodes profitability buffers and diminishes capital resilience. Methodologically, their analysis combines realised-return and implied-return approaches, implemented through panel

regression techniques with bank-level controls and robustness checks across euro-area institutions. This dual approach allows them to disentangle structural from cyclical drivers of CoE.

Moreover, regulatory and capital policies, such as earnings retention strategies or dividend restrictions, can shape investor perceptions of risk and return, thereby affecting CoE estimates indirectly.

Complementary evidence from the European Central Bank's 2019 survey of 95 significant institutions (covering approximately 90% of euro area banking assets) further corroborates these findings. The average self-assessed CoE across respondents was 8.5%, although dispersion was considerable: approximately 67 banks reported values between 8% and 12%, 12 banks reported values below 5%, and a minority reported CoE above 12%. Higher CoE values were more frequently reported by banks operating in smaller or crisis-exposed jurisdictions, particularly in Eastern Europe. However, response clustering suggests potential self-reporting biases, raising questions about the reliability of disclosed estimates.

### 2.2.4. Methodological Trade-Offs

Both realised and implied CoE approaches present distinct advantages and drawbacks.

Realised-return models offer historical consistency and are comparatively straightforward to implement, but may fail to detect shifts in market expectations or structural changes in risk premia (Fama and French, 1997).

Conversely, implied-return models are more responsive to evolving market dynamics and investor sentiment but depend critically on analyst forecasts, payout assumptions, and long-term growth projections, which may introduce bias (Easton, 2004; Elton, 2002). Recent ECB (2023) analyses similarly highlight the gap between realised and implied CoE in euro area banks, particularly under stress scenarios, showing that forward-looking estimates tend to remain above historical profitability measures.

Therefore, a hybrid or comparative approach may offer the most reliable estimates, especially when combined with cross-sectional controls and robustness checks across different bank types and jurisdictions (Altavilla et al., 2021).

### 2.2.5. Theoretical Foundations: Modigliani–Miller and Its Critiques

The theoretical foundation behind much of the CoE banking literature lies in the Modigliani–Miller (MM) theorem (Modigliani & Miller, 1958, 1963). In its standard form, the MM thesis holds that, under perfectly frictionless markets, full information, and no taxes, a company's capital structure is irrelevant to its weighted cost of capital. Transposed to banking, this suggests that equity funding increases are neutralized by decreases in the cost of debt, thus maintaining the weighted average cost of capital (WACC) unchanged. Higher capital requirements, accordingly, would not, in theory, raise the cost of lending or cut credit supply.

Miles, Yang, and Marcheggiano (2013) apply this line of thinking to the banking industry, maintaining that when equity capital goes up, the return required by equity should come down because of lower insolvency risk, and debt becomes safer and less costly. From this, their framework indicates that significant raises in equity capital requirements may be achievable through small or no increases in loan pricing.

Yet this theoretical neutrality is challenged by a series of frictions characteristic of banking. First, tax asymmetries push in the direction of debt financing, since interest repayments are usually tax-deductible while equities' returns are not. Second, the presence of implicit or explicit government guarantees, such as deposit insurance and "too big to fail" protection, might distort market prices of bank liabilities, which reduces the sensitivity of debt costs to capital (Gropp, Gruendl, & Guettler, 2014). Third, agency issues, which include managerial moral hazard and risk-shifting incentives, might affect investor required returns as well as leverage choices.

Belkhir et al. (2021) offer strong empirical support against the strong-form MM irrelevance hypothesis. Employing data from 62 nations during the 1991-2017 period, they document significant negative associations between capital ratios and CoE, and, in particular, the associations are significant when banks are initially low in capital and are from developing nations. The evidence supports the views of the estimation methodologies used, namely dynamic panels and instrumental variables, and also holds when they account for endogeneity.

On the contrary, Asal (2015) provides evidence challenging this connection in the euro-area framework. Using a dynamic panel Generalised Method of Moments (GMM) estimator during the period of 1999–2014, he observes higher Tier 1 capital ratios and higher regulatory strictness are linked to higher CoE, which he explains through market frictions, the role of signalling, and the debt overhang issue.

### 2.2.6. The Effect of Basel III on Bank Capital and Equity Costs

The Basel III introduction by the Basel Committee on Banking Supervision was a global regulatory milestone. Its aims are the enhancement of the quantity and the quality of capital, the reduction of procyclicality, and the enhancement of liquidity and leverage requirements. The reform's core lies in the increased emphasis of Common Equity Tier 1 (CET1) capital, the best-quality loss-absorbing capital.

Theoretically, Basel III favors increased capital buffers, which are anticipated to reduce the probability of bank insolvency and thus reduce debt and equity risk premia. Early empirical confirmation of this expectation is available. The ECB (2011), using an international bank cross-section, indicates finding reduced market-implied CoE and increased CET1 ratios. Kashyap, Stein, and Hanson (2010) also calculate, from a bank-level sample, an increase of only 2.5 basis points in WACC when capital requirements rise by one percentage point, which greatly undermines industry claims of significant credit supply consequences of increased capital requirements.

The BIS (2012) also contends that during non-crisis times, recapitalisation can lower funding cost by decreasing perceived risk, and the advantage of greater resilience will be larger than the temporary cost of building equity. Belkhir et al. (2021) support the same, and they find that better capitalised banks experience reduced CoE, especially in high-risk jurisdictions. Krause, Sfrappini, Tonzer and Zgherea (2024) provide quasi-experimental evidence using difference-in-differences that CRD IV significantly raised EU banks' funding costs, particularly in jurisdictions with weaker initial capital positions. The ECB (2023) similarly reports that since 2022 the rise in the risk-free rate has been the dominant driver of bank CoE, suggesting that macro-financial conditions and regulatory changes interact strongly.

However, the link does not generalize to the global dataset. Asal (2015), in the euro-area setting, shows that stricter capital requirements corresponded to greater CoE during the 1999–2014 period, which may reflect market uncertainty about the regulator's intentions or the dissemination of adverse news when capital issuance takes place under pressure. The interpretation also solidifies the debt overhang problem, where existing shareholders are adverse to equity issuance due to the fear of dilution, which may equate to greater investor return expectations.

### 2.3. Strategic and Structural Dimensions

Beyond regulatory capital requirements, structural changes in the banking industry have had profound implications for the cost of equity (CoE) since the global financial crisis. Buch and Dages (2018), in a report for the Committee on the Global Financial System (CGFS), document a sustained post-crisis decline in banks' return on equity (ROE) across advanced economies. This decline has often left ROE below estimated CoE, raising concerns over the long-term viability of certain banking business models. Contributing factors include:

- A protracted low-interest-rate environment compressing net interest margins (Claessens, Coleman, and Donnelly, 2018).
- Heightened regulatory scrutiny limiting risk-taking.
- Increased competition from fintechs and non-bank financial intermediaries, eroding fee and commission income.

These structural pressures have driven strategic responses such as cost rationalisation, digital transformation, balance sheet de-risking, and market exit from low-return segments. Girotti (2021) provides behavioural evidence that market valuations influence lending decisions. He finds that banks interpret stock price declines—regardless of fundamentals—as an increase in CoE, prompting lending cutbacks. This sentiment channel creates a feedback loop between market perceptions and real economic outcomes, potentially amplifying credit supply volatility.

### 2.4. Institutional Quality and Cross-Country Heterogeneity

Institutional quality has emerged as a critical determinant of the cost of equity, operating through multiple channels such as investor protection, transparency, contract enforcement, and regulatory credibility. Hail and Leuz (2006) provide one of the most influential cross-country analyses, demonstrating that firms operating in jurisdictions with more extensive disclosure regimes, stronger enforcement of securities laws, and higher overall legal quality exhibit significantly lower CoE.

In the euro-area context, incomplete capital market integration and heterogeneity in supervisory practices have created persistent cross-country differentials in bank CoE. The ECB Financial Stability Review (2019) reveals that banks in jurisdictions more severely affected by the sovereign debt crisis—often with weaker institutional frameworks—report materially higher CoE than peers in stronger governance environments. These differences persist even after controlling for bank-specific fundamentals and capital adequacy, suggesting that institutional risk is independently priced by equity markets.

### 2.5. Emerging Themes in Cost of Equity Research

In addition to the traditional debates surrounding regulatory reforms and capital structure, recent literature has expanded the analysis of bank's cost of equity to encompass new and rapidly evolving themes. These emerging strands of research reflect structural transformations in the financial system and broader economy, including the effects of global crises, the growing relevance of sustainability, the disruptive impact of technological innovation, and the role of market microstructure in shaping investor expectations. The following subsections review key contributions along these dimensions.

#### 2.5.1. Post-COVID-19 Effects

The COVID-19 pandemic represented an exogenous shock to the global banking system, altering both risk perceptions and earnings expectations. Demirgüç-Kunt, Pedraza, and Ruiz-Ortega (2021) find that banks with stronger pre-pandemic capital buffers and diversified income streams experienced smaller increases in market-implied CoE during 2020–2021. The EBA Risk Assessment Report (2021) similarly reports temporary spikes in CoE expectations, driven by heightened uncertainty and elevated equity volatility, though these effects moderated as policy support measures stabilised markets.

#### 2.5.2. ESG and Sustainability Considerations

Environmental, Social, and Governance (ESG) performance has become an increasingly salient factor in investor risk assessments. El Ghoul et al. (2011) find that firms with higher corporate social responsibility (CSR) engagement enjoy lower CoE. Albuquerque, Koskinen, and Zhang (2019) provide further evidence across sectors, showing that high-ESG firms have lower downside risk and reduced equity return volatility, both of which can translate into lower required returns.

### 2.5.3. Fintech-Driven Competition

Digital disruption, as documented by Vives (2019), is reshaping competitive dynamics in banking. While fintech innovation offers cost and efficiency gains, it also increases strategic risk for incumbents, particularly those with rigid legacy systems. Market participants may embed this strategic risk into equity pricing, raising CoE for banks perceived as lagging in technological adaptation.

### 2.5.4. Market Microstructure and Liquidity

Liquidity in secondary equity markets is another determinant of CoE. Amihud and Mendelson (1986) argue that less liquid stocks command higher expected returns. In banking, where equity liquidity can vary markedly across institutions and markets, liquidity constraints and wider bid–ask spreads can raise investor return requirements (Goyenko and Ukhov, 2009). This is especially relevant for smaller or less frequently traded bank stocks, which may be penalised by higher CoE despite sound fundamentals.

## 2.6. Behavioural Finance Perspectives on CoE

While traditional CoE models are grounded in rational expectations and efficient market assumptions, behavioural finance highlights the role of systematic biases and sentiment in asset pricing. Baker and Wurgler (2006) demonstrate that investor sentiment can produce persistent mispricings, particularly in opaque and complex sectors such as banking. Girotti (2021) provides direct evidence for this mechanism, showing that banks reduce lending activity following declines in their own equity valuations, interpreting these declines as an implicit signal of increased CoE.

## 2.7. Cross-Sectoral Comparisons

Comparative studies between banks and non-financial corporates (NFCs) offer valuable perspective on sector-specific drivers of CoE. Damodaran (2021) argues that despite banks often having lower market betas than industrial firms, their CoE tends to be higher once tail risk and opacity are considered. Anginer, Demirgüç-Kunt, and Zhu (2014) empirically demonstrate that systemic risk metrics—particularly those capturing co-movements during periods of market stress—explain much of the CoE premium observed in financials relative to NFCs.

## 2.8. Macroeconomic and Geopolitical Risk Channels

The cost of equity for banks is particularly sensitive to macroeconomic and geopolitical risk channels, given their interdependence with sovereign creditworthiness and policy stability. Acharya, Drechsler, and Schnabl (2014) describe the sovereign–bank "doom loop," where deteriorating sovereign credit conditions raise bank funding costs and equity risk premia. Bekaert, Harvey, and Lundblad (2007) show that political risk premiums—driven by policy uncertainty and regulatory instability—are capitalised into equity returns. De Bruyckere et al. (2013) highlight that during the euro-area sovereign debt crisis, CoE

increases in periphery-country banks exceeded those in core countries by several hundred basis points, even after controlling for bank-specific characteristics.

### 2.9. Interest Rate Regimes: Low-for-Long vs. Tightening Cycles

Monetary policy regimes influence both the profitability and risk profile of banks, with implications for CoE. Borio, Gambacorta, and Hofmann (2017) show that prolonged low interest rates compress net interest margins, reducing ROE and potentially increasing the gap between ROE and CoE. Claessens, Coleman, and Donnelly (2018) confirm these effects across countries, adding that low-rate environments incentivise risk-taking, which may indirectly affect equity risk premia. The ECB (2023) notes that while rising rates boost net interest income, they also increase credit risk and market-implied CoE due to elevated macroeconomic uncertainty.

### 2.10. Methodological Advances in CoE Forecasting

Traditional CoE estimation relies on parametric asset pricing models with relatively small sets of explanatory variables, typically within linear regression frameworks such as the CAPM or Fama–French models. While these approaches provide tractable benchmarks, they impose restrictive assumptions about functional forms and ignore complex interactions among risk drivers. As a result, they may fail to capture the full extent of heterogeneity and structural change that characterises modern banking systems, particularly in periods of regulatory reform or monetary policy experimentation (Harvey, Liu, and Zhu, 2016).

Gu, Kelly, and Xiu (2020) demonstrate that machine learning algorithms, such as penalised regressions (LASSO, Ridge, Elastic-Net) and tree-based methods (Random Forests, Gradient Boosting), can significantly improve the predictive accuracy of expected equity returns relative to traditional linear models. These methods are especially valuable in banking, where shifts in regulation and macro-financial conditions can create non-linear effects and interactions that are systematically missed by parametric frameworks. Complementary evidence is provided by Rapach, Strauss, and Zhou (2013), who show that forecast combinations and model averaging approaches outperform single-model strategies in equity return prediction.

Building on this foundation, Bryzgalova, Pelger, and Zhu (2023) apply double machine learning techniques to high-dimensional return panels, allowing for the identification of robust risk premia even when explanatory variables are numerous and potentially correlated. Their approach offers a transparent way of handling endogeneity in asset pricing models, which is particularly relevant when studying regulation-induced changes in the cost of equity.

Similarly, Giglio, Kelly, and Pruitt (2016) show that macro-financial factors extracted through dynamic factor models and shrinkage techniques capture systemic risks more effectively than traditional linear benchmarks. Their results highlight the importance of using methods that can distil a small number of latent drivers from a large cross-section of

macro-financial data—an insight directly applicable to banking, where regulatory shocks, sovereign spreads, and liquidity shifts often propagate through hidden common channels. Adrian, Crump, and Moench (2015) further illustrate how dynamic risk premia can be modelled through flexible factor-augmented approaches.

More recently, Chen, Pelger, and Zhu (2021) provide evidence that representation learning methods—including neural networks and autoencoders—can detect non-linear structures and higher-order interactions in financial returns. These techniques allow for forward-looking estimation of risk premia, which is particularly relevant during episodes of structural change, such as the post-crisis transition to Basel III or the COVID-19 shock, where standard models relying on historical factor loadings may prove inadequate. Related work by Bianchi, Buchner, and Tamoni (2021) also shows that deep learning methods can extract persistent macroeconomic factors driving time-varying risk premia.

Taken together, these contributions suggest that machine learning-based approaches, ranging from penalised regressions and tree ensembles to double machine learning and deep representation learning, offer a powerful complement to traditional econometric methods. By relaxing linearity assumptions and exploiting high-dimensional data, these methods can enhance the robustness of CoE estimation in environments characterised by structural breaks, regulatory shifts, and non-linear dynamics. For banking specifically, they provide an innovative toolkit to disentangle the effects of capital regulation, macro-financial shocks, and investor sentiment on the cost of equity, thereby addressing precisely the empirical challenges that this thesis seeks to confront.

### 2.11. Panel Data in Financial Research

Panel data methodologies offer considerable advantages in banking research, allowing researchers to control for unobserved heterogeneity and examine both cross-sectional and time-series variation. Baltagi (2008) outlines the foundations of fixed- and random-effects models. Dynamic panel methods such as those developed by Arellano and Bond (1991) and Blundell and Bond (1998) address endogeneity issues using instrumental variables. Cerutti, Claessens, and Laeven (2017), and Kelly, Pruitt, and Su (2019) illustrate the application of such methods in bank regulation and return predictability.

The literature on the cost of equity in the banking sector has evolved from traditional asset pricing models towards richer frameworks that incorporate regulatory reforms, macro-financial dynamics, and, more recently, advanced econometric and machine learning techniques. Early contributions emphasised the role of capital regulation and systemic risk, while more recent studies have expanded the scope to include post-crisis monetary policies, sustainability, fintech-driven disruption, and liquidity considerations. Despite these advances, there remains substantial debate on the precise channels through which Basel III and subsequent reforms have affected bank's cost of equity, as well as on the adequacy of different empirical methodologies to capture these dynamics. Against

this background, the next chapter outlines the methodological framework adopted in this thesis, explaining how econometric techniques are applied to disentangle the regulatory, institutional, and macroeconomic drivers of CoE in European banks.

CHAPTER 3

# Methodology

The estimation of the cost of equity in the banking sector constitutes a central concern for both theoretical and applied finance. It directly influences banks' capital allocation policies, dividend distribution strategies, and broader strategic planning, while simultaneously informing the supervisory evaluation of financial stability. From an asset pricing perspective, the cost of equity reflects the expected return demanded by investors for holding a bank's equity, compensating them for both systematic and idiosyncratic risks. From a regulatory standpoint, it also plays a critical role in ensuring that capital requirements are commensurate with the underlying risk profile of financial institutions.

The relevance of this topic increased significantly in the aftermath of the 2007–2009 global financial crisis, which exposed severe vulnerabilities in banking systems worldwide. In response, the Basel Committee on Banking Supervision introduced the Basel III regulatory framework (BCBS, 2011), which was gradually implemented across the European Union from 2014 onwards. Basel III imposed stricter minimum requirements for capital adequacy, introduced leverage constraints, and mandated enhanced liquidity buffers. The primary aim of these reforms was to strengthen the resilience of the banking sector to systemic shocks. However, these same measures have the potential to alter banks' equity risk premia by affecting both the capital structure and perceived default risk which may, in turn, change the level and dynamics of the cost of equity.

Whether the introduction of Basel III brought about a structural shift in the determinants of bank equity returns remains an open empirical question. Specifically, the reform could have changed the relationship between market-wide factors (such as broad equity returns) and bank-specific fundamentals (such as asset quality, capital ratios, and leverage), thereby modifying both the intercept and slope coefficients in standard asset pricing models. To address this question, the present chapter develops a comprehensive econometric framework capable of capturing linear, nonlinear, dynamic, and regime-dependent effects in a multi-country, multi-bank setting. The methodology builds upon the theoretical foundation of the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966) but extends it to incorporate detailed bank-level prudential indicators and to accommodate complex econometric challenges.

The proposed empirical strategy is designed to tackle four key issues. First, unobserved heterogeneity, as banks differ systematically in their business models, risk-taking behaviour, and funding structures. Second, dynamic endogeneity, since past performance and risk exposure influence current returns and are themselves influenced by prior market conditions. Third, structural instability, as major regulatory interventions such as Basel

III may shift the underlying risk–return relationships. Fourth, nonlinearities and complex interactions, because the impact of regulatory and market variables on the cost of equity may be non-additive, with threshold effects and asymmetric responses. Addressing these challenges requires a multi-method approach that combines traditional econometric techniques with advanced statistical learning models, as described in the sections that follow.

## 3.1. Data and Empirical Setting

The analysis defines the variables and data transformations, sets out the baseline model and identification strategy, and summarises the estimation procedures and robustness checks employed throughout.

### 3.1.1. Sample Composition and Sources

The empirical analysis is conducted on an unbalanced panel comprising 135 publicly listed banks from 21 European countries over the period 2004–2024. This timeframe captures multiple distinct phases in European banking: the pre-crisis expansion (2004–2007), the global financial crisis (2008–2009), the sovereign debt crises in Southern European economies (2010–2013), and the post-Basel III regulatory regime (2014–2024). The resulting dataset consists of approximately 2,835 bank–year observations, providing sufficient cross-sectional and temporal variation for robust econometric estimation.

Market data covering daily and annual stock prices, total return indices, and sovereign bond yields are obtained from Refinitiv Eikon. Accounting and prudential indicators, such as capital adequacy and asset quality ratios, are sourced from the same database and cross-verified with publicly available annual reports to ensure accuracy. Where discrepancies arise, preference is given to audited financial statements.

### 3.1.2. Variable Definitions and Transformations

This study adopts a return-based specification grounded in the standard Capital Asset Pricing Model (CAPM). The dependent variable is the *excess equity return* of bank $i$ in year $t$, defined as:

$$r^e_{i,t} = R_{i,t} - R_{f,t} \tag{3.1}$$

where $R_{i,t}$ represents the bank's annual equity return in relative terms (inclusive of dividends when available), and $R_{f,t}$ denotes the risk-free rate, proxied by the 10-year sovereign bond yield of the bank's home country. The equity return $R_{i,t}$ is computed as the percentage change in price:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \times 100 \tag{3.2}$$

with $P_{i,t}$ and $P_{i,t-1}$ being the closing prices of the bank's equity at the end of years $t$ and $t-1$, respectively. This formulation follows conventional asset pricing literature (e.g.,

Fama and French, 2004; Barberis, 2013) and is consistent with the dataset construction, where returns are expressed as relative variations.

The main explanatory variable is the *excess market return*, constructed as:

$$r^e_{m,t} = R_{m,t} - R_{f,t} \tag{3.3}$$

where $R_{m,t}$ is the annual total return of the domestic stock market index corresponding to the bank's country of listing (e.g., FTSE MIB for Italy, DAX for Germany).

To control for differences in banks' risk exposures and financial structure, the empirical model incorporates the following seven institution-specific variables:

(1) **Loan Loss Provisions to Equity (LLP/Equity):** a proxy for expected credit losses relative to capital buffers.

(2) **Total Capital Adequacy Ratio (CAR):** the ratio of regulatory capital to risk-weighted assets.

(3) **Tier 1 Capital Ratio (T1CAR):** the share of core equity capital in risk-weighted assets.

(4) **Non-Performing Loans to Net Loans (NPL ratio):** an indicator of asset quality deterioration.

(5) **Risk-Weighted Assets to Total Assets (RWA/Assets):** captures the intensity of risk exposures on the balance sheet.

(6) **Debt-to-Equity Ratio:** a measure of financial leverage and capital structure.

(7) **Free Cash Flow to Bank Income (FCF/Income):** an indicator of internal liquidity generation capacity.

TABLE 1. Key Variables: Definitions and Interpretations

| **Variable** | **Formula** | **Interpretation** |
|---|---|---|
| Excess Equity Return ($r^e_{i,t}$) | $R_{i,t} - R_{f,t}$ | Bank equity return above the risk-free rate. Measures abnormal performance. |
| Equity Return ($R_{i,t}$) | $\frac{P_{i,t}-P_{i,t-1}}{P_{i,t-1}}$ | Total return including dividends. Reflects market performance. |
| Excess Market Return ($r^e_{m,t}$) | $R_{m,t} - R_{f,t}$ | Market-wide excess return. Proxy for systematic risk. |
| LLP / Equity | – | Expected credit losses relative to capital. |
| CAR (Capital Adequacy Ratio) | – | Regulatory capital as % of risk-weighted assets. |
| Tier 1 Capital Ratio | – | Core equity to risk-weighted assets. |
| NPL Ratio | – | Share of non-performing loans. Asset quality proxy. |
| RWA / Total Assets | – | Degree of risk exposure. |
| Debt-to-Equity | – | Financial leverage indicator. |
| FCF / Income | – | Internal liquidity generation capacity. |

### 3.1.3. Basel III Segmentation and Structural Break Design

To capture the regulatory regime shift introduced by Basel III, the sample is segmented into:

- **Pre-Basel III period:** 2004–2013
- **Post-Basel III period:** 2014–2024

This binary segmentation reflects the formal EU implementation timeline. However, to account for possible unobserved shifts in the relationship between equity returns and explanatory variables, we also apply an endogenous structural break test using the Bai–Perron (2003) methodology.

To investigate potential changes in the relationship between excess stock returns and their explanatory variables over time the multiple structural break procedure proposed by Bai and Perron (2003) is employed as it allows for the endogenous estimation of both the number and the location of breakpoints within a linear regression model without requiring prior specification of the break dates the general form of the model is defined as:

$$y_t = X_t^\top \beta_j + \varepsilon_t \quad \text{for } t = T_{j-1} + 1, \ldots, T_j \quad \text{with } j = 1, \ldots, m+1 \tag{3.4}$$

where $y_t$ denotes the dependent variable at time $t$ representing the excess return on equity $X_t$ is a vector of explanatory variables including market return macro-financial indicators and banking-specific controls $\beta_j$ is the vector of coefficients corresponding to

regime $j$, $\varepsilon_t$ is a random error term assumed to have zero mean and constant variance $T_j$ represents the unknown structural break dates such that $T_0 = 0$ and $T_{m+1} = T$ and $m$ is the number of breaks to be estimated.

The estimation aims to identify the optimal breakpoints $\{T_1, \ldots, T_m\}$ and the corresponding parameter vectors $\{\beta_1, \ldots, \beta_{m+1}\}$ by minimizing the sum of squared residuals across all regimes given by

$$\min_{T_1,\ldots,T_m} \sum_{j=1}^{m+1} \sum_{t=T_{j-1}+1}^{T_j} \left(y_t - X_t^\top \beta_j\right)^2 \tag{3.5}$$

This optimization is subject to a trimming condition to ensure that each regime contains a sufficient number of observations specifically each segment must have at least a fraction $\varepsilon$ of the total sample size $T$ commonly $\varepsilon = 0.15$ is adopted which implies that each regime must include at least 15% of the total number of observations.

The statistical inference for the presence of structural breaks is based on the following hypothesis test:

$$H_0 : \beta_1 = \beta_2 = \cdots = \beta_{m+1} \tag{3.6}$$

$$H_1 : \exists j \text{ such that } \beta_j \neq \beta_{j+1} \tag{3.7}$$

To test these hypotheses, robust structural-break statistics are employed, namely the *sup-F* test for one or more breaks, the *UDmax* test (a global test for an unknown number of breaks), and the *WDmax* test (a weighted version that accommodates unequal regime lengths). In the Bai and Perron (1998; 2003) framework—building on Andrews (1993)—these tests are implemented with heteroskedasticity- and autocorrelation-consistent (HAC) covariance estimators, which makes them suitable for financial time series with volatility clustering and serial dependence.

This framework is applied to a dataset comprising **2,835 bank–year observations** at an **annual** frequency (135 publicly listed banks across 21 European countries, 2004–2024). The explanatory vector $X_{i,t}$ includes variables such as the excess market return, liquidity ratios, credit spreads, interest rates, and indicator variables capturing periods of financial crisis or regulatory intervention. This specification allows for the identification of significant shifts in the sensitivity of equity returns to these factors over time through regime-specific coefficient changes.

### 3.2. The Cost of Equity: Theoretical Framework

The cost of equity is a fundamental concept in finance, representing the return that investors require for holding a firm's equity in lieu of risk-free alternatives. It captures the compensation demanded for bearing the inherent risk of equity investments and serves as a crucial input in corporate valuation, capital budgeting, and risk management. One of the most widely used approaches to estimate the cost of equity is the *Capital Asset*

*Pricing Model (CAPM)*, which provides a linear relationship between expected returns and systematic market risk.

The CAPM framework posits that investors are only rewarded for exposure to non-diversifiable (systematic) risk, while firm-specific (idiosyncratic) risks are assumed to be eliminated through portfolio diversification. According to this model, the expected return on equity for a given firm is determined by:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \tag{3.8}$$

where $E(R_i)$ is the expected return on the firm's equity, $R_f$ is the risk-free rate (commonly proxied by long-term government bond yields), $\beta_i$ is the firm's beta measuring its sensitivity to market-wide risk, and $(E(R_m) - R_f)$ is the market risk premium. Although the CAPM offers a parsimonious and elegant theoretical representation of the risk-return trade-off, it has been criticized for its simplifying assumptions—such as market efficiency, the absence of transaction costs, and the homogeneity of investor expectations—which may not hold in real-world settings. Furthermore, it overlooks other relevant determinants of equity returns, including firm-specific fundamentals, macroeconomic shocks, and changes in the regulatory environment.

### 3.3. Baseline Model: Static CAPM in a Panel Framework

To bridge the gap between theory and practice, and to enable empirical testing of the CAPM in a dynamic environment, we employ a *panel data framework* that captures both cross-sectional and temporal variations in equity returns. Specifically, we estimate a static CAPM specification in *excess return form*, which isolates the portion of returns attributable to risk premia by subtracting the risk-free rate:

$$r^e_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \tag{3.9}$$

In this specification, $r^e_{i,t} = R_{i,t} - R_{f,t}$ denotes the excess return on the equity of bank $i$ at time $t$, while $r_{m,t} = R_{m,t} - R_{f,t}$ represents the excess return on the market portfolio. The coefficient $\alpha_i$, known as Jensen's alpha, captures any abnormal return that is not explained by market risk. The central parameter of interest, $\beta_i$, reflects the bank's exposure to systematic risk. The error term $\varepsilon_{i,t}$ encompasses residual influences specific to bank $i$ and period $t$, which are presumed to be uncorrelated with the regressors.

For the empirical implementation, we rely on panel data techniques, which allow us to model heterogeneity across banks and exploit temporal information. Under the assumption of a *homogeneous market beta* across banks ($\beta_i = \beta$), the model simplifies to:

$$r^e_{i,t} = \alpha + \beta r_{m,t} + u_{i,t}, \quad u_{i,t} = \mu_i + \nu_{i,t} \tag{3.10}$$

In this formulation, $\mu_i$ represents time-invariant, unobserved characteristics unique to each bank—such as management quality, risk culture, or regulatory environment—while $\nu_{i,t}$ captures purely idiosyncratic shocks.

This structure gives rise to three principal estimation strategies: *Pooled Ordinary Least Squares (Pooled OLS)*, which sets the individual effect to zero ($\mu_i = 0$); the *Fixed Effects (FE)* model, which allows for bank-specific intercepts and permits arbitrary correlation between $\mu_i$ and the regressors; and the *Random Effects (RE)* model, which assumes that $\mu_i$ is orthogonal to the explanatory variables and treats it as part of the composite error, $\varepsilon_{i,t} = \mu_i + \nu_{i,t}$. The choice among these approaches hinges on the maintained assumptions about the bank-specific component and its relationship with market-wide returns and controls.

Model selection between FE and RE is formally assessed with the Hausman specification test (Hausman, 1978). Under the null hypothesis, the individual effects are uncorrelated with the regressors, so RE is consistent and efficient; rejection of the null indicates inconsistency of RE and favours FE. When relevant, the comparison between RE and Pooled OLS is complemented with a Lagrange Multiplier test for random effects. Inference is based on heteroskedasticity- and autocorrelation-robust covariance matrices, with standard errors clustered at the bank level. Results are reported by subsample (pre- versus post-2014) and by specification.

By combining the theoretical elegance of the CAPM with the flexibility of panel data estimation, this empirical framework allows for a more nuanced and robust analysis of the cost of equity across a heterogeneous sample of financial institutions. The model serves not only to validate the CAPM's predictions but also to uncover persistent abnormal returns or structural deviations from market expectations.

### 3.3.1. Pooled OLS Estimation

In the pooled ordinary least squares (OLS) specification it is assumed that the unobserved individual effect $\mu_i$ is equal to zero for all cross-sectional units such that the model can be expressed as:

$$r^e_{i,t} = \alpha + \beta r_{m,t} + \nu_{i,t} \tag{3.11}$$

Where $r^e_{i,t}$ represents the excess return of bank $i$ at time $t$ $r_{m,t}$ denotes the excess return of the market portfolio at time $t$ $\alpha$ is the common intercept $\beta$ is the coefficient of interest capturing the sensitivity of bank returns to market returns and $\nu_{i,t}$ is the idiosyncratic error term assumed to satisfy standard OLS assumptions.

This specification treats the dataset as a single pooled cross-section over time ignoring unobserved heterogeneity across banks that could be driving systematic differences in returns The pooled OLS estimator remains unbiased and consistent only under the strong assumption that the unobserved effect $\mu_i$ is either exactly zero or uncorrelated with the regressors in particular with $r_{m,t}$ if this condition fails and $\mu_i$ is correlated with the explanatory variables the estimates will suffer from omitted variable bias leading to inconsistency and potential misinterpretation of the effect of market exposure.

Despite these limitations pooled OLS plays a fundamental role as a benchmark model in empirical finance it provides a parsimonious baseline against which more complex

specifications can be evaluated in terms of explanatory power estimation robustness and predictive accuracy By applying the model separately to the pre- and post-Basel III subperiods we are able to capture potential shifts in the average sensitivity of bank equity returns to market movements under different regulatory regimes while keeping the structure intentionally simple.

The main purpose of this approach is not to assert the validity of the pooled model in capturing all relevant dimensions of bank-level risk but rather to establish a comparison point from which the added value of incorporating unobserved heterogeneity through fixed effects or random effects can be assessed in both statistical and economic terms improvements in fit forecast accuracy or coefficient stability observed in alternative specifications can then be attributed to a better handling of cross-sectional variation in risk exposures.

### 3.3.2. Fixed Effects Estimation

The fixed effects (FE) estimator accommodates heterogeneity across banks by allowing the unobserved effect $\mu_i$ to vary arbitrarily and to be potentially correlated with the regressors unlike pooled OLS which imposes a common intercept across all units the FE model controls for all time-invariant unobserved characteristics by applying the within transformation which demeans each variable over time for each cross-sectional unit the transformed model can be written as:

$$r^e_{i,t} - \bar{r}^e_i = \beta \left( r_{m,t} - \bar{r}_{m,i} \right) + \left( \nu_{i,t} - \bar{\nu}_i \right) \tag{3.12}$$

Where $\bar{r}^e_i$ and $\bar{r}_{m,i}$ denote the time averages of the excess return and the market return respectively for bank $i$ this transformation effectively removes $\mu_i$ from the model eliminating any time-invariant omitted variable bias and ensuring that identification of $\beta$ relies solely on within-bank variation over time rather than on cross-sectional differences.

The primary advantage of the fixed effects estimator lies in its ability to capture the effect of changes in the independent variables on the dependent variable while holding constant all unobserved characteristics that do not vary over time for example institutional factors such as governance quality capital structure regulatory environment or managerial style that persist throughout the sample period are differenced out by construction.

In the context of Basel III implementation this specification is particularly well-suited as it enables the estimation of within-bank changes in sensitivity to market returns isolating the regulatory effect from other fixed institutional characteristics by focusing exclusively on temporal variation within each bank the FE estimator provides a cleaner identification strategy for assessing the impact of macroprudential reforms on equity market behavior while remaining robust to potential omitted variable bias arising from cross-sectional unobservables.

### 3.3.3. Random Effects Estimation

The Random Effects (RE) estimator provides an alternative approach to controlling for unobserved heterogeneity in panel data models. Unlike the Fixed Effects (FE) model,

which allows the individual-specific effect $\mu_i$ to correlate freely with the regressors, the RE model assumes that $\mu_i$ is random and uncorrelated with the explanatory variables. Formally, this assumption is expressed as:

$$\mathbb{E}[\mu_i \mid r_{m,t}] = 0 \tag{3.13}$$

The regression model under the random effects specification is given by:

$$r^e_{i,t} = \alpha + \beta r_{m,t} + \mu_i + \nu_{i,t} \tag{3.14}$$

where $r^e_{i,t}$ is the excess return for bank $i$ at time $t$, $r_{m,t}$ is the market excess return, $\alpha$ is the common intercept, $\beta$ captures the sensitivity of bank returns to market returns, $\mu_i$ represents the unobserved individual-specific effect, and $\nu_{i,t}$ is the idiosyncratic error term. The composite error term is thus:

$$u_{i,t} = \mu_i + \nu_{i,t} \tag{3.15}$$

with $\mu_i \sim IID(0, \sigma^2_\mu)$ and $\nu_{i,t} \sim IID(0, \sigma^2_\nu)$. The RE estimator retains both within-unit and between-unit variation, making it more efficient than the FE estimator when the orthogonality condition holds. This efficiency gain is particularly valuable in panels with a small number of time periods or when between-entity differences are of substantive interest.

However, the main limitation of the RE model lies in its sensitivity to violations of the exogeneity assumption. If the individual effect $\mu_i$ is correlated with any of the regressors — in this case, the market return $r_{m,t}$ — the estimator becomes inconsistent due to omitted variable bias. For this reason, it is common practice to compare RE and FE estimates using the Hausman test, which formally assesses whether the RE assumptions are valid.

In the context of evaluating bank-level equity return sensitivities before and after Basel III, the RE model offers a flexible compromise. It allows for the inclusion of time-invariant characteristics and takes advantage of both cross-sectional and temporal variation. If the orthogonality assumption is credible — for example, if regulatory environments or governance structures are exogenous to market returns — the RE estimator can provide consistent and more efficient estimates than its fixed-effects counterpart.

### 3.3.4. Model Selection Tests

To determine the most appropriate panel data specification among pooled OLS, fixed effects (FE), and random effects (RE), we rely on a set of formal statistical tests. These procedures assess the presence and structure of unobserved heterogeneity, as well as the validity of key assumptions regarding correlation with the regressors. The three canonical tests considered are presented below.

#### 3.3.4.1 F-test: Fixed Effects vs. Pooled OLS

The F-test evaluates whether unobserved individual-specific effects $\mu_i$ are jointly equal

to zero. It compares the restricted pooled OLS model with the unrestricted FE model, using the residual sum of squares (RSS) from both estimations. The hypotheses are:

$$H_0 : \mu_i = 0 \quad \forall i \quad \text{(no fixed effects; pooled OLS is valid)}$$
$$H_1 : \mu_i \neq 0 \quad \text{for at least one } i \quad \text{(fixed effects present)}$$

The test statistic is defined as:

$$F = \frac{(RSS_{Pooled} - RSS_{FE})/(N-1)}{RSS_{FE}/(N(T-1)-K)} \tag{3.16}$$

where $RSS_{Pooled}$ and $RSS_{FE}$ denote the residual sum of squares from the pooled OLS and fixed effects estimations, respectively, $N$ is the number of cross-sectional units, $T$ the number of time periods, and $K$ the number of regressors. Under the null hypothesis, the statistic follows an $F$ distribution:

$$F \sim F_{N-1,N(T-1)-K} \tag{3.17}$$

The p-value is computed as:

$$p = \mathbb{P}\left(F_{N-1,N(T-1)-K} > F_{\text{obs}}\right) \tag{3.18}$$

Rejection of $H_0$ at a chosen significance level $\alpha$ (e.g., 5%) indicates that fixed effects are statistically significant, favoring the FE specification over pooled OLS.

#### 3.3.4.2 Breusch–Pagan Lagrange Multiplier Test: Random Effects vs. Pooled OLS

The LM test proposed by Breusch and Pagan (1979) tests for the presence of random effects by examining whether the variance component $\sigma_\mu^2$ is significantly greater than zero. The model is based on the composite error term:

$$u_{i,t} = \mu_i + \nu_{i,t}, \quad \mu_i \sim IID(0, \sigma_\mu^2), \quad \nu_{i,t} \sim IID(0, \sigma_\nu^2) \tag{3.19}$$

The hypotheses are:

$$H_0 : \sigma_\mu^2 = 0 \quad \text{(no random effects; pooled OLS is valid)}$$
$$H_1 : \sigma_\mu^2 > 0 \quad \text{(presence of random effects)}$$

The LM statistic can be computed from the pooled OLS residuals as:

$$LM = \frac{NT}{2(T-1)} \left( \frac{\hat{\sigma}_u^2 - \hat{\sigma}_\nu^2}{\hat{\sigma}_u^2} \right)^2 \tag{3.20}$$

Under the null, the test statistic asymptotically follows a chi-squared distribution with one degree of freedom:

$$LM \sim \chi_1^2 \tag{3.21}$$

and the p-value is given by:

$$p = \mathbb{P}\left(\chi_1^2 > LM_{\text{obs}}\right) \tag{3.22}$$

A small p-value leads to rejection of $H_0$, indicating significant unobserved heterogeneity and supporting the use of the RE model over pooled OLS.

#### 3.3.4.3 Hausman Specification Test: Fixed Effects vs. Random Effects

The Hausman test (Hausman, 1978) is designed to detect endogeneity of the unobserved effects with respect to the regressors. It tests whether the RE estimator remains consistent, which depends on the orthogonality assumption:

$$\begin{aligned} H_0 &: \mathbb{E}[\mu_i \mid X_{i,t}] = 0 \quad \text{(RE is consistent and efficient)} \\ H_1 &: \mathbb{E}[\mu_i \mid X_{i,t}] \neq 0 \quad \text{(RE is inconsistent; FE preferred)} \end{aligned}$$

The Hausman statistic is constructed as:

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})^\top \left[\text{Var}(\hat{\beta}_{FE}) - \text{Var}(\hat{\beta}_{RE})\right]^{-1} (\hat{\beta}_{FE} - \hat{\beta}_{RE}) \tag{3.23}$$

Under $H_0$, $H$ follows an asymptotic chi-squared distribution with degrees of freedom equal to the number of regressors $K$:

$$H \sim \chi_K^2 \tag{3.24}$$

The p-value is:

$$p = \mathbb{P}\left(\chi_K^2 > H_{\text{obs}}\right) \tag{3.25}$$

If the p-value is small, we reject $H_0$ and conclude that the RE estimator is inconsistent due to correlation between $\mu_i$ and $X_{i,t}$, making the FE model the appropriate specification.

#### 3.3.4.4 Model Selection Implications

The sequential testing framework outlined above serves as a rigorous and methodologically sound approach to model selection in panel data analysis. Each test addresses a specific econometric assumption about the nature of unobserved heterogeneity and its relationship with the regressors.

The process typically begins by testing whether individual (bank-specific) effects are statistically relevant. A significant result from either the F-test (for fixed effects) or the Breusch–Pagan Lagrange Multiplier (LM) test (for random effects) implies that the

pooled OLS model is misspecified because it incorrectly assumes homogeneity across cross-sectional units. In this case, a model that accounts for heterogeneity either FE or RE is more appropriate.

Once the presence of unobserved heterogeneity is established, the choice between the FE and RE specifications depends on whether the individual-specific effects $\mu_i$ are correlated with the explanatory variables. The Hausman test provides a formal statistical criterion for this decision. If the null hypothesis is not rejected, the RE model is preferred due to its higher efficiency, as it uses both within and between variation in the data. However, if the test rejects the null, the FE model is favored because it remains consistent even when the individual effects are endogenous.

In empirical applications, especially in financial settings such as assessing the sensitivity of bank-level equity returns to market factors before and after regulatory reforms (e.g., Basel III), controlling for unobserved heterogeneity is critical. Institutions may differ systematically in terms of governance, capital structure, risk management practices, and regulatory exposure all of which are time-invariant but potentially correlated with financial outcomes. Failure to account for such heterogeneity leads to biased and inconsistent estimates, undermining the credibility of the analysis.

Therefore, this model selection sequence F-test or LM test followed by the Hausman test ensures that the estimated coefficients reflect genuine within-bank dynamics rather than spurious cross-sectional variation. It supports robust inference on how financial institutions respond to market conditions and policy interventions over time.

### 3.4. Extended CAPM with Bank-Specific Fundamentals

The traditional Capital Asset Pricing Model (CAPM) offers a parsimonious representation of asset pricing by relating expected excess returns to systematic market risk. However, its baseline formulation omits firm-specific characteristics that are particularly relevant in the context of the banking sector. Given the heterogeneous nature of bank's balance sheets, capital structures, and risk profiles, incorporating institution-level fundamentals is essential to more accurately estimate the cost of equity.

This need becomes even more pronounced under the Basel III regulatory framework, which introduced stricter capital, liquidity, and leverage requirements aimed at strengthening financial system resilience. In this context, prudential and accounting indicators not only serve regulatory purposes but also influence market-based perceptions of bank risk and valuation. Accordingly, extending the CAPM to account for such fundamentals allows for a more comprehensive and theoretically grounded evaluation of the determinants of equity risk premia in the banking sector.

#### 3.4.1. Model Specification and Variables

To capture the joint influence of market risk and bank-specific characteristics on equity returns, we extend the baseline CAPM by augmenting it with a vector of financial ratios

that reflect key prudential dimensions. The resulting empirical model is specified as follows:

$$r^e_{i,t} = \alpha_i + \beta_m r_{m,t} + \beta_1 \text{LLP}_{i,t} + \beta_2 \text{TCAR}_{i,t} + \beta_3 \text{T1CAR}_{i,t} + \beta_4 \text{NPL}_{i,t} + \beta_5 \text{RWA}_{i,t} + \beta_6 \text{DTE}_{i,t} + \beta_7 \text{FCF}_{i,t} + \varepsilon_{i,t} \tag{3.26}$$

In this specification, $r^e_{i,t}$ denotes the excess equity return of bank $i$ at time $t$, $r_{m,t}$ is the excess return on the market portfolio, and $\varepsilon_{i,t}$ is the error term. The additional regressors $Z_{k,i,t}$ consist of the following seven bank-level financial indicators:

- $\mathbf{LLP}_{i,t}$ — Loan Loss Provisions to Equity: captures expected credit losses relative to capital buffers; higher values may reflect deteriorating loan performance or more conservative risk provisioning.
- $\mathbf{TCAR}_{i,t}$ — Total Capital Adequacy Ratio: measures total regulatory capital as a proportion of risk-weighted assets, reflecting solvency and regulatory compliance.
- $\mathbf{T1CAR}_{i,t}$ — Tier 1 Capital Ratio: core equity capital to risk-weighted assets; a key measure of capital strength under Basel III.
- $\mathbf{NPL}_{i,t}$ — Non-Performing Loans to Net Loans: proxies for asset quality deterioration and latent credit risk.
- $\mathbf{RWA}_{i,t}$ — Risk-Weighted Assets to Total Assets: quantifies the risk intensity of the asset portfolio; higher values suggest greater capital requirements under regulatory constraints.
- $\mathbf{DTE}_{i,t}$ — Debt-to-Equity Ratio: indicates financial leverage; higher leverage is generally associated with increased equity risk.
- $\mathbf{FCF}_{i,t}$ — Free Cash Flow to Income: approximates internal liquidity generation capacity; a higher ratio suggests stronger financial flexibility.

The selection of variables is grounded in the post-crisis empirical literature on bank performance and regulation, which emphasizes the relevance of capital structure, credit risk, and liquidity for both market valuation and regulatory assessment (BCBS, 2011; Berger and Bouwman, 2013; Gambacorta and Shin, 2018).

### 3.4.2. Economic Rationale in the Basel III Context

From a theoretical standpoint, the Basel III framework modifies the risk-return relationship for banks through multiple transmission channels. These adjustments are expected to be reflected in equity pricing mechanisms, as follows:

(1) **Capital Adequacy Ratios (TCAR, T1CAR):** Higher capital buffers reduce insolvency risk and limit downside exposure, potentially lowering systematic risk exposure ($\beta_m$). However, over-capitalization may imply reduced operational leverage or inefficiencies, which markets could interpret negatively.

(2) **Loan Loss Provisions (LLP):** Increased provisioning can be interpreted either as a signal of deteriorating credit quality raising equity risk premia or as a sign

of conservative risk management, which may mitigate perceived risk and reduce the cost of equity.

(3) **Non-Performing Loans (NPL):** A higher NPL ratio directly signals asset quality deterioration, which typically increases investors' required returns due to heightened credit risk and reduced earnings visibility.

(4) **Risk-Weighted Assets (RWA):** This ratio reflects the regulatory capital intensity of the bank's asset base. A higher RWA-to-assets ratio implies greater capital charges under Basel III, which may constrain return on equity (ROE) and elevate required returns to compensate for increased regulatory friction.

(5) **Debt-to-Equity Ratio (DTE):** Higher financial leverage increases the volatility of equity returns and thus raises required returns. While leverage is structurally high in banking, relative differences across institutions remain relevant for market valuation.

(6) **Free Cash Flow to Income (FCF):** Strong internal liquidity generation reduces dependence on external financing and may improve the bank's resilience to funding shocks, thus lowering equity risk premia.

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TABLE 2. Expected Signs for Coefficient Estimates (CoE determinants)

| **Variable** | **Proxy** | **Effect on $\beta_m$** | **Effect on CoE** |
|---|---|---|---|
| Capital adequacy | TCAR, T1CAR | $\downarrow$ | $-$ |
| Loan loss provisions | LLP / Equity | $\pm$ | $\pm$ |
| Asset quality | NPL ratio | $\uparrow$ | $+$ |
| Risk intensity | RWA / Total Assets | $\uparrow$ | $+$ |
| Leverage | Debt-to-Equity (DTE) | $\uparrow$ | $+$ |
| Internal funding | FCF / Income | $\downarrow$ | $-$ |

By incorporating these prudential dimensions into the pricing framework, the extended CAPM allows for a more nuanced empirical analysis of how regulation interacts with market-based assessments of bank risk. This is particularly valuable in identifying the extent to which Basel III has reshaped investor expectations regarding bank solvency, risk management, and financial discipline.

### 3.4.3. Estimation Strategies

The extended CAPM specification can be estimated using three main panel data approaches: pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). Each approach relies on distinct assumptions regarding the unobserved heterogeneity across banks and its correlation with explanatory variables.

Pooled OLS. The pooled OLS estimator treats the panel as a simple cross-section, assuming that all banks share the same slope coefficients and that no unobserved bank-specific effects are present. Formally, the model is specified as:

$$r^e_{i,t} = \alpha + \beta_m r_{m,t} + \sum_{k=1}^{7} \beta_k Z_{k,i,t} + \nu_{i,t} \tag{3.27}$$

where $\nu_{i,t}$ is the composite error term. The pooled OLS estimator is consistent only if the unobserved bank-specific effects are both absent and uncorrelated with the regressors. Otherwise, the estimates suffer from omitted variable bias.

Fixed Effects. The FE estimator controls for all time-invariant bank-specific heterogeneity by applying the within transformation, which de-means each variable over time for each bank. The transformed equation is given by:

$$\left(r^e_{i,t} - \bar{r}^e_i\right) = \beta_m \left(r_{m,t} - \bar{r}_{m,i}\right) + \sum_{k=1}^{7} \beta_k \left(Z_{k,i,t} - \bar{Z}_{k,i}\right) + \left(\nu_{i,t} - \bar{\nu}_i\right) \tag{3.28}$$

This approach removes the individual effect $\mu_i$ by differencing it out, thereby producing consistent estimates even when $\mu_i$ is correlated with the regressors. However, time-invariant variables are dropped from the model and cannot be estimated under FE.

Random Effects. The RE model treats the unobserved bank-specific effect $\mu_i$ as a random variable that is uncorrelated with the regressors. The composite error term is written as $u_{i,t} = \mu_i + \nu_{i,t}$. The key identifying assumption is:

$$\mathbb{E}[\mu_i \mid r_{m,t}, Z_{k,i,t}] = 0 \tag{3.29}$$

Under this assumption, the RE estimator is both consistent and more efficient than FE, as it exploits both within-bank and between-bank variation. However, if the orthogonality condition is violated — that is, if $\mu_i$ is correlated with any explanatory variable — the RE estimator becomes inconsistent. In such cases, the FE estimator is preferred.

As discussed in Section 3.3.4, formal specification tests such as the F-test, the Breusch–Pagan LM test, and the Hausman test are applied to determine the appropriate estimation strategy. These tests provide guidance on whether to account for unobserved heterogeneity and whether it should be modelled as fixed or random. The choice among pooled OLS, FE, and RE is therefore both theoretically and empirically grounded. This workflow is standard in the banking CoE literature: for example, Altavilla et al. (2021) estimate bank-level panel models with fixed effects and report specification tests; Lafuerza (2024) employs panel regressions with fixed effects and contrasts them with alternative specifications; Anginer, Demirgüç-Kunt, and Zhu (2014) use cross-country bank panels with fixed effects; and ECB (2023) analyse euro-area banks using panel regressions to assess the drivers of the cost of equity. Classic methodological references include Hausman (1978) for the FE–RE test, Breusch and Pagan (1980) and Honda (1985) for LM tests of random effects, and standard treatments in Wooldridge (2010), Greene (2012), and Baltagi (2013).

### 3.5. Diagnostic Tests and Econometric Assumptions

Before drawing valid statistical inference from panel data estimations, it is essential to evaluate whether the core assumptions underlying the chosen econometric models are satisfied. In international banking datasets, especially those covering multiple jurisdictions and spanning multiple decades, violations of classical assumptions such as homoskedasticity, serial independence, and cross-sectional independence are common due to structural heterogeneity, policy synchronisation, and exposure to systemic shocks. These violations distort the covariance structure of the error term, resulting in biased standard errors and invalid hypothesis testing, even when coefficient estimates remain consistent. This section describes the set of formal specification tests implemented and outlines the associated remedies used to ensure robustness.

#### 3.5.1. Heteroskedasticity

Heteroskedasticity arises when the variance of the idiosyncratic error differs across observations or units. In bank-level panels this is to be expected, given the heterogeneity in size, business models, capitalization, and operating environments. If ignored, estimators remain unbiased under the usual exogeneity conditions, but standard errors become inconsistent and hypothesis tests are unreliable. We screen for this issue using the Breusch–Pagan test (Breusch and Pagan, 1979). Across specifications and subsamples, the null of homoskedasticity is rejected at conventional levels. Accordingly, all regressions report heteroskedasticity-robust standard errors: for fixed- and random-effects models we use White–Arellano corrections (White, 1980; Arellano, 1987), and when cross-sectional dependence is also detected we resort to Driscoll–Kraay standard errors (Driscoll and Kraay, 1998).

#### 3.5.2. Serial Correlation

Serial correlation refers to correlation of the idiosyncratic error across time within a bank. It can emerge from persistence in credit cycles, provisioning, or regulatory and macro-financial conditions that evolve gradually. Autocorrelation does not bias coefficient estimates in linear panel models under strict exogeneity, but it invalidates conventional standard errors by understating uncertainty. We test for first-order serial correlation with the (panel) Durbin–Watson statistic (Durbin and Watson, 1950, 1951). In our baseline and extended specifications the null of no AR(1) cannot be rejected, indicating no evidence of first-order autocorrelation. Nevertheless, the reported standard errors remain robust to generic forms of heteroskedasticity and serial correlation at the bank level; and, where cross-sectional dependence is present, Driscoll–Kraay corrections provide additional protection.

#### 3.5.3. Cross-Sectional Dependence

Cross-sectional dependence arises when residuals are correlated across units at a given time. In the context of European banking, such dependence is likely due to integrated

regulatory regimes, macroeconomic spillovers, and exposure to common monetary policy shocks.

To test for cross-sectional correlation, we use the Pesaran CD test. The hypotheses are:

$$H_0 : \rho_{ij} = 0 \quad \forall i \neq j \quad \text{(no cross-sectional dependence)}$$
$$H_1 : \rho_{ij} \neq 0 \quad \text{for some } i \neq j \quad \text{(dependence present)}$$

The test statistic is given by:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{3.30}$$

where $\hat{\rho}_{ij}$ is the sample correlation between the residuals of banks $i$ and $j$. The test reveals strong evidence of cross-sectional dependence in all periods, consistent with the hypothesis of common shocks affecting multiple institutions simultaneously.

### 3.5.4. Robust Covariance Estimation Strategy

Based on the diagnostic evidence of heteroskedasticity and cross-sectional dependence, standard errors are adjusted to maintain valid inference. For fixed-effects specifications, we report Driscoll–Kraay standard errors, which are robust to heteroskedasticity, serial correlation, and general cross-sectional dependence (Driscoll and Kraay, 1998). For pooled OLS and random-effects models, standard errors are clustered at the bank level, a widely recommended approach for panel data with within-cluster correlation (White, 1980; Arellano, 1987; Cameron and Miller, 2015). In dynamic panels estimated by GMM, we use the two-step estimator (Arellano and Bond, 1991) and apply Windmeijer's finite-sample correction to the two-step covariance matrix (Windmeijer, 2005).

This combined strategy preserves estimator consistency under the maintained assumptions and delivers *consistent standard errors* under non-standard error structures; for two-step GMM, it also attains asymptotic efficiency while correcting the small-sample bias in variance estimation.

## 3.6. Dynamic Panel Models

This section checks that the main results do not depend on specific modelling choices. We re-estimate using alternative return definitions, different risk-free and market proxies, varied winsorisation thresholds and control sets, compare estimators and covariance corrections, and repeat the analysis across key subsamples.

### 3.6.1. Rationale for Dynamic Modelling

In the context of bank equity returns, static panel specifications may be restrictive because they fail to account for the persistence of the dependent variable over time. In practice, the cost of equity is influenced not only by current market and bank-specific

conditions but also by its own past values. This persistence arises from several mechanisms, including gradual regulatory capital adjustments under Basel III due to balance sheet inertia, investor risk perceptions that change slowly in response to reputation or governance, and macroeconomic forces that exhibit inertia in shaping funding costs and profitability.

When the lagged dependent variable is omitted from the model, its effect may be misattributed to other regressors, introducing omitted variable bias. Yet, directly including a lagged dependent variable in a static fixed effects model induces the Nickell bias, due to correlation between the transformed lag and the error term. This bias, of order $O(1/T)$, can be substantial when the time dimension is limited.

To address these issues, Generalized Method of Moments (GMM) estimators for dynamic panels are employed. Two prominent estimators are adopted in this study: the Arellano–Bond difference GMM estimator (Arellano and Bond, 1991), which removes fixed effects via first differencing and uses lagged levels as instruments; and the Blundell–Bond system GMM estimator (Blundell and Bond, 1998), which augments difference GMM by incorporating additional moment conditions in levels with lagged differences as instruments.

### 3.6.2. Arellano–Bond Difference GMM

The baseline dynamic panel model in levels is specified as:

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{3.31}$$

where $y_{i,t}$ denotes excess returns (cost of equity), $X_{i,t}$ is a vector of regressors including market return and bank fundamentals, $\mu_i$ captures time-invariant heterogeneity, and $\varepsilon_{i,t}$ is an idiosyncratic error term.

Applying the first-difference transformation:

$$\Delta y_{i,t} = \alpha \Delta y_{i,t-1} + \beta' \Delta X_{i,t} + \Delta \varepsilon_{i,t} \tag{3.32}$$

To address endogeneity of $\Delta y_{i,t-1}$, lagged levels of $y$ dated $t-2$ and earlier are used as instruments:

$$\mathbb{E}[y_{i,t-s} \cdot \Delta \varepsilon_{i,t}] = 0 \quad \text{for } s \geq 2 \tag{3.33}$$

Additional instruments for endogenous regressors are included via:

$$\mathbb{E}[Z_i' \Delta \varepsilon_i] = 0 \tag{3.34}$$

where $Z_i$ denotes the instrument matrix.

#### 3.6.2.1 Diagnostic Tests

Autocorrelation Test (AR(m)) The null hypothesis of no serial correlation in differenced residuals is tested via:

$$H_0 : \text{No serial correlation at order } m$$

$$H_1 : \text{Serial correlation present at order } m$$

The test statistic is:

$$m_j = \frac{\sum_{i,t} \hat{\varepsilon}_{i,t}\hat{\varepsilon}_{i,t-j}}{\sqrt{\sum_{i,t} \hat{\varepsilon}^2_{i,t} \sum_{i,t} \hat{\varepsilon}^2_{i,t-j}}} \sim \mathcal{N}(0,1) \tag{3.35}$$

Hansen J-Test of Overidentification

$$H_0 : \text{All instruments are valid}$$

$$H_1 : \text{Some instruments are invalid}$$

with the test statistic:

$$J = n \cdot R^2_{\text{IV residuals}} \sim \chi^2_{q-p} \tag{3.36}$$

Empirically, the AR(2) test fails to reject $H_0$ and the Hansen J-test supports instrument validity in all samples.

### 3.6.3. Blundell–Bond System GMM

When $y_{i,t}$ is highly persistent, the weak instrument problem in difference GMM may arise. To address this, the system GMM estimator augments the model by including a levels equation:

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{3.37}$$

With additional moment conditions:

$$\mathbb{E}[\Delta y_{i,t-1} \cdot (\mu_i + \varepsilon_{i,t})] = 0 \tag{3.38}$$

Instrument proliferation is controlled by collapsing the instrument matrix and restricting lag depth. Estimates show a higher persistence coefficient $\alpha$, notably post-Basel III, indicating more gradual adjustment in the cost of equity.

## 3.7. Advanced Nonlinear and Machine Learning Models

This section provides additional validity checks and extensions. We study heterogeneity across banks and countries, run placebo/falsification exercises, test alternative instrument sets and lag structures in dynamic specifications, and contrast in-sample with out-of-sample performance and model-based CoE with market-implied benchmarks.

### 3.7.1. Motivation and Context

Traditional linear models, such as the CAPM and its panel data extensions, rely on strong assumptions of linearity, additivity, and constant marginal effects. These assumptions may not adequately capture the complexity of the relationship between bank-level equity returns and risk factors, especially under the structural shifts introduced by Basel

III. Nonlinearities, thresholds, asymmetries, and latent heterogeneity are empirically observed and theoretically expected in banking data. To address these limitations, this section explores several advanced econometric and machine learning models, each offering distinct advantages for uncovering rich dynamics in the cost of equity.

### 3.7.2. Generalized Additive Models (GAMs)

Generalized Additive Models (GAMs) provide a semi-parametric extension of classical linear regression by allowing each explanatory variable to enter the model via a smooth, non-parametric function. This flexible structure makes GAMs particularly suitable for capturing complex, nonlinear relationships that are commonly observed in financial and economic data.

The general specification of the model is as follows:

$$r_{i,t}^{e} = \alpha + f_1(r_{m,t}) + \sum_{k=1}^{7} f_{k+1}(Z_{k,i,t}) + \varepsilon_{i,t} \tag{3.39}$$

where $r_{i,t}^{e}$ denotes the adjusted return of entity $i$ at time $t$, $\alpha$ is the intercept, $f_j(\cdot)$ represents smooth functions associated with the covariates, and $\varepsilon_{i,t}$ is the idiosyncratic error term. The functions $f_j(\cdot)$ are estimated using penalized regression splines, with smoothing parameters selected via Generalized Cross-Validation (GCV), following the methodology proposed by Wood (2017).

The main advantage of GAMs lies in their ability to capture nonlinear marginal effects, such as diminishing returns to capital buffers or threshold effects around regulatory minima. These characteristics are not well accommodated by linear models, making GAMs a valuable tool in empirical studies where such features are relevant.

Linearity tests can be conducted by examining whether the estimated functions $f_j(\cdot)$ significantly deviate from a straight line. This provides a formal statistical basis for determining whether a nonlinear specification is warranted for each predictor.

Overall, GAMs offer a flexible yet interpretable modeling framework that balances complexity and explanatory power, especially in applications where structural assumptions about functional forms are difficult to justify.

### 3.7.3. Bayesian Hierarchical Models

Bayesian Hierarchical Models (BHMs) provide a structured probabilistic framework to model cross-sectional and temporal heterogeneity by introducing layers of stochasticity into the parameter space. Specifically, they treat individual-level model parameters as random variables drawn from higher-level (population-wide) distributions, thus enabling coherent learning across multiple entities. This approach is particularly suitable in panel data settings such as banking studies where multiple units (e.g., banks) are observed over time but may differ in unobserved characteristics.

Formally, for each bank $i$, the observational model is specified as:

$$r^e_{i,t} \sim \mathcal{N}(\alpha_i + \beta_{m,i}\, r_{m,t} + \boldsymbol{\beta}'_{Z,i}\mathbf{Z}_{i,t}, \sigma^2) \tag{3.40}$$

where $r^e_{i,t}$ denotes the excess return of bank $i$ at time $t$, $r_{m,t}$ represents a market-wide factor (e.g., benchmark return), and $\mathbf{Z}_{i,t}$ is a vector of bank-specific covariates, such as capital adequacy, asset quality, or liquidity indicators. The coefficients $\alpha_i, \beta_{m,i}, \boldsymbol{\beta}_{Z,i}$ are allowed to vary across banks, capturing unit-specific intercepts and sensitivities.

To incorporate information sharing across banks while preserving heterogeneity, the model specifies the following hierarchical (second-level) priors:

$$\alpha_i \sim \mathcal{N}(\alpha, \tau^2_\alpha), \quad \beta_{m,i} \sim \mathcal{N}(\beta_m, \tau^2_\beta), \quad \boldsymbol{\beta}_{Z,i} \sim \mathcal{N}(\boldsymbol{\beta}_Z, \boldsymbol{\Sigma}_Z) \tag{3.41}$$

Here, $\alpha, \beta_m, \boldsymbol{\beta}_Z$ are hyperparameters representing the population-level mean effects, and $\tau^2_\alpha, \tau^2_\beta, \boldsymbol{\Sigma}_Z$ capture the between-group variance (heterogeneity) in the corresponding parameters. These priors induce a *partial pooling* effect: individual parameter estimates are shrunk toward the group-level mean, with the degree of shrinkage determined endogenously by the data.

Estimation is carried out via *Markov Chain Monte Carlo* (MCMC) methods, such as the Gibbs sampler or Hamiltonian Monte Carlo (HMC), which allow sampling from the joint posterior distribution over all parameters and hyperparameters. The full Bayesian inference provides not only point estimates but also measures of uncertainty through posterior distributions, credible intervals, and predictive densities.

This framework is particularly powerful when data availability per unit is limited, as the hierarchical structure enables borrowing of statistical strength across units. Additionally, BHMs naturally accommodate model uncertainty, allow for robust probabilistic forecasting, and facilitate hypothesis testing on both individual-level and population-level effects. In regulatory applications, for instance, one can derive posterior probabilities that the effect of capital buffers on returns exceeds a given threshold—information that is often more informative than binary significance tests.

Bayesian hierarchical modeling thus offers a flexible and rigorous tool for empirical research in financial and regulatory contexts, especially where heterogeneity, uncertainty, and limited observations per unit are of concern.

### 3.7.4. Random Forests

Random Forests (RF) constitute a powerful nonparametric ensemble learning technique, introduced by Breiman (2001), that has proven effective in a wide range of predictive tasks, particularly when the data-generating process is highly nonlinear or involves complex interactions among covariates. In contrast to parametric models that impose functional assumptions on the relationship between predictors and outcomes, RFs offer a data-driven approach that flexibly captures unknown structures with minimal *a priori* specification.

Formally, the predicted excess return $\hat{r}^e_{i,t}$ for entity $i$ at time $t$ is computed as the average output of an ensemble of $B$ regression trees:

$$\hat{r}^e_{i,t} = \frac{1}{B} \sum_{b=1}^{B} T_b(X_{i,t}) \tag{3.42}$$

where $T_b(\cdot)$ represents the prediction of the $b$-th tree, and $X_{i,t}$ is the vector of explanatory variables (e.g., regulatory indicators, market-based variables) for entity $i$ at time $t$. Each tree is trained on a bootstrap sample drawn with replacement from the original dataset, introducing variability into the training process.

A key innovation in the RF algorithm lies in its dual-randomization mechanism. At each node split, only a random subset of candidate predictors is considered. This random feature selection, in conjunction with bootstrap resampling (bagging), serves to decorrelate the individual trees, thereby reducing the overall variance of the ensemble and enhancing generalization performance. Unlike traditional decision trees, which tend to overfit, RFs achieve regularization implicitly through aggregation.

In the context of financial econometrics, RFs are particularly valuable for their ability to model nonlinear effects of regulatory measures (e.g., capital buffers, liquidity coverage ratios) and market signals without requiring functional form assumptions. Additionally, RFs provide diagnostic tools such as variable importance measures computed through metrics like Mean Decrease in Impurity (MDI) or Mean Decrease in Accuracy (MDA) which help identify the most influential predictors in determining asset returns or risk profiles.

Among their advantages, RFs exhibit robustness to multicollinearity, heteroscedasticity, and outliers, and are scalable to high-dimensional settings. However, one limitation is interpretability: while individual trees are transparent, the ensemble behaves as a black-box. Nevertheless, recent advances such as partial dependence plots, SHAP values, and permutation importance have enhanced the interpretability of RFs in empirical applications.

Extensions of the RF framework, including Quantile Regression Forests (Meinshausen, 2006) and Conditional Inference Forests (Hothorn et al., 2006), further broaden its scope by enabling distributional modeling, heteroskedastic inference, and hypothesis testing. These tools make RFs particularly suited to tasks involving risk estimation, stress testing, or sensitivity analysis under regulatory scenarios.

### 3.7.5. Artificial Neural Networks

Artificial Neural Networks (ANNs) represent a class of highly flexible, nonparametric models designed to approximate complex nonlinear functions. Originating from the study of biological neural systems, ANNs have become a foundational tool in modern machine learning due to their capacity to model intricate, high-dimensional relationships without

imposing restrictive parametric assumptions. This property makes them especially relevant in financial contexts, where regulatory indicators and market variables often interact in nonlinear and latent ways.

A standard feedforward ANN with a single hidden layer can be formalized as follows:

$$\hat{r}^e_{i,t} = \sigma_o \left( \sum_{j=1}^{H} w_j^{(2)} \, \sigma_h \left( \sum_{k=1}^{K} w_{jk}^{(1)} X_{k,i,t} + b_j^{(1)} \right) + b^{(2)} \right) \tag{3.43}$$

where $\hat{r}^e_{i,t}$ denotes the predicted excess return of entity $i$ at time $t$, $X_{k,i,t}$ represents the $k$-th explanatory variable, and $H$ is the number of hidden units. The inner summation represents a linear combination of the inputs, which is transformed by a nonlinear activation function $\sigma_h(\cdot)$, typically chosen as ReLU, sigmoid, or hyperbolic tangent. The output layer applies an activation function $\sigma_o(\cdot)$, which, in regression settings, is commonly the identity function. Parameters $w^{(1)}, w^{(2)}$ and biases $b^{(1)}, b^{(2)}$ are learned from the data.

From a theoretical perspective, ANNs with even a single hidden layer are considered universal function approximators, capable of representing any Borel-measurable function to arbitrary accuracy, provided a sufficient number of hidden units. This theoretical flexibility translates into practical power in modeling economic systems where functional forms are unknown, highly nonlinear, and involve complex interactions.

Model training is typically conducted via stochastic gradient descent (SGD) or adaptive optimizers such as Adam, with the objective of minimizing a loss function—often the mean squared error (MSE) in regression contexts. Given the large number of parameters and potential for overfitting, regularization strategies are essential. These include $L_2$ penalties, dropout (randomly omitting units during training), and early stopping based on validation error.

While ANNs offer substantial predictive performance, particularly in complex environments, their interpretability is often limited. Unlike additive models or tree-based methods, neural networks do not yield direct marginal effects or decision paths. However, recent developments in explainable artificial intelligence (XAI)—such as SHAP values, integrated gradients, and layer-wise relevance propagation—allow for the extraction of interpretable insights from trained networks, even in high-dimensional regulatory applications.

### 3.7.6. LASSO Regularisation

The Least Absolute Shrinkage and Selection Operator (LASSO) is a regularisation technique designed to address overfitting and variable selection simultaneously in linear regression models. Originally proposed as an alternative to ridge regression, LASSO introduces an $\ell_1$-norm penalty on the magnitude of the regression coefficients, encouraging sparsity in the estimated parameter vector. This makes it particularly well-suited for high-dimensional settings, where the number of predictors $p$ may be large relative to the number of observations $n$, or when multicollinearity among covariates is present.

The LASSO estimator solves the following convex optimisation problem:

$$\min_{\boldsymbol{\beta}} \left\{ \frac{1}{2n} \sum_{i=1}^{n} \left( y_i - \mathbf{X}_i^\top \boldsymbol{\beta} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{3.44}$$

where $\mathbf{X}_i \in \mathbb{R}^p$ denotes the predictor vector for observation $i$, $y_i \in \mathbb{R}$ is the response, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_p)^\top$ is the coefficient vector, and $\lambda \geq 0$ is the tuning parameter controlling the strength of the regularisation. When $\lambda = 0$, the solution corresponds to the standard Ordinary Least Squares (OLS) estimator. As $\lambda$ increases, the penalty term induces shrinkage on the coefficients, with some being driven exactly to zero.

This feature zeroing out coefficients renders LASSO a model selection method in addition to a shrinkage estimator. Unlike ridge regression, which imposes an $\ell_2$-norm penalty and shrinks coefficients continuously without eliminating any, LASSO provides a sparse representation of the underlying model. In many applications, this results in a more interpretable model with fewer explanatory variables, reducing the risk of overfitting and enhancing generalisation.

In empirical financial modeling, LASSO is particularly effective in contexts involving numerous, potentially collinear explanatory variables, such as balance sheet ratios, capital adequacy measures, liquidity indicators, and macroprudential variables. Its ability to automatically select relevant features is beneficial in stress testing, forecasting default probabilities, or constructing early warning systems, where parsimony and robustness are critical.

From a computational standpoint, the optimisation problem remains convex but non-differentiable due to the absolute value penalty. Efficient algorithms such as coordinate descent, least-angle regression (LARS), and pathwise optimisation are commonly used to solve the LASSO problem. The regularisation parameter $\lambda$ is typically selected via $K$-fold cross-validation to balance model fit and complexity.

Despite its advantages, LASSO has limitations. In the presence of highly correlated predictors, it tends to select one variable from a group and ignore the others, leading to instability in variable selection. Extensions such as the Elastic Net address this issue by combining $\ell_1$ and $\ell_2$ penalties to retain grouped variable structures.

### 3.7.7. Finite Mixture Models

Finite Mixture Models (FMMs) provide a flexible probabilistic framework for modeling unobserved heterogeneity in cross-sectional or panel data. Rather than assuming a single homogeneous data-generating process, FMMs posit that the observed outcomes arise from a mixture of $C$ latent subpopulations, each governed by its own parameterisation. This is particularly relevant in applied financial settings where entities such as banks may differ structurally, yet the analyst does not observe group membership explicitly.

The conditional density of the excess return $r^e_{i,t}$, given the covariates $X_{i,t}$, is specified as a convex combination of component-specific Gaussian densities:

$$f(r_{i,t}^{e} \mid X_{i,t}) = \sum_{c=1}^{C} \pi_c \mathcal{N}(X_{i,t}^{\top}\beta_c, \sigma_c^2), \tag{3.45}$$

where $\pi_c$ denotes the mixing proportion associated with regime $c$, satisfying $0 \leq \pi_c \leq 1$ and $\sum_{c=1}^{C} \pi_c = 1$. Each component is defined by a regime-specific regression model with its own parameters $\beta_c$ and variance $\sigma_c^2$, and the mixing proportions $\pi_c$ represent the unconditional probability of an observation belonging to each latent group. Importantly, this formulation allows for distinct conditional distributions across components while preserving a unified likelihood structure.

Estimation of FMMs is typically conducted via the Expectation-Maximization (EM) algorithm, an iterative procedure that handles the latent nature of regime membership. In the E-step, posterior probabilities of component membership are computed for each observation. In the M-step, the model parameters $(\beta_c, \sigma_c^2, \pi_c)$ are updated to maximize the expected complete-data log-likelihood. This algorithm converges under mild regularity conditions and provides maximum likelihood estimates even when class membership is not directly observed.

In the context of European banking, FMMs are particularly well suited to uncover latent segmentation within the sector. Systemically important banks and smaller institutions may operate under distinct return-generating mechanisms due to differences in regulatory treatment, risk profiles, or market access. The mixture model accommodates such structural divergence without requiring prior classification, enabling the estimation of group-specific sensitivities to capital buffers, liquidity ratios, or macroeconomic shocks.

Beyond this, FMMs can capture distributional features such as skewness, excess kurtosis, or multimodality, which are often present in financial return series but are not well addressed by single-regime linear models. When combined with panel structures or extended to include time-varying mixing weights, mixture models also offer the potential to describe dynamic regime-switching behaviour.

# CHAPTER 4

Empirical Results

This chapter presents the empirical results of the study, focusing on how the determinants of the cost of equity for euro area banks evolved before and after the regulatory reforms of Basel III. In line with the implementation of the Single Supervisory Mechanism and the rollout of CRR/CRD IV, the analysis adopts 2014–2015 as the structural breakpoint. This choice is consistent with both the statistical evidence and the regulatory timeline, and it provides a coherent division of the sample for the subsequent estimations.

The empirical strategy applied multiple econometric and statistical frameworks to ensure robustness and breadth of insight. Linear panel data models (pooled OLS, fixed effects, and random effects) were complemented by time-fixed effects specifications to control for common shocks. To address potential dynamic endogeneity, both Arellano–Bond and Blundell–Bond GMM estimators were employed. The analysis was further extended with non-linear models, including Generalised Additive Models (GAM), Random Forests, Neural Networks, and Mixture Models to capture potential non-linearities and heterogeneity in responses across banks. Bayesian hierarchical models and penalised regression methods (LASSO) were also estimated to explore parameter uncertainty and variable selection effects.

## 4.1. Structural Break Analysis

The analysis of potential structural breaks was conducted using the Bai and Perron methodology. Several tests were performed across alternative dates, and the results suggested different sets of breakpoints depending on the model specification: the simple model indicated changes around 2008–2012 and 2015–2017, while the extended model pointed to 2015 and 2019. Considering these outcomes together with the regulatory implementation of Basel III, which began in 2014, the period 2014–2015 emerges as a consistent reference point. The full set of outputs, diagnostics, and graphical representations is presented in Appendix B, while in the main analysis this breakpoint is used to split the sample and examine the impact on the cost of equity.

## 4.2. Baseline CAPM Panel Models

The baseline analysis investigates the sensitivity of euro area bank's equity returns to market-wide risk factors, providing a CAPM-based benchmark for subsequent specifications that incorporate bank-level fundamentals. The dependent variable is the monthly excess return of bank $i$ at time $t$, defined as the stock return net of the risk-free rate. The

explanatory variable is the excess market return, measured as the main country index return above the risk-free rate.

The general specification is given by:

$$ExcessStock_{it} = \alpha_i + \beta\, ExcessMarket_t + \delta_t + \varepsilon_{it}, \tag{4.1}$$

where $\alpha_i$ captures bank-specific heterogeneity, $\beta$ represents the market beta, $\delta_t$ are time dummies (when included), and $\varepsilon_{it}$ is the idiosyncratic disturbance term.

We begin with pooled OLS, fixed-effects (within), and random-effects estimators for both subperiods, pre-2014 and post-2014, before augmenting the models with year dummies to capture macro-financial events.

### 4.2.1. Results without Time Effects

TABLE 1. Baseline panel regressions without year dummies

| Period | Model | Beta Estimate | Std. Error | t/z-value | Adj. $R^2$ | $N$ | Banks |
|---|---|---|---|---|---|---|---|
| Pre-2014 | Pooled OLS | 0.885*** | 0.028 | 31.1 | 0.426 | 1306 | 135 |
| | Fixed Effects | 0.923*** | 0.029 | 32.0 | 0.404 | 1306 | 135 |
| | Random Effects | 0.890*** | 0.028 | 31.5 | 0.432 | 1306 | 135 |
| Post-2014 | Pooled OLS | 0.966*** | 0.044 | 21.8 | 0.244 | 1484 | 135 |
| | Fixed Effects | 0.988*** | 0.046 | 21.4 | 0.179 | 1484 | 135 |
| | Random Effects | 0.966*** | 0.044 | 21.8 | 0.243 | 1484 | 135 |

Notes: Standard errors in parentheses. *** $p < 0.01$.

The results indicate that prior to 2014, estimated betas clustered closely around 0.92 across all estimators, with narrow confidence intervals and highly significant coefficients. This suggests that bank equity returns were strongly linked to overall market movements, though with sensitivity slightly below unity. The adjusted $R^2$ values (0.40–0.43) indicate a moderate fit: around 40% of the variation in bank excess returns is accounted for by aggregate market risk.

Post-2014, the estimated market beta rises to 0.97–0.99 and remains statistically significant at conventional levels across all specifications, indicating an almost one-to-one comovement with the market index. The drop in adjusted $R^2$ (0.18–0.24) is not central for inference on $\beta$; it mainly reflects higher idiosyncratic variation in the post-crisis period. What matters for our purposes is that the coefficients of interest are precisely estimated and robust to alternative controls and covariance corrections.

The consistency across pooled, fixed-effects, and random-effects estimates reinforces the robustness of these findings, as no significant estimator-specific bias appears to drive the results. The shift from sub-unitary betas pre-2014 to nearly unitary values post-2014 reflects a structural convergence of banks with market-wide dynamics, while simultaneously highlighting a loss of explanatory capacity of the pure CAPM factor.

### 4.2.2. Results with Time-Fixed Effects

TABLE 2. Fixed-effects models with year dummies

| Period | Beta Estimate | Std. Error | t-value | Adj. $R^2$ | $N$ | Banks |
|---|---|---|---|---|---|---|
| Pre-2014 | 0.473*** | 0.048 | 9.81 | 0.489 | 1306 | 135 |
| Post-2014 | 0.871*** | 0.060 | 14.4 | 0.213 | 1484 | 135 |

Notes: Standard errors in parentheses. *** $p < 0.01$.

Once year dummies are incorporated, estimated betas decline substantially. For the pre-2014 subsample, the beta falls from ∼0.92 to 0.47, while for the post-2014 subsample, it decreases from ∼0.99 to 0.87. This shift indicates that a significant portion of the systematic exposure captured in baseline models was actually driven by common shocks associated with macro-financial crises rather than pure market risk.

The adjusted $R^2$ improves, especially before 2014 (rising from ∼0.40 to 0.49), showing that macroeconomic shocks explain an additional share of the variation in returns. The crisis years emerge as particularly influential: in 2008, the model captures a reduction in excess returns of more than 40 percentage points, far exceeding the continuous effect implied by the market beta. Similarly, the sovereign debt crisis around 2011 introduces further large downward shocks. In contrast, the years 2021–2024 exhibit significant positive coefficients (ranging from +7% to +15%), corresponding to post-pandemic recovery and stabilisation of the European financial system.

These results illustrate that the apparent strength of market exposure in CAPM-only models was inflated by the influence of large episodic shocks. Once these shocks are explicitly accounted for, the continuous beta effect remains significant but notably reduced, indicating a weaker—but more precise—role for systematic risk.

### 4.2.3. Systematic Risk, Crisis Effects, and the Post-Basel III Shift

Taken together, the models yield several key insights. First, the market beta remains consistently positive and highly significant, confirming that systematic risk is an essential determinant of bank's cost of equity, in line with CAPM predictions. Second, the magnitude of the beta rises after 2014, converging toward unity, which points to stronger co-movement between banks and the overall market. Yet this occurs alongside a sharp decline in model explanatory power, reflecting that investors increasingly evaluated banks based on idiosyncratic fundamentals such as capital adequacy, asset quality, or business model resilience.

Third, including time fixed effects shows that discrete macro shocks often dominate continuous market exposure. The 2008 crisis year alone contributes a shift of about −5.6 percentage points (p.p.) to excess returns, while the COVID–19 shock in 2020 reduces excess returns by roughly −5.6 p.p., again overshadowing the incremental role of the market factor. Conversely, the recovery phase from 2021 onwards delivers strong positive

contributions, with year-specific coefficients exceeding +10 p.p., indicating that post-crisis rebounds shaped the cost of equity as powerfully as downturns.

Finally, these findings must be interpreted within the regulatory context. The implementation of Basel III through CRR/CRD IV in 2014 and the establishment of the Single Supervisory Mechanism altered the structure of risk transmission in the European banking sector. By reducing systemic fragility, the reforms diminished the explanatory power of the aggregate market factor, while simultaneously increasing investor focus on bank-level resilience. In essence, systematic risk remains necessary but is no longer sufficient to explain the cost of equity in the post-2014 environment.

### 4.3. Augmented Models with Bank-Specific Variables

While the baseline CAPM estimations established the dominance of market risk in determining the cost of equity, this approach neglects bank-specific characteristics that are particularly relevant in the post-crisis regulatory landscape. To address this limitation, the augmented models introduce a set of financial fundamentals that capture credit risk, capital adequacy, asset quality, portfolio risk density, leverage, and liquidity. The specification is expressed as:

$$ExcessStock_{it} = \alpha_i + \beta_m ExcessMarket_t + \boldsymbol{\gamma}^\top \mathbf{X}_{it} + \varepsilon_{it}, \tag{4.2}$$

where $ExcessStock_{it}$ denotes the excess return of bank $i$ at time $t$, $\alpha_i$ captures bank-specific fixed effects, $\beta_m$ reflects the market beta, $\mathbf{X}_{it}$ represents the bank-level covariates. The covariates include: (i) LLP/EQ as a proxy for credit risk management quality; (ii) CAR_Total and CAR_Tier1 as measures of regulatory capital buffers; (iii) NPL ratio as an indicator of asset quality; (iv) RWA/Assets as a measure of portfolio risk density; (v) D/E as a measure of leverage; and (vi) FCF/Income as a proxy for liquidity and operational efficiency.

The models are estimated using pooled OLS, fixed effects (FE), random effects (RE), and fixed effects with time dummies, for both the pre-2014 (crisis and immediate post-crisis) and post-2014 (Basel III implementation) periods.

#### 4.3.1. Pooled OLS

Table 3. Pooled OLS Augmented Models

| Period | Market Beta | Significant Variables | Adj. $R^2$ |
|---|---|---|---|
| 2004–2014 | 0.71*** | LLP/EQ (-), CAR_Tier1 (+) | 0.42 |
| 2015–2024 | 1.02*** | NPL ratio (-), FCF/Income (-) | 0.28 |

Notes: *** $p < 0.01$.

The pooled OLS estimates highlight the continued importance of market risk, with considerable differences across periods. Prior to 2014, a higher Loan Loss Provisions to

Equity ratio exerted a strong negative impact, consistent with investors penalising weak credit quality during the global financial crisis. Tier 1 capital displayed a weak positive association, suggesting some role for core capitalisation in reassuring markets.

Post-2014, the emphasis shifted. Market beta rose to unity, pointing that bank stocks became fully integrated with systemic market risk. At the same time, investors redirected their focus toward fundamentals such as non-performing loans and free cash flow. The strong negative coefficient on the NPL ratio indicates that asset quality became central in equity pricing, while the significance of FCF/Income reveals that liquidity and operational efficiency gained importance under the Basel III environment.

### 4.3.2. Fixed Effects

Table 4. Fixed Effects Augmented Models

| Period | Market Beta | Significant Estimates | Adj. $R^2$ |
|---|---|---|---|
| 2004–2013 | 0.66*** | LLP/EQ (−), CAR_Tier1 (+, weak) | 0.49 |
| 2014–2024 | 1.10*** | NPL ratio (−), FCF/Income (−) | 0.26 |

Notes: *** $p < 0.01$.

Controlling for unobserved heterogeneity strengthens the explanatory power of the models in the pre-2014 sample, with an adjusted $R^2$ close to 0.5. Here, provisioning costs retain a significant negative effect, reinforcing the view that credit losses were the key driver of equity risk premia during the financial crisis. Tier 1 capital remains weakly positive, consistent with evidence that higher-quality capital provided a buffer against market scepticism, though without overwhelming explanatory power. In contrast, the post-2014 FE results confirm the shift away from capital ratios toward asset quality and liquidity. Post-2014, the market beta rises to values close to unity and remains the most consistently significant continuous determinant of excess returns across specifications. Excluding the market factor worsens model fit ($\Delta$ BIC/adjusted $R^2$) more than dropping any other single continuous regressor, and the partial $R^2$ and median $|t|$ for $\beta$ exceed those of bank-specific controls. The negative association of the NPL ratio reflects heightened market discipline in monitoring loan books, while the negative coefficient on FCF/Income highlights the premium placed on stable liquidity and efficient earnings generation. The decline in adjusted $R^2$ suggests that bank-specific heterogeneity became less relevant in explaining equity returns, consistent with a more homogeneous regulatory environment under Basel III.

### 4.3.3. Random Effects

TABLE 5. Random Effects Augmented Models

| Period | Market Beta | Significant Estimates | Adj. $R^2$ |
|---|---|---|---|
| 2004–2013 | 0.69*** | LLP/EQ (−), CAR_Tier1 (+) | 0.45 |
| 2014–2024 | 1.08*** | NPL ratio (−), FCF/Income (−) | 0.27 |

Notes: *** $p < 0.01$.

The RE results broadly align with the FE estimates, though coefficients are slightly moderated. The consistency between FE and RE provides robustness to the findings: market beta strengthens post-2014, while investors shift their pricing criteria from provisioning (LLP/EQ) to asset quality (NPL ratio) and liquidity (FCF/Income). This robustness suggests that the structural change in determinants of equity returns is not model-dependent, but rather reflects a deeper transformation in investor behaviour under Basel III.

### 4.3.4. Fixed Effects with Time Dummies

TABLE 6. Fixed Effects with Time Dummies

| **Period** | **Market Beta** | **Significant Estimates** | **Notable Year Effects** | **Adj.** $R^2$ |
|---|---|---|---|---|
| 2004–2013 | 0.68*** | LLP/EQ (−); CAR_Tier1 (+, weak) | 2007–08; 2011 | 0.50 |
| 2014–2024 | 1.12*** | NPL ratio (−); FCF/Income (−) | 2020 | 0.26 |

Notes: *** $p < 0.01$. Signs indicate association with excess returns. Year ranges use en-dash (e.g., 2007–08).

Adding time dummies captures the impact of systemic shocks. In the pre-2014 period, the financial crisis and subsequent sovereign debt crisis explain sharp declines in excess returns, beyond bank fundamentals. Provisioning costs remained a central driver of returns, while capital adequacy retained only limited explanatory power.

In the post-2014 period, the 2020 dummy captures the significant disruption caused by COVID-19, while the structural determinants remain consistent: market beta strengthens, NPLs dominate as a measure of asset quality, and liquidity efficiency becomes a priced attribute. Notably, capital ratios lose significance entirely, underscoring that, in a regime of uniformly higher capitalisation, they cease to provide differential information to equity investors.

### 4.3.5. Comparative Assessment

Taken together, the augmented models yield three important conclusions. First, the role of market risk increased substantially, with beta coefficients rising from around 0.7 pre-2014 to above 1.1 post-2014, suggesting a stronger integration of bank equity returns

with overall market dynamics. Second, the drivers of idiosyncratic risk shifted: before 2014, provisioning and capital adequacy weakly influenced returns, consistent with a crisis-driven focus on credit losses; after 2014, non-performing loans and liquidity efficiency emerged as the primary priced risks. Third, capital adequacy ratios lost explanatory power, reflecting that Basel III capital buffers, while enhancing resilience, are perceived by markets as a baseline standard rather than as a differentiating signal.

These findings reinforce the view that Basel III succeeded in harmonising capital conditions, but also redirected investor scrutiny toward transparency in asset quality and efficiency in liquidity management. The market thus appears to have internalised the regulatory framework, while continuing to discipline banks through the pricing of their risk exposures.

### 4.3.6. Comparative Insights with Baseline CAPM Models

TABLE 7. Baseline CAPM Models (only $ExcessMarket_t$)

| Period | Method | Time FE | $\beta_m$ (SE) | Adj. $R^2$ | $N$ | Banks |
|---|---|---|---|---|---|---|
| Pre-2014 | Pooled OLS | No | 0.8847 (0.0284) *** | 0.4259 | 1306 | 135 |
| | Fixed Effects (within) | No | 0.9228 (0.0289) *** | 0.4045 | 1306 | 135 |
| | Random Effects (SA) | No | 0.8903 (0.0283) *** | 0.4318 | 1306 | 135 |
| | Fixed Effects (within) | Yes | 0.4734 (0.0483) *** | 0.4892 | 1306 | 135 |
| Post-2014 | Pooled OLS | No | 0.9664 (0.0442) *** | 0.2431 | 1484 | 135 |
| | Fixed Effects (within) | No | 0.9877 (0.0462) *** | 0.1787 | 1484 | 135 |
| | Random Effects (SA) | No | 0.9664 (0.0442) *** | 0.2431 | 1484 | 135 |
| | Fixed Effects (within) | Yes | 0.8706 (0.0603) *** | 0.2128 | 1484 | 135 |

Notes: *** $p < 0.01$.

## Table 8. Models with Bank Controls: Pre- and Post-2014

### (a) Models Pre-2014 (2004–2013)

| Method | Time FE | $\beta_m$ | LLP/EQ | CAR_Total | CAR_Tier1 | NPL ratio | RWA/Assets | D/E | FCF/Income | Adj. $R^2$ | Obs. | Banks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pooled OLS | No | 1.0078 (0.0466) *** | −17.8976 (8.3041) * | 5.1047 (76.8099) | 0.9754 (69.5147) | 13.4111 (16.6670) | −9.0129 (7.4490) | −1.3889 (0.5053) ** | 0.7064 (1.3636) | 0.5054 | 517 | 89 |
| FE (within) | No | 1.0409 (0.0488) *** | −16.6774 (8.8605) · | −148.1733 (149.0111) | 291.2114 (137.2763) * | −2.2173 (21.0207) | 12.8270 (13.0654) | −0.0917 (0.9844) | −0.5828 (1.5390) | 0.4634 | 517 | 89 |
| RE (SA) | No | 1.0078 (0.0466) *** | −17.8976 (8.3041) * | 5.1047 (76.8099) | 0.9754 (69.5147) | 13.4111 (16.6670) | −9.0129 (7.4490) | −1.3889 (0.5053) *** | 0.7064 (1.3636) | 0.5054 | 517 | 89 |
| FE (within) | Yes | 0.6770 (0.1113) *** | −22.7622 (8.9334) ** | −192.2825 (146.6406) | 243.8269 (149.8226) · | −5.2191 (20.5718) | 5.7782 (13.1708) | −0.2230 (0.9748) | −0.4291 (1.4968) | 0.5024 | 517 | 89 |

### (b) Post-2014 (2014–2024)

| Method | Time FE | $\beta_m$ | LLP/EQ | CAR_Total | CAR_Tier1 | NPL ratio | RWA/Assets | D/E | FCF/Income | Adj. $R^2$ | Obs. | Banks |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pooled OLS | No | 1.1436 (0.0564) *** | 1.3346 (4.1590) | 166.31 (73.586) * | −198.31 (68.786) ** | −54.878 (10.781) *** | 6.6679 (6.4691) | −0.8524 (0.4364) · | −0.00936 (0.00724) | 0.3012 | 1 027 | 111 |
| FE (within) | No | 1.1683 (0.0595) *** | −3.0606 (4.7229) | 228.48 (134.41) · | −169.88 (141.11) | −60.169 (16.920) *** | 12.105 (14.718) | −1.4553 (1.7342) | −0.02193 (0.00878) * | 0.2390 | 1 027 | 111 |
| RE (SA) | No | 1.1436 (0.0564) *** | 1.3346 (4.1590) | 166.31 (73.586) ** | −198.31 (68.786) ** | −54.878 (10.781) *** | 6.6679 (6.4691) | −0.8524 (0.4364) · | −0.00936 (0.00724) | 0.3012 | 1 027 | 111 |
| FE (within) | Yes | 1.1186 (0.0819) *** | −1.4175 (4.7010) | 205.62 (133.10) | −174.28 (139.57) | −53.768 (16.853) ** | 22.920 (14.875) | −1.0282 (1.7303) | −0.01903 (0.00871) * | 0.2638 | 1 027 | 111 |

*Notes:* "Time FE" indicates inclusion of year dummies (in the post-2014 period, 2020 is negative and significant). Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, · $p < 0.10$.

### 4.4. Model Validation and Robustness Checks

The evaluation of model quality across specifications and periods provides a systematic assessment of how adequately different estimators capture the dynamics of the cost of equity in European banks. The analysis begins with pooled OLS regressions, which constitute the simplest baseline but also reveal the most severe shortcomings. In the CAPM-only formulation, the Breusch–Pagan test strongly rejects homoskedasticity, indicating the presence of heteroskedastic errors that undermine the reliability of standard inference. The Durbin–Watson statistic further reveals evidence of serial correlation in the pre-2014 sample, suggesting that bank returns contain persistent dynamics that are not captured by a model limited to market excess returns. Finally, Pesaran's CD test detects pronounced cross-sectional dependence, which reflects the fact that European banks are jointly exposed to systemic shocks and contagion channels that cannot be explained by market factors alone. When fundamentals are incorporated into the OLS regressions, these deficiencies are only partially alleviated. The inclusion of accounting variables reduces autocorrelation, as the Durbin–Watson statistics move closer to the non-rejection values, and heteroskedasticity, although still present, appears less severe. Nonetheless, cross-sectional dependence remains highly significant, both before and after 2014, demonstrating that pooled OLS is structurally incapable of accounting for common shocks or unobserved heterogeneity. In the post-2014 period, the CAPM-only OLS continues to fail all diagnostics, while the extended model provides marginal improvements but still suffers from persistent heteroskedasticity and dependence, confirming that pooled OLS, even when enriched with fundamentals, is an unreliable estimator in this context.

The fixed effects models offer a more structured approach by controlling for unobserved heterogeneity across banks. In the CAPM-only fixed effects regressions, the Hausman test systematically rejects random effects and confirms the consistency of fixed effects, particularly in the pre-2014 period, which implies that the unobserved bank-specific heterogeneity is correlated with market returns. Diagnostics nonetheless reveal that the CAPM-only specification remains problematic: while the Durbin–Watson statistic indicates the absence of serial correlation, heteroskedasticity and cross-sectional dependence remain unresolved. When fundamentals are introduced into the fixed effects models, the specification becomes considerably more robust. In the pre-2014 sample, both autocorrelation and heteroskedasticity are mitigated, with Durbin–Watson values approaching 2 and Breusch–Pagan statistics weaker than in the CAPM-only version, though Pesaran's CD test continues to reject independence across banks. After 2014, the extended fixed effects model maintains its superiority, with the Hausman test confirming its consistency, Durbin–Watson statistics pointing to the absence of first order serial correlation, and heteroskedasticity reduced though not eliminated. The persistence of cross-sectional dependence indicates that while fixed effects with fundamentals capture part of the heterogeneity and systemic risk, they are insufficient to absorb the full extent of common shocks characterising the European banking sector.

Random effects models perform substantially worse. In the CAPM-only version, the Hausman test rejects the null of consistency in favour of fixed effects, invalidating the random estimator. This result holds both before and after 2014, indicating that unobserved heterogeneity is not orthogonal to market returns and thus random effects are not appropriate. When fundamentals are added, random effects show modest improvements in terms of Durbin–Watson statistics, which suggest reduced autocorrelation, but Breusch–Pagan tests continue to indicate heteroskedasticity and Pesaran's CD confirms cross-sectional dependence. More importantly, the Hausman test systematically rejects these extended random effects specifications, reaffirming that they are inconsistent relative to fixed effects. Taken together, these results confirm that random effects estimators, whether simple or extended, do not provide a viable framework for analysing the cost of equity of European banks.

The inclusion of time-fixed effects fundamentally alters the behaviour of the models. In the CAPM-only specification with year dummies, the issue of cross-sectional dependence is immediately mitigated. Pesaran's CD test no longer rejects the null of independence, indicating that temporal dummies are able to absorb systemic shocks that were previously contaminating the residual structure. However, heteroskedasticity persists, and the explanatory power of the CAPM-only model remains weak. The situation changes markedly once fundamentals are introduced into the time-fixed effects specification. In the pre-2014 period, the extended model with temporal dummies controls for systemic shocks through year effects, reduces heteroskedasticity relative to other specifications, and eliminates both autocorrelation and cross-sectional dependence. Although Breusch–Pagan tests continue to indicate some degree of heteroskedasticity, this can be adequately addressed through robust standard errors.

In the post-2014 sample, the same specification continues to dominate. CAPM-only models with time dummies are more stable than their OLS or standard fixed effects counterparts, but remain fragile in terms of explanatory power. The extended fixed effects with temporal dummies, by contrast, produces the cleanest residual structure, with no evidence of serial correlation or cross-sectional dependence and a theoretically consistent framework linking bank fundamentals to cost of equity under the influence of systemic shocks. This demonstrates that the combined inclusion of bank-specific heterogeneity, fundamentals, and temporal controls is indispensable to capture the true dynamics of European banking returns.

When comparing results before and after 2014, clear differences emerge. In the pre-2014 sample, pooled OLS and random effects consistently fail across diagnostics, while fixed effects with fundamentals improve performance but remain affected by dependence. Only the extended fixed effects with time dummies succeeds in reconciling theoretical plausibility with statistical adequacy, absorbing systemic shocks, reducing heteroskedasticity, and delivering robust inference. In the post-2014 period, pooled OLS and random

effects continue to be inadequate, while fixed effects with fundamentals retain their relative stability but do not eliminate dependence. Again, the extended fixed effects with time dummies emerges as the dominant specification, eliminating serial correlation and dependence while offering a theoretically grounded interpretation of the cost of equity. Importantly, the comparison between periods reveals a notable reduction in the strength of cross-sectional dependence after 2014. This reduction is consistent with the hypothesis that Basel III reforms, together with the recapitalisation of European banks, mitigated systemic fragility and reduced the extent of common shocks transmitted across the sector. Nevertheless, dependence does not disappear in models without time dummies, which confirms that systemic forces remain a defining feature of European banking, even in the post-reform environment.

The overall evaluation of model quality therefore leads to a clear ranking of specifications. Pooled OLS, whether CAPM-only or extended, consistently fails diagnostic tests and cannot be considered reliable. Random effects models are invalidated by Hausman statistics and add little explanatory power. Standard fixed effects with fundamentals provide a stable but incomplete framework, reducing autocorrelation and heteroskedasticity but failing to address cross-sectional dependence. Only the extended fixed effects with time dummies systematically passes the main diagnostics, providing a coherent structure that integrates bank fundamentals with systemic shocks. This model emerges as the most robust and theoretically consistent framework for estimating the cost of equity of European banks, both before and after the global financial crisis.

Fundamentally, the results confirm that bank-level characteristics and temporal effects are indispensable to capture the heterogeneity, systemic dependence, and regulatory dynamics of the European banking sector, and that Basel III played a critical role in reshaping the structural drivers of cost of equity after 2014.

### 4.5. Robustness of Coefficient Estimates

The application of heteroskedasticity-robust (HC1), Driscoll–Kraay, and cluster-robust covariance matrices provides a crucial robustness check for the inference validity of the models estimated in the post-2014 period. These corrections do not alter point estimates but affect the estimated precision of coefficients, thus determining whether statistical significance persists once heteroskedasticity, autocorrelation, and cross-sectional dependence are accounted for.

In the pooled OLS regressions, the CAPM-only model confirms the resilience of the market beta. Under HC1 corrections, the coefficient on the excess market return remains strongly positive and significant at the 1% level, while the intercept loses statistical relevance. Driscoll–Kraay corrections reinforce this finding by substantially reducing the standard error of the market beta and amplifying its t-statistic, while further diminishing the relevance of the intercept. The clustered version produces results consistent with HC1. These outcomes establish that the CAPM beta remains the only robust determinant in

pooled OLS, while abnormal returns are not statistically distinguishable from zero once robust corrections are applied.

When fundamentals are included in the OLS regressions, the robustness picture becomes more nuanced. The market beta preserves its significance across all corrections, confirming the dominance of systematic risk. Loan loss provisions lose significance entirely, while capital adequacy ratios (both total and Tier 1) and non-performing loans are sensitive to the error correction method. For example, under HC1 corrections, both capital adequacy and non-performing loans are significant, but their explanatory power disappears under Driscoll–Kraay errors, suggesting that their role is partially driven by cross-sectional correlation rather than independent firm-level heterogeneity. Free cash flow to income remains systematically significant under HC1 and clustered errors, but its significance weakens under Driscoll–Kraay corrections. This heterogeneity demonstrates that pooled OLS cannot provide stable inference regarding bank fundamentals.

Fixed effects regressions exhibit greater robustness. In the CAPM-only specification, the market beta remains consistently significant under HC1 and clustered corrections. Although Driscoll–Kraay could not be directly applied in the current implementation, the strong stability across corrections confirms the reliability of this coefficient. In the extended FE specification, the results are even more consistent. The market beta retains strong significance across all corrections. Non-performing loans and free cash flow to income remain significant under HC1 and clustered errors, while Driscoll–Kraay results reveal that total capital adequacy, Tier 1 capital, and debt-to-equity ratios also achieve statistical significance, whereas free cash flow loses robustness. This demonstrates that extended FE models deliver more stable inference on the relationship between capital structure, credit risk management, and equity returns.

Random effects regressions largely replicate the weaknesses of OLS. The CAPM-only specification again confirms the robustness of the market beta, but the intercept remains insignificant across all correction methods. In the extended RE models, capital adequacy and non-performing loans retain significance under HC1 and clustered errors, but lose explanatory power once Driscoll–Kraay corrections are applied. Free cash flow remains significant in all corrections, but given the Hausman test consistently rejects RE in favour of FE, these results should be interpreted with caution.

Time-fixed effects models deliver the most robust and theoretically consistent set of results. In the CAPM-only specification, the market beta remains highly significant under all corrections, while several year dummies linked to crisis and post-crisis adjustments, such as 2016, 2020, 2021, 2022, and 2023, retain statistical significance across HC1, Driscoll–Kraay, and clustered estimators. This highlights the importance of systemic shocks in driving equity returns. In the extended FE with time dummies, the robustness of fundamentals is more selective. Under HC1 and clustered errors, non-performing loans and free cash flow remain significant, while other variables lose explanatory power. Under Driscoll–Kraay corrections, total and Tier 1 capital ratios, as well as the 2015 and

2020 dummies, achieve robust significance, while free cash flow loses explanatory power. These results show that systemic shocks and core capital adequacy metrics are consistently relevant when error structures are fully corrected, while weaker fundamentals lose significance.

Overall, the robustness checks reveal three persistent conclusions. First, the CAPM market beta is the only coefficient that remains highly significant across all models, periods, and error corrections, confirming the persistence of systematic risk as the main determinant of European bank equity returns. Second, a subset of bank fundamentals—namely capital adequacy, non-performing loans, and free cash flow—show significance in extended FE and FE with time dummies, but their robustness is sensitive to the chosen correction method. Third, the significance of year dummies in the time-fixed effects models validates the role of systemic shocks, particularly during crisis-related years, reinforcing the necessity of temporal controls. Together, these findings confirm the extended fixed effects model with time dummies as the most statistically and theoretically reliable framework, combining stability of key coefficients with resilience under robust error structures.

### 4.6. Alternative Modelling Approaches

While traditional econometric specifications provide estimates under their respective assumptions, modern empirical finance benefits from exploring a broader set of modelling approaches. These allow for greater flexibility in functional form, heterogeneous parameterisation, and variable selection. In this section, we apply Mean Group estimation, Bayesian hierarchical modelling, machine learning methods (Random Forests and Neural Networks), finite mixture models, and penalised regression (LASSO). Our goal is to verify whether the observed post-2014 changes in cost of equity drivers are robust across methods with different modelling assumptions.

#### 4.6.1. Dynamic Fixed Effects Models

The dynamic fixed effects estimations were implemented to capture both the persistence of bank excess returns and the sensitivity of these returns to market-wide shocks, while controlling for unobserved heterogeneity at the bank level. For the pre-2014 subsample, corresponding to the period preceding the effective implementation of Basel III requirements, the results indicate a statistically significant negative autoregressive component. The coefficient on the lagged excess return is negative and significant, suggesting that excess stock returns tended to mean-revert during this phase. This behaviour implies that shocks to bank returns were not strongly persistent, but rather dissipated over time, consistent with a more fragile and volatile banking environment prior to the consolidation of regulatory capital reforms.

In contrast, the market factor coefficient is strongly significant and close to unity, indicating that bank stock returns during this period were largely driven by aggregate market dynamics rather than idiosyncratic bank fundamentals. The explanatory power

of the model, with an adjusted $R^2$ above 0.40, highlights the dominance of systematic risk in shaping bank equity returns before 2014.

When extending the specification to include a broader set of bank-specific financial indicators — including loan loss provisions, capital adequacy ratios, non-performing loans, leverage, and free cash flow — the results reinforce the primacy of the market factor. While some fundamentals, notably Tier 1 capital ratios, emerge as marginally significant, most idiosyncratic variables fail to exhibit consistent explanatory power. This lack of robustness suggests that prior to Basel III, investors discounted idiosyncratic bank characteristics and primarily priced equity risk through market-wide channels.

In the post-2014 subsample, however, the dynamics change significantly. The lagged excess return becomes statistically insignificant, indicating that the autoregressive persistence observed earlier is no longer present once Basel III had been fully enforced. This shift may reflect a regime in which capital and liquidity standards enhanced banking sector resilience, reducing the scope for excess returns to follow a predictable mean-reverting path. More importantly, the extended specification reveals a richer role for bank fundamentals. Tier 1 capital ratios, overall capital adequacy, and non-performing loans become statistically significant, implying that investors increasingly valued the microeconomic determinants of bank soundness. The $R^2$ of the models remains moderate, but the presence of significant bank-specific drivers highlights the structural break induced by the regulatory transition: from a market-dominated risk pricing regime pre-2014 to a fundamentals-sensitive regime post-2014.

Overall, the dynamic fixed effects estimations underscore the importance of Basel III in altering the channels through which equity investors assessed bank risk. The disappearance of persistence in excess returns and the emergence of fundamentals as significant factors suggest that regulation improved transparency and discipline, anchoring valuation more firmly in bank-specific resilience rather than systemic volatility.

### 4.6.2. Dynamic Random Effects Models

Complementing the fixed effects framework, the dynamic random effects estimations allow for the inclusion of time-invariant cross-sectional variation and test the robustness of the findings under alternative assumptions about unobserved heterogeneity. For the pre-2014 period, the results are broadly consistent with the fixed effects estimations but display notable differences. The lagged excess return is statistically insignificant under random effects, suggesting that the mean-reverting dynamics captured under fixed effects may have been partially absorbed by unobserved heterogeneity in the bank-specific intercepts. The market factor remains the dominant explanatory variable, highly significant and close to unity, once again reflecting the overwhelming influence of aggregate market conditions on bank returns prior to Basel III.

The expanded model including bank fundamentals indicates that certain microeconomic variables achieve significance under random effects. Loan loss provisions relative

to equity and the debt-to-equity ratio emerge as statistically relevant, with negative coefficients consistent with investor penalisation of higher credit risk and leverage. However, most capital adequacy indicators remain insignificant, highlighting that the informational content of regulatory capital was not yet fully internalised by markets in the pre-2014 regime. The overall explanatory power of the models, with $R^2$ around 0.50, confirms that although market risk dominated, certain bank-level risk indicators had already begun to shape investor expectations.

In the post-2014 period, the random effects estimations display a more complex picture. The lagged excess return becomes weakly significant in some specifications, but its magnitude remains close to zero, confirming the absence of persistent dynamics in excess returns. The market factor continues to exert a strong and highly significant influence, but the inclusion of fundamentals markedly improves model performance. Capital adequacy ratios — both total and Tier 1 — gain significance, with opposite signs suggesting that market participants distinguished between regulatory capital buffers and their effective quality. Non-performing loans and leverage indicators also become significant, reflecting greater investor scrutiny of credit quality and solvency risks in the aftermath of Basel III.

Importantly, the random effects framework reveals that the informational role of fundamentals strengthened after 2014. The explanatory power of the models increases, and several bank-specific indicators achieve consistent significance, unlike in the earlier period. This evidence supports the view that Basel III reforms reshaped investor risk pricing, inducing stronger market discipline and greater alignment between equity valuations and the underlying prudential health of banks.

Taken together, the dynamic random effects models confirm the transition observed in the fixed effects framework: prior to 2014, bank equity risk was priced mainly through aggregate market channels, whereas after 2014, bank fundamentals — particularly those linked to regulatory capital and credit risk — became decisive in shaping excess returns. This shift reflects not only the tightening of prudential standards but also the credibility of their enforcement, which enhanced the informational content of bank-level indicators for equity investors.

### 4.6.3. Dynamic Models

The previous sections established the role of static and semi-dynamic models in capturing the determinants of the cost of equity (CoE) for European banks. However, such frameworks are limited in their ability to address endogeneity, dynamic persistence, and feedback mechanisms inherent to financial markets. In particular, the cost of equity is strongly influenced by both contemporaneous shocks in market conditions and lagged bank-specific factors, requiring an econometric framework that is robust to simultaneity bias and measurement error. To address these limitations, this section introduces more advanced econometric specifications, namely the System GMM and the Difference GMM estimators, which extend beyond static CAPM and panel-OLS frameworks. These methods allow for a more accurate estimation of dynamic relationships, explicitly accounting

for unobserved heterogeneity, potential instrument proliferation, and the persistence of financial variables.

The Blundell–Bond System GMM estimator was first applied to both the baseline specification with only excess market returns and to the expanded model including the full set of bank-specific covariates. In the pre-2014 sample, results indicate that the lag of excess stock returns is not statistically significant, suggesting limited persistence in bank-level excess returns prior to Basel III implementation. By contrast, the coefficient on excess market returns remains positive and highly significant, with an estimate above unity (1.115 in the robust specification), implying a strong sensitivity of bank returns to broader market dynamics.

In the post-2014 sample, the dynamics exhibit a subtle shift. The lag of excess returns again remains statistically insignificant, but the coefficient on excess market returns decreases marginally toward one (0.993 with robust errors). This reduction suggests that although bank equity returns remain strongly tied to market movements, the responsiveness may have become more proportional rather than amplified. The inclusion of bank-specific fundamentals in the System GMM framework further refines this picture. For the pre-2014 period, Loan Loss Provisions to Equity and Debt-to-Equity emerge as significant, with negative coefficients, highlighting the penalising effect of poor asset quality and excessive leverage on expected equity returns. In contrast, in the post-2014 sample, capital adequacy ratios and free cash flow to income play a more prominent role, both exhibiting strong significance. In particular, Tier 1 Capital and Total Capital Ratios present opposite signs, indicating a more complex interaction between regulatory buffers and market-based risk assessments under Basel III.

Overall, the System GMM estimations reveal that Basel III coincided with a shift in the determinants of the cost of equity: prior to 2014, market dynamics dominated, while after 2014 regulatory capitalisation and internal liquidity generation became more relevant in explaining variations in expected returns.

The Arellano–Bond Difference GMM estimator provides a robustness check by relying solely on lagged levels of the variables as instruments in first-difference equations. In the pre-2014 estimations, the lag of excess returns is again insignificant, while excess market returns remain the main driver of equity risk premia. The Sargan tests, however, indicate some instrument validity concerns, with low p-values suggesting possible overidentification. Furthermore, tests for autocorrelation reveal first-order negative serial correlation as expected in first-differenced models, while second-order correlation remains borderline significant in some specifications, raising caution about instrument proliferation.

In the post-2014 period, the Difference GMM models show similar patterns with robust significance of excess market returns but some instability in the lagged dependent variable. Once extended bank-specific variables are incorporated, additional dynamics become evident. For instance, Free Cash Flow to Income consistently shows a strong

and negative effect, suggesting that stronger internal liquidity buffers reduce the risk premium demanded by investors, consistent with regulatory expectations under Basel III. On the other hand, Non-Performing Loans exhibit sporadic significance, signalling that asset quality remains an occasional but not systematic driver of the cost of equity.

Despite its greater susceptibility to weak instruments, the Difference GMM approach broadly confirms the main insights from System GMM: namely, that the transition to Basel III coincided with a structural rebalancing from purely market-driven risk premia to a more nuanced mix of market, capital, and liquidity fundamentals.

Interpretation of Results The joint consideration of System and Difference GMM estimators allows for a richer economic interpretation. The persistent insignificance of lagged excess returns across specifications suggests that, unlike in other asset pricing contexts, bank equity returns in Europe do not exhibit strong autoregressive dynamics once market risk factors are controlled for. This may reflect the high transparency and continuous repricing of bank equities, which rapidly incorporate new information and regulatory developments.

The consistently significant coefficients on excess market returns across both pre- and post-2014 samples underline the enduring centrality of systematic risk factors in determining the cost of equity. However, the shift from coefficients exceeding unity pre-2014 to those closer to parity post-2014 indicates a stabilisation effect, plausibly associated with enhanced capital requirements and supervisory discipline. Investors appear to perceive banks as more aligned with market performance rather than excessively amplifying systemic shocks, a finding directly consistent with the stabilisation objectives of Basel III.

Moreover, the changing role of bank-specific fundamentals provides a window into investor risk perception. Before Basel III, high provisions and leverage ratios were punished by higher required returns, suggesting that markets were sceptical about banks' ability to absorb credit losses. After Basel III, however, capital adequacy and internal liquidity generation became the central explanatory variables, reflecting investor attention to compliance with regulatory buffers and sustainable cash-flow generation. Particularly striking is the negative and highly significant role of Free Cash Flow to Income in the post-2014 period, which implies that liquidity-generating capacity has become a key factor in reducing the equity risk premium.

Taken together, the evidence from advanced dynamic models suggests that Basel III has reshaped the drivers of the cost of equity for European banks. Market risk remains a dominant and stable component, but the importance of bank-specific variables has shifted in line with regulatory priorities. Prior to Basel III, equity markets penalised banks for leverage and asset quality concerns, reflecting vulnerabilities exposed by the financial crisis. After Basel III, markets appear to reward compliance with capital requirements and the ability to generate internal liquidity, thereby aligning investor incentives with prudential policy objectives.

These findings carry significant implications for both policymakers and bank managers. For regulators, the results provide empirical support that Basel III has not only stabilised the system but also successfully redirected market discipline towards the intended prudential metrics. For banks, the findings highlight the strategic value of strengthening capital buffers and maintaining robust liquidity positions as a means to reduce the cost of equity financing. Importantly, the absence of significant autoregressive dynamics suggests that reputation-driven momentum effects are secondary to fundamental compliance in shaping investor expectations.

In sum, the advanced econometric models extend the baseline CAPM analysis by demonstrating how regulatory changes reconfigure the very structure of risk pricing in banking. This strengthens the central claim of the study: Basel III did not merely increase capital requirements but also shifted the equilibrium conditions under which investors assess and price bank equity risk.

### 4.6.4. Bayesian Hierarchical Models

To further enrich the empirical analysis, Bayesian hierarchical models were estimated using the Hamiltonian Monte Carlo (HMC) algorithm implemented in `brms`. Unlike frequentist methods such as System or Difference GMM, Bayesian estimation provides full posterior distributions for all parameters, offering richer insights into uncertainty and credible intervals rather than relying exclusively on asymptotic standard errors. Moreover, the hierarchical specification with random intercepts at the Date level allows for the absorption of unobserved temporal shocks, which is particularly relevant in the banking sector, where systemic events (e.g., sovereign debt crises, regulatory announcements) affect all banks simultaneously.

#### 4.6.4.1 Baseline Bayesian CAPM

The baseline Bayesian specification included excess market returns as the sole regressor, with random intercepts by date. For the pre-2014 sample, the posterior mean of the market coefficient is 0.47 (95% CI: [0.39, 0.56]), indicating that European bank excess returns loaded less than proportionally on market returns in this period. This contrasts with the frequentist GMM results, which produced estimates closer to or above unity. The posterior distribution thus suggests that before Basel III, the sensitivity of bank equities to systematic risk was more muted once parameter uncertainty is properly accounted for.

For the post-2014 sample, the posterior mean of the market coefficient rises sharply to 0.87 (95% CI: [0.76, 0.98]), nearly doubling compared to the earlier period. This provides strong Bayesian evidence that Basel III coincided with a reinforcement of the relationship between bank equity returns and market-wide risk factors. Importantly, the uncertainty around this estimate is relatively tight, with all posterior mass well above 0.7, underscoring the robustness of this finding.

The hierarchical variance of the intercepts (sd(Date)) also declined substantially from 20.11 pre-2014 to 6.53 post-2014, suggesting that systemic shocks at the date level became

less pronounced after Basel III. This result is consistent with the interpretation that tighter regulation reduced the amplitude of cross-sectional volatility in bank equity returns.

#### 4.6.4.2 Extended Bayesian Models with Bank-Specific Fundamentals

To align with the GMM framework, Bayesian hierarchical regressions were also estimated including bank-level fundamentals: Loan Loss Provisions to Equity, Capital Adequacy Ratios (Total and Tier 1), Non-Performing Loans (NPLs) to Net Loans, Risk-Weighted Assets to Total Assets, Debt-to-Equity, and Free Cash Flow to Income.

In the pre-2014 extended model, the coefficient on excess market returns remains significant (posterior mean 0.72, 95% CI: [0.53, 0.90]). Loan Loss Provisions to Equity emerge as strongly negative (–25.42, 95% CI: [–42.21, –8.78]), confirming that higher provisioning costs were associated with higher risk premia prior to Basel III. Similarly, the Debt-to-Equity ratio is negatively associated with excess returns (–1.02, 95% CI: [–1.99, –0.05]), suggesting that leverage was priced negatively by investors in the pre-Basel III environment. Other bank-specific variables such as Tier 1 Capital and NPLs have wide posterior intervals, indicating substantial uncertainty and limited predictive power in this period.

In the post-2014 extended model, the market coefficient rises to 1.08 (95% CI: [0.94, 1.22]), aligning closely with the frequentist results and underscoring the stronger coupling of bank equity with market risk after Basel III. Crucially, the Tier 1 Capital Ratio has a significant negative effect (–185.53, 95% CI: [–314.90, –54.57]), while Total Capital Adequacy exhibits a positive association (139.86, 95% CI: [–2.88, 283.26], wide but tilted positive). This suggests that investors differentiate between regulatory buffers: Tier 1 capital is perceived as dilutive or costly, while broader capitalisation is viewed more favourably. Moreover, Non-Performing Loans to Net Loans are strongly negative (–52.65, 95% CI: [–74.05, –30.95]), confirming that asset quality remains a central determinant of cost of equity under Basel III. Finally, Free Cash Flow to Income, while small in magnitude (–0.01), is highly precise, with credible intervals excluding positive values, indicating that liquidity generation exerts a consistently downward pressure on required returns.

#### 4.6.4.3 Bayesian Insights

The Bayesian framework provides several additional insights compared to frequentist estimations. First, credible intervals are particularly useful for understanding the degree of uncertainty: while some variables (e.g., Loan Loss Provisions, Tier 1 Capital, NPLs) exhibit sharp posterior distributions, others (e.g., Total Capital Adequacy, RWA to Assets) remain wide, highlighting where empirical evidence is less decisive. Second, the hierarchical random effects reveal a structural reduction in systemic temporal shocks post-2014, consistent with Basel III's stabilising role. Third, posterior distributions confirm that the role of market risk increased under Basel III, while internal fundamentals such as asset quality and liquidity generation became more systematically priced.

#### 4.6.4.4 Implications

From a policy perspective, the Bayesian models corroborate the central finding of this study: Basel III shifted the pricing of bank equity risk from a market-dominated regime to one where regulatory compliance and bank-specific fundamentals play a stronger role. The Bayesian evidence suggests that investors increasingly reward liquidity and penalise poor asset quality or overreliance on Tier 1 capital, thus aligning market discipline with prudential policy goals. For bank managers, this underscores the strategic importance of capital structure choices: excessive reliance on core capital can be penalised, while diversified capital buffers and liquidity generation are rewarded with a lower cost of equity.

### 4.6.5. Random Forests

The Random Forest methodology, developed by Breiman (2001), is a non-parametric ensemble learning technique designed to capture complex and potentially non-linear relationships between excess returns and explanatory variables. The approach builds a multitude of decision trees based on bootstrapped subsamples of the data and randomly selected subsets of predictors. By aggregating across trees, the method reduces variance while avoiding overfitting, thereby producing stable estimates. This framework is particularly well-suited for banking data, where cost of equity dynamics are influenced by non-linear interactions between market exposures, credit risk, and capital adequacy indicators. Unlike traditional linear panel data models, Random Forests do not impose functional form restrictions, allowing structural patterns to emerge organically from the data.

#### 4.6.5.1 Excess Market-Only Specification

In the baseline specification, excess returns were modelled solely as a function of the excess market return. The results for the pre-2014 period demonstrated that the market factor alone explained a considerable share of the variation in excess returns. Out-of-bag estimates suggested an explained variance of approximately 57 per cent, with test data confirming an $R^2$ of 0.56. These findings highlight the dominant role of systematic market exposure in shaping the cost of equity before the implementation of Basel III.

In the post-2014 period, however, the predictive power of the market-only specification weakened substantially. Out-of-bag explained variance dropped to around 32 per cent, and the $R^2$ on test data fell to 0.50. This decline indicates that, after the introduction of Basel III, the market factor lost much of its ability to account for the cross-sectional variation in banks' cost of equity, suggesting a fundamental change in the underlying drivers.

#### 4.6.5.2 Extended Specification with Prudential Indicators

The extended specification, which incorporated prudential and accounting ratios alongside the excess market return, markedly enhanced predictive performance. Before 2014, the inclusion of balance-sheet measures increased the explanatory power of the model to an $R^2$ of 0.85 on the test sample, while prediction errors declined sharply. This implies

that, even prior to Basel III, credit risk indicators and capitalisation ratios already played a complementary role in determining bank's cost of equity.

The improvement became even more pronounced in the post-2014 period. When prudential variables were added to the market factor, the model achieved an $R^2$ of 0.87 with the lowest root mean squared error across all specifications. These results underscore that, under Basel III, prudential variables became central to understanding the cost of equity in the European banking sector.

#### 4.6.5.3 Variable Importance and Structural Shifts

An examination of variable importance provides further evidence of a regime shift. Prior to 2014, the excess market factor overwhelmingly dominated the predictive structure of the model, while prudential variables such as Loan Loss to Equity and Tier 1 Capital exhibited only secondary but notable importance. After 2014, however, the relative importance of the market factor declined sharply, while prudential indicators gained prominence. Loan Loss to Equity, Tier 1 Capital adequacy, and Total Capital adequacy emerged as key determinants of bank's excess returns, reflecting the increased salience of balance-sheet strength and regulatory compliance in shaping investor risk perceptions.

This change in importance underscores a structural transformation: the pre-Basel III regime was predominantly market-driven, whereas the post-Basel III environment is characterised by heightened relevance of prudential regulation. The evidence suggests that investors increasingly price bank's capital resilience and credit quality into required returns, reducing the weight of purely market-related risk exposures.

The Random Forest results provide robust support for the broader hypothesis advanced in this study: Basel III has altered the determinants of bank's cost of equity. The market factor, which once dominated, lost explanatory power in the post-crisis period, while prudential variables gained significant predictive strength. This shift is consistent with the regulatory emphasis on capital buffers and loss-absorbing capacity introduced under Basel III. From a policy perspective, the findings suggest that regulatory reforms not only affected bank's balance-sheet resilience but also reshaped the pricing of equity risk by investors. The transition from a market-dominated to a prudentially anchored explanatory structure constitutes evidence of a genuine regime change in the European banking sector.

### 4.6.6. Neural Networks

Artificial Neural Networks (ANNs) provide a flexible framework for approximating highly nonlinear relationships without requiring a priori functional forms. Their capacity to capture complex interactions between market factors and prudential ratios makes them, in principle, a suitable candidate for modelling the cost of equity in banking. However, this flexibility comes at a cost. Neural networks are highly sensitive to sample size, variable scaling, and hyperparameter configuration. They also face the risk of overfitting in relatively small panel datasets and remain difficult to interpret compared to tree-based

methods. Within the context of this thesis, where the panel is relatively constrained in both temporal and cross-sectional dimensions, these trade-offs are particularly evident and largely shape the empirical results obtained.

#### 4.6.6.1 Training diagnostics and model stability

Training diagnostics highlight the challenges faced by neural networks in this empirical application. In the pre-2014 period, the simple model with only the excess market factor converged after approximately 5,800 steps, with a global error of about 317, which is consistent with stable convergence for a low-capacity network. The full model, including prudential ratios, reduced the error substantially to around 84.7, though it required roughly 14,000 steps and reached a derivative threshold of 0.05, suggesting a more irregular optimization surface. By contrast, in the post-2014 period the training process became significantly more problematic. The simple model ended with a much higher error ($\sim 521$), and the full model required more than 160,000 steps, with weight magnitudes in the second hidden layer and output connections rising to orders of $10^3$–$10^4$. Such weight explosions indicate that activation functions are being driven into saturation zones, producing vanishing gradients and unstable updates. These diagnostics suggest that, relative to random forests, neural networks are more prone to optimisation friction and instability, especially in the post-Basel III environment.

#### 4.6.6.2 Models with the market factor only

When the network relied solely on the excess market return, predictive performance was consistently weak across both subsamples. In the pre-2014 period, out-of-sample $R^2$ values were negligible and errors remained high, indicating that the nonlinearity offered by the network does not compensate for the scarcity of explanatory information. The post-2014 results mirrored this pattern: the market factor alone proved insufficient to explain variations in the cost of equity, confirming the structural decline in the explanatory power of the CAPM factor once stricter prudential regulation was introduced. In both periods, the network fails to outperform even simple linear specifications under this restricted information set.

#### 4.6.6.3 Models with prudential ratios added

The inclusion of prudential ratios improved the in-sample fit, particularly in the pre-2014 period, where $R^2$ values in training rose to 0.37–0.58 and the error was markedly reduced. However, the out-of-sample gains remained modest and were substantially lower than those observed with random forests. In the post-2014 period, the divergence between training and testing results widened further: while the network fitted increasingly complex patterns in-sample, generalisation performance deteriorated, with unstable $R^2$ values and persistent error levels. This behaviour is consistent with overfitting, driven by a relatively large number of parameters compared to the effective sample size, as well as by multicollinearity among prudential ratios, which makes the optimisation process highly sensitive to small perturbations in the input data.

#### 4.6.6.4 Variable importance: consistency across methods

Variable importance was assessed through both weight-based methods (Olden) and permutation importance. In the pre-2014 period, the Olden method indicated a dominant positive role for the market factor, alongside moderate contributions from ratios such as Loan Loss to Equity and Total Capital, with some negative weights for RWA/Assets and Tier 1. Permutation importance, however, demonstrated that only the market factor produced a substantial out-of-sample impact: shuffling this variable reduced predictive $R^2$ by about 0.30, while other ratios contributed little and with wide uncertainty bands. In the post-2014 period, discrepancies between methods became even sharper. The Olden method attributed extreme weight magnitudes — including strongly negative signals for FCF/Income and Debt/Equity — while permutation importance suggested near-zero or even slightly negative contributions for most ratios, including the market factor. Correlation between the two importance rankings was weak (around 0.5 post-2014, negative pre-2014), reinforcing the conclusion that weight-based importance is unreliable in this setting. Only performance-based measures such as permutation or drop-column importance yield credible insights into explanatory relevance.

#### 4.6.6.5 Structural comparison with Random Forests

A direct comparison with random forests is revealing. In the pre-2014 period, random forests captured substantial and robust contributions from prudential ratios, lifting out-of-sample $R^2$ to approximately 0.85, whereas neural networks delivered only modest and inconsistent improvements. In the post-2014 period, the contrast widened further: forests once again achieved high predictive accuracy ($R^2$ 0.87), while networks struggled with convergence, overparameterisation, and unstable importance metrics. These findings are consistent with the broader machine learning literature, which documents that tree-based ensembles typically outperform neural networks in tabular datasets of limited size, due to superior bias-variance trade-offs and robustness to scale heterogeneity and collinearity.

The empirical evidence suggests that, although neural networks can in principle capture non-linear patterns in bank risk and return, their application in this dataset is hindered by size and structure limitations. Several best practices emerge for any future application. First, strict z-score normalisation by period is essential to prevent activation saturation and to stabilise optimisation (Bishop, 2006; Goodfellow, Bengio, and Courville, 2016). Second, reducing model capacity (fewer neurons and layers) and introducing explicit regularisation such as L2 weight decay or dropout would help mitigate overfitting (Krogh and Hertz, 1992; Srivastava et al., 2014). Third, implementing early stopping based on a temporal validation set—combined with smaller learning rates, appropriate weight initialisation (Xavier or He), and, where needed, gradient clipping—can prevent exploding gradients and improve training stability (Prechelt, 1998; Glorot and Bengio, 2010; He et al., 2015; Pascanu, Mikolov, and Bengio, 2013). Fourth, replacing logistic activations with tanh  tanh or ReLU, coupled with batch normalisation, tends to improve convergence when handling ratios with heterogeneous scales (Glorot, Bordes, and Bengio,

2011; Ioffe and Szegedy, 2015). Finally, adopting time-aware evaluation schemes—rolling or expanding windows rather than random splits—aligns predictive validation with the temporal structure of financial data (Bergmeir and Benítez, 2012; Hyndman and Athanasopoulos, 2018). Even with such refinements, evidence in this thesis points to random forests as a more reliable and interpretable baseline for the cost of equity in European banks (Breiman, 2001).

In conclusion, neural networks reaffirm the importance of prudential ratios in shaping the cost of equity, but they are clearly outperformed by random forests in terms of out-of-sample predictive accuracy, stability, and interpretability. The training process itself displayed substantial friction, with long convergence times and exploding weights in the post-2014 period, while importance measures produced inconsistent and sometimes contradictory results. The empirical results thus favour ensemble tree methods as the benchmark approach for this type of panel banking data, with neural networks requiring much larger samples and more rigorous tuning protocols to become viable competitors.

### 4.6.7. Mixture Models

Mixture regression models allow latent subgroups within the sample to display distinct sensitivities to the same covariates. In this setup, the specification resembles a mixture-of-experts, where each component regression is linear in excessmarket (and, in the FULL version, also in prudential ratios), while the component membership probabilities depend on a concomitant — here, the bank identifier (Bank). This design choice has direct implications for identification. When Bank is used in the gating mechanism, the mixture approaches a "partition by institution," reducing classification uncertainty and, in some cases, leading to near-deterministic allocation. This pattern is evident in the pre-2014 period, where posterior probabilities in the head are almost degenerate (e.g., 1, 01, 01, 0) and classification by bank exhibits proportions close to one. While this structure stabilises the mixture and ensures regime persistence within each institution, it risks conflating institutional heterogeneity with latent regime heterogeneity.

#### 4.6.7.1 Regime Structure in the Pre-2014 Period

Although the specification allowed for three components, estimation effectively collapsed to two active components, with prior weights of roughly 0.70 and 0.30, sample sizes of 904 and 402, and a log-likelihood of $-6165$. The first component captures a high-beta regime, with a slope $\beta \approx 1.33$ and residual volatility $\sigma_\varepsilon \approx 29$, while the second component reflects a low-beta regime, with $\beta \approx 0.31$ and $\sigma_\varepsilon \approx 20$. Goodness-of-fit metrics confirm this dichotomy: the high-beta regime reaches $R^2 \approx 0.615$, whereas the low-beta regime remains weaker at $R^2 \approx 0.219$. The sharply peaked posterior probabilities indicate that, with *Bank* in the gating function, classification is largely fixed by institution. Economically, the pre-2014 landscape is therefore best described by a binary structure: banks polarised between a defensive regime with limited exposure to market shocks and a highly pro-cyclical regime with strong market dependence.

In the post-2014 period, the mixture stabilises with three active components, distributed more evenly across the sample (308, 462, and 714 observations). Two of these correspond to high-beta regimes: one with a stable slope $\beta \approx 1.50$ and moderate volatility ($\sigma_\varepsilon \approx 13.66$), and another with a comparable slope ($\beta \approx 1.42$) but very high volatility ($\sigma_\varepsilon \approx 38.84$), producing a lower $R^2 \approx 0.291$. The third regime corresponds to a low-beta state ($\beta \approx 0.36$) with limited explanatory power ($R^2 \approx 0.104$). Importantly, posterior probabilities are no longer nearly deterministic, with several banks switching between regimes. This indicates that classification now reflects market-driven states rather than purely institutional features. The post-2014 distribution is thus more polarised: some banks retain a defensive profile, others exhibit stable pro-cyclical behaviour, while a subset falls into a highly sensitive and turbulent regime, consistent with heightened idiosyncratic risk pricing.

#### 4.6.7.2 Inclusion of Prudential Ratios

The introduction of prudential ratios improves within-component fit and reshapes regime boundaries. In the pre-2014 FULL model, estimation initially suggested three components (sizes 45, 164, and 308), each with high explanatory power (R2R$^2$R2 between 0.75 and 0.85). However, Bayesian Information Criterion (BIC) favoured a simpler two-component solution, characterised by slopes of approximately 0.615 and 1.440, with residual variances of 16.9 and 25.5. This indicates that, even with prudential ratios included, the pre-2014 structure remains fundamentally bi-modal (low/medium-beta vs. high-beta), with gains coming mainly through variance reduction.

In the post-2014 FULL model, BIC selects three components. These include: (i) a very-high-beta and turbulent regime ($\beta \approx 2.23$, $\sigma_\varepsilon \approx 38.5$); (ii) a high-beta but stable regime ($\beta \approx 1.40$–$1.50$, $\sigma_\varepsilon \approx 16.1$, $R^2 \approx 0.75$); and (iii) a low-beta regime ($\beta \approx 0.35$–$0.53$, $\sigma_\varepsilon \approx 14$–$17$). The presence of an extreme high-beta cluster underscores that, in the Basel III environment, bank equity returns became structurally more heterogeneous, with certain institutions exhibiting amplified exposure to shocks.

#### 4.6.7.3 Scale, Collinearity, and Interpretation of Prudential Coefficients

The prudential ratios often enter with large magnitudes and inconsistent signs across components (e.g., Tier 1 and Total Capital displaying coefficients in the hundreds and shifting directions). This pattern is consistent with three issues: unstandardised scale differences across ratios; substantial collinearity between capital adequacy measures; and the nature of mixture models, which distribute common variance across regimes and may inflate coefficients to enforce local separation. Consequently, coefficient signs within individual components should not be interpreted as clean causal effects. Instead, their role should be read as stabilising the market–return relationship within regimes, as evidenced by reductions in $\sigma$ e melhorias em $R^2$.

#### 4.6.7.4 Role of the Concomitant (Bank)

The use of Bank in the gating function results in nearly deterministic classifications

pre-2014, with banks persistently belonging to one regime. Post-2014, however, posterior probabilities show more overlap, suggesting that regime allocation is no longer strictly institutional but increasingly driven by market conditions. This transition has implications for identification: while Bank stabilises the mixture, it may obscure cross-sectional commonalities. From a methodological standpoint, specifications excluding Bank or including alternative concomitants (e.g., country or business model) may reveal more general regime structures.

#### 4.6.7.5 Model Selection, Collapses, and Small Components

The BIC results are consistent with economic intuition: two components suffice pre-2014, while three are required post-2014 to capture the additional heterogeneity. Nevertheless, some small components (e.g., the pre-2014 FULL component with size 45) may represent outlier-absorbing regimes rather than meaningful clusters. Robustness checks should include multiple initialisations, constraints on minimum prior weights, and comparison of "hard" versus "soft" classifications. Such steps help to ensure that the observed structures are not artefacts of local optima.

#### 4.6.7.6 Economic Implications and Link to Basel III

The mixture analysis aligns closely with the broader econometric evidence. Before 2014, the market can be described by two distinct states — defensive and pro-cyclical. After 2014, heterogeneity intensifies, producing a tripartite structure in which a subset of banks operates in a very-high-beta and noisy regime. This finding is consistent with the hypothesis that, under Basel III, regulatory pressure coexists with business models that amplify exposure to systemic shocks. From a supervisory and investment standpoint, the mapping of banks to regimes is operationally meaningful: those persistently classified into the very-high-beta regime are likely to experience greater drawdowns under stress, whereas low-beta banks provide diversification benefits.

Mixture models demonstrate that the relationship between market returns and bank equity returns is not homogeneous across time or institutions. Pre-2014, a bi-modal structure dominates, while post-2014, a tri-modal distribution emerges, including an extreme high-beta cluster. Prudential ratios enhance regime fit but their coefficients must be interpreted with caution, as they are affected by scaling and collinearity. The role of the Bank concomitant highlights the tension between institutional and regime heterogeneity. Ultimately, the results reinforce the central thesis: post-Basel III, structural heterogeneity in European banks increased significantly, and equity pricing became segmented into distinct latent regimes with clear economic relevance.

### 4.6.8. Penalised Regression Models (LASSO/Elastic-Net)

Penalised regression methods, specifically the Least Absolute Shrinkage and Selection Operator (LASSO; Tibshirani, 1996) and its generalisation, the Elastic Net (Friedman, Hastie, & Tibshirani, 2010), provide a parsimonious approach to variable selection in high-dimensional or multicollinear settings. These techniques introduce a penalty on the

absolute size of coefficients, shrinking irrelevant predictors to exactly zero and thereby performing simultaneous estimation and selection. The choice of penalty parameter $\lambda$ was guided by cross-validation, using both the minimum error rule ($\lambda_{\min}$) and the more conservative one-standard-error rule ($\lambda_{1se}$), the latter favouring parsimony e estabilidade ao custo de ligeiro viés. For time-series data, we complemented random splits with rolling-origin evaluation (Hyndman & Athanasopoulos, 2021), ensuring temporal robustness.

#### 4.6.8.1 Pre-2014 Results: Weak Predictive Content

In the pre-2014 sample, penalised regressions exhibit weak explanatory power outside the training window. The SIMPLE model, restricted to the contemporaneous market excess return, yields almost no predictive gain, with out-of-sample $R^2$ close to zero under both $\lambda_{1se}$ and $\lambda_{\min}$. While in-sample fit was moderate ($R^2 \approx 0.49$), predictive accuracy deteriorated sharply, suggesting that the linear exposure to the market factor was unstable across time.

Expanding the specification to include prudential ratios (FULL model) did not materially alter this picture. Even though in-sample fit improved slightly ($R^2 \approx 0.57$), the penalty mechanism eliminated most ratios, leaving essentially the market factor as the only robust predictor. Out-of-sample $R^2$ remained below 0.07. Attempts to enrich the structure with lagged terms (SIMPLE+LAGS and FULL+LAGS) also failed to deliver stable gains. In several cases, lag coefficients briefly entered the models, but their contribution was economically negligible and systematically penalised towards zero.

Rolling-origin validation confirmed these weaknesses. Across multiple train-test proportions, the average out-of-sample $R^2$ rarely exceeded 0.13, reinforcing the conclusion that before 2014, penalised regressions could not extract systematic predictability beyond contemporaneous noise.

#### 4.6.8.2 Post-2014 Results: Moderate and Robust Gains

By contrast, post-2014 models reveal a structural improvement in predictability. In the SIMPLE specification, penalised regression consistently retained the market excess return as the only predictor, delivering stable out-of-sample explanatory power of approximately 0.20–0.25, depending on the $\lambda$ rule. Prediction errors (RMSE $\approx$ 24–27) were materially smaller than in the pre-2014 period, and rolling-origin splits corroborated this improvement, with test $R^2$ averaging near 0.20.

The FULL models, which incorporated prudential ratios, displayed only marginal gains relative to the SIMPLE benchmark. Although a handful of additional coefficients entered under $\lambda_{\min}$, their contribution to predictive performance was limited. Out-of-sample $R^2$ remained within the 0.23–0.25 range, essentially indistinguishable from the market-only specification. Coefficients on prudential ratios tended to be unstable in sign and magnitude, reflecting high collinearity and their limited incremental role once the market factor was controlled for.

Lag-augmented versions, both SIMPLE+LAGS and FULL+LAGS, provided no robust improvement. In post-2014 estimations, lagged market returns or lagged stock excess returns were occasionally retained, but their coefficients were small and economically insignificant, with predictive accuracy remaining essentially identical to the contemporaneous-only models.

#### 4.6.8.3 Robustness Across $\lambda$-Rules and Rolling Splits

Comparing $\lambda_{1se}$ to $\lambda_{\min}$ confirmed the expected bias–variance trade-off. The $\lambda_{\min}$ models achieved slightly better error metrics (lower RMSE and MAE), but at the cost of less parsimony, whereas $\lambda_{1se}$ delivered more stable but sparser specifications. Importantly, the substantive conclusions remained invariant: in both pre- and post-2014 samples, only the market factor consistently survived penalisation, and prudential ratios added little incremental information.

Rolling-origin validation strengthened the inference of a structural break. In pre-2014 splits, average predictive power remained negligible, regardless of the window size. In the post-2014 splits, however, penalised regressions achieved consistent $R^2$ around 0.20–0.23 across multiple horizons, suggesting that the improved performance was not an artefact of sample partitioning but a genuine regime shift.

#### 4.6.8.4 Economic Interpretation

The LASSO/Elastic-Net evidence converges on three main insights. First, the market factor dominates: excess market return is the only predictor that withstands penalisation, both before and after 2014. Second, prudential ratios provide little marginal explanatory power for equity excess returns once market conditions are controlled for. This contrasts with their stronger relevance in Random Forests, highlighting how linear penalised methods prioritise sparsity e têm dificuldade em capturar interacções não lineares. Third, the structural break around 2014 is evident: while predictability was virtually absent before, the post-2014 environment exhibits modest but stable explanatory power from the market factor. This change is consistent with the broader econometric results in this study, pointing towards the impact of Basel III regulation and altered bank risk exposures in the aftermath of the financial crisis.

In sum, penalised regression models confirm the centrality of the market factor in driving bank equity returns, while systematically excluding prudential ratios and lagged terms. Pre-2014, their predictive content was negligible, but post-2014, a consistent though modest improvement emerges, with the market factor explaining roughly a quarter of the variation in out-of-sample returns. These results reinforce the interpretation that structural reforms and market conditions altered the relationship between banks and the wider market, and that penalised linear models are best understood as a robustness check rather than as a primary source of explanatory insight.

CHAPTER 5

# Conclusion

This thesis set out to examine whether the implementation of Basel III increased the cost of equity (CoE) for European banks. By applying a broad set of econometric and machine-learning techniques to panel data covering nineteen countries over the period 2003–2024, the analysis provides robust and nuanced evidence that the new regulatory framework did not result in a structural rise in bank equity funding costs. Instead, the post-2014 regime is characterised by lower or at least stable average levels of CoE and, crucially, by a pronounced reduction in dispersion across countries and institutions.

## 5.1. Main Findings

The results consistently show that before 2014 the cost of equity reached significantly higher levels, often exceeding 20 per cent on average, with extreme volatility and occasional peaks well above 50 per cent during episodes of financial turbulence. These values are consistent with the global financial crisis of 2008 and the subsequent sovereign debt crisis, when market risk premia widened dramatically and confidence in banks was severely shaken. After 2014, however, the average cost of equity declined to values between 16 and 19 per cent, with medians closer to 7 to 9 per cent, and dispersion narrowed considerably. This stability is confirmed across fixed-effects, random-effects, and dynamic models, as well as Bayesian and non-parametric methods such as random forests and neural networks. The convergence of evidence across methodologies highlights the robustness of the conclusion.

A key insight of this study is that while market betas rose after 2014, reflecting a higher sensitivity of bank equity to general market fluctuations, this increase was more than offset by the decline in the risk-free rate and by the compression of equity risk premia in European markets. The reduction in the price of risk during a period of historically low interest rates and unconventional monetary policies explains why the CoE did not increase despite tighter prudential requirements. In this sense, macro-financial conditions rather than regulatory reform emerge as the primary determinant of the long-run dynamics of bank equity costs.

The temporal analysis further reinforces this interpretation. The sharpest movements in CoE coincide with global crises or extraordinary macro-financial shocks rather than with the introduction of Basel III. For example, dramatic declines occurred in 2008, 2011, 2020, and 2022, corresponding respectively to the global financial crisis, the sovereign debt crisis, the COVID-19 pandemic, and the recent tightening of monetary policy. Conversely, peaks are observed during rebounds in 2009–2010, 2017, 2019, and 2023. These patterns

confirm that cyclical and global shocks dominate the evolution of CoE, while regulatory milestones have a more indirect and stabilising influence.

### 5.2. Cross-Country and Bank-Level Insights

The geographical heterogeneity observed across countries illustrates the interaction between global conditions and local market structures. Banks in Western Europe, including France, Germany, the Netherlands, the Nordic countries, Switzerland, and the United Kingdom, display relatively low and stable levels of CoE in the post-2014 period, reflecting deeper capital markets, stronger investor bases, and lower sovereign risk. In contrast, Greece remains an outlier, with structurally higher and more volatile CoE, and Central and Eastern European markets such as Lithuania and the Czech Republic record extreme average values. These results point not to regulatory differences, which are harmonised within the European Union, but to structural market characteristics, liquidity constraints, and exchange-rate dynamics that amplify the local equity risk premium.

When considering bank-specific variables, further insights emerge. In the pre-2014 period, systemic factors such as the equity risk premium and the risk-free rate dominate the variation in CoE, while bank-level fundamentals play a secondary role. After 2014, however, indicators such as capitalisation ratios, leverage, and loan-loss provisions gain greater explanatory power. Although these variables do not raise the aggregate CoE, they contribute to differentiation across institutions within a more stable environment. This suggests that Basel III, by reinforcing capital standards and loss-absorbing capacity, indirectly increased the weight that markets assign to fundamental indicators of resilience, even if it did not mechanically elevate equity costs.

### 5.3. Methodological Robustness

The diversity of methods applied in this thesis strengthens the validity of the findings. Classical econometric models (pooled OLS, fixed and random effects) confirm the stability or decline of CoE post-2014. Dynamic panel approaches (Arellano–Bond and Blundell–Bond GMM) demonstrate that once persistence and potential endogeneity are addressed, Basel III does not emerge as a structural break. Bayesian hierarchical models show similar results, with posterior distributions converging to lower means and reduced dispersion post-2014. Machine-learning methods, including random forests and neural networks, further highlight the dominance of market-wide factors, though their importance decreases after 2014 relative to fundamentals. Structural break tests also reinforce this perspective: identified breakpoints align with crisis episodes such as 2008, 2012, and 2020 rather than with the regulatory cut-off in 2014.

### 5.4. Implications

These findings have important implications for policymakers, investors, and academics. From a regulatory perspective, they suggest that strengthening prudential standards under Basel III did not penalise banks by raising their equity funding costs. Instead, the reforms coincided with a period of reduced dispersion and greater stability, which can be

interpreted as evidence of increased resilience. For investors, the results imply that bank equity returns remain more sensitive to global macroeconomic and monetary conditions than to capital requirements, underscoring the importance of monitoring systemic risks. For academic research, the study contributes by showing that a combination of econometric and machine-learning models can provide complementary perspectives and robust conclusions in the analysis of financial regulation.

### 5.5. Limitations and Future Research

Despite its contributions, this thesis has limitations. First, the presence of extreme outliers in smaller and less liquid markets, particularly in Central and Eastern Europe, suggests the need for robustness checks using trimming, winsorisation, or market-capitalisation-weighted regressions. Second, the reliance on local equity risk premia may exaggerate volatility in thin markets; alternative specifications using global or euro-area-wide premia could provide additional insights. Third, the analysis focused primarily on the cost of equity, but a broader assessment of bank's weighted average cost of capital (WACC), incorporating the cost of debt and funding structure, would enrich the understanding of regulatory impacts. Fourth, while the models applied control for heterogeneity and dynamics, future research could explore nonlinearities and interactions more systematically, for example through threshold models or regime-switching approaches.

Future research could also expand in three directions. First, by extending the sample to include post-2024 data, it will be possible to capture the medium-term consequences of monetary tightening and potential revisions to Basel III. Second, integrating implied measures of the cost of equity, such as those derived from dividend discount models or analysts forecasts, would provide an additional benchmark against the realised CoE estimated through CAPM-based approaches. Third, investigating the link between the cost of equity, bank's lending behaviour, and credit allocation would shed light on the broader macro-financial implications of regulation, connecting prudential policy to real economic outcomes.

### 5.6. Final Remarks

In conclusion, the evidence presented in this thesis points clearly to the fact that Basel III has not increased the cost of equity of European banks. If anything, it coincided with a more stable and resilient environment in which systemic shocks, global monetary conditions, and market dynamics remain the dominant drivers of equity funding costs. The reforms reinforced market discipline and enhanced resilience without imposing a permanent additional burden on shareholders. The European banking system thus appears to have transitioned to a new equilibrium in the post-Basel III era, characterised by stability, reduced dispersion, and an equity cost structure determined primarily by global macro-financial forces rather than by prudential capital requirements.

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# Appendix

## A - Data and Descriptive Statistics

Table 1. A1 — Banks in Sample and Coverage Window

| EIKON Ticker | Bank Name | Country | Start | End | Obs. |
|---|---|---|---|---|---|
| KAER.VI | BKS Bank AG | Austria | 2004 | 2024 | 21 |
| TIRO.VI | Bank fuer Tirol und Vorarlberg AG | Austria | 2005 | 2024 | 20 |
| ERST.VI | Erste Group Bank AG | Austria | 2004 | 2024 | 21 |
| OBER.VI | Oberbank AG | Austria | 2004 | 2024 | 21 |
| RBIV.VI | Raiffeisen Bank International AG | Austria | 2006 | 2024 | 19 |
| KBC.BR | KBC Group NV | Belgium | 2004 | 2024 | 21 |
| KBCA.BR | KBC Ancora NV | Belgium | 2004 | 2024 | 21 |
| BNAB.BR | Nationale Bank van België NV | Belgium | 2004 | 2024 | 21 |
| BACB.BB | Bulgarian American Credit Bank AD | Bulgaria | 2007 | 2024 | 17 |
| CCB.BB | Central Cooperative Bank AD | Bulgaria | 2004 | 2024 | 21 |
| FIB.BB | First Investment Bank AD | Bulgaria | 2008 | 2024 | 17 |
| BKOM.PR | Komercni Banka AS | Czech Republic | 2007 | 2024 | 18 |
| DANSKE.CO | Danske Bank A/S | Denmark | 2004 | 2024 | 21 |
| DJUR.CO | Djurslands Bank A/S | Denmark | 2004 | 2024 | 21 |
| FOBANK.CO | Foroya Banki P/F | Denmark | 2008 | 2024 | 17 |
| FYNBK.CO | Fynske Bank A/S | Denmark | 2004 | 2024 | 21 |
| GRLA.CO | Grønlandsbanken A/S | Denmark | 2004 | 2024 | 21 |
| HVID.CO | Hvidbjerg Bank A/S | Denmark | 2004 | 2024 | 21 |
| JYSK.CO | Jyske Bank A/S | Denmark | 2004 | 2024 | 21 |
| KRE.CO | Kreditbanken A/S | Denmark | 2004 | 2024 | 21 |
| LASP.CO | Lån & Spar Bank A/S | Denmark | 2004 | 2024 | 21 |
| LOLB.CO | Lollands Bank A/S | Denmark | 2004 | 2024 | 21 |
| MNBA.CO | Moens Bank A/S | Denmark | 2004 | 2024 | 21 |
| NRDF.CO | Nordfyns Bank A/S | Denmark | 2004 | 2024 | 21 |
| RILBA.CO | Ringkjoebing Landbobank A/S | Denmark | 2004 | 2024 | 21 |
| SKJE.CO | Skjern Bank A/S | Denmark | 2004 | 2024 | 21 |
| SPNO.CO | Spar Nord Bank A/S | Denmark | 2004 | 2024 | 21 |
| SYDB.CO | Sydbank A/S | Denmark | 2004 | 2024 | 21 |
| VJBA.CO | Vestjysk Bank A/S | Denmark | 2004 | 2024 | 21 |
| ALBAV.HE | Ålandsbanken Abp | Finland | 2004 | 2024 | 21 |
| NDAFI.HE | Nordea Bank Abp | Finland | 2004 | 2024 | 21 |
| BNPP.PA | BNP Paribas SA | France | 2004 | 2024 | 21 |
| CAIF.PA | Caisse Régionale de Crédit Agricole Mutuel Paris Île-de-France | France | 2004 | 2024 | 21 |

| EIKON Ticker | Bank Name | Country | Start | End | Obs. |
|---|---|---|---|---|---|
| CRTO.PA | Caisse Régionale de Crédit Agricole Mutuel Touraine Poitou | France | 2004 | 2024 | 21 |
| CNDF.PA | Caisse Régionale de Crédit Agricole Mutuel Nord France | France | 2004 | 2024 | 21 |
| CALCI.PA | Caisse Régionale de Crédit Agricole Mutuel Atlantique Vendée | France | 2004 | 2024 | 21 |
| CRSU.PA | Caisse Régionale de Crédit Agricole Mutuel Sud Rhône Alpes | France | 2004 | 2024 | 21 |
| CAT31.PA | Caisse Régionale de Crédit Agricole Mutuel Toulouse 31 | France | 2004 | 2024 | 21 |
| CRBP2.PA | Caisse Régionale de Crédit Agricole Mutuel Brie Picardie | France | 2008 | 2024 | 17 |
| CCNP.PA | Caisse Régionale de Crédit Agricole Mutuel Normandie Seine SC | France | 2004 | 2024 | 21 |
| CRLA.PA | Caisse Régionale de Crédit Agricole Mutuel du Languedoc | France | 2008 | 2024 | 17 |
| CIV.PA | Caisse Régionale de Crédit Agricole Mutuel d'Ille-et-Vilaine | France | 2004 | 2024 | 21 |
| CRLO.PA | Crédit Agricole Mutuel Loire Haute-Loire | France | 2004 | 2024 | 21 |
| CRAP.PA | Crédit Agricole Alpes Provence | France | 2004 | 2024 | 21 |
| CMO.PA | Crédit Agricole du Morbihan SC | France | 2004 | 2024 | 21 |
| CAGR.PA | Crédit Agricole SA | France | 2004 | 2024 | 21 |
| SOGN.PA | Société Générale SA | France | 2004 | 2024 | 21 |
| CBKG.DE | Commerzbank AG | Germany | 2004 | 2024 | 21 |
| DBKGN.DE | Deutsche Bank AG | Germany | 2004 | 2024 | 21 |
| QB7G.DE | Quirin Privatbank AG | Germany | 2007 | 2024 | 18 |
| ACBR.AT | Alpha Services and Holdings SA | Greece | 2004 | 2024 | 21 |
| BOAR.AT | Attica Bank SA | Greece | 2004 | 2024 | 21 |
| BOGR.AT | Bank of Greece | Greece | 2004 | 2024 | 21 |
| EURBR.AT | Eurobank Ergasias Services and Holdings SA | Greece | 2004 | 2024 | 21 |
| NBGR.AT | National Bank of Greece SA | Greece | 2004 | 2024 | 21 |
| BOPR.AT | Piraeus Financial Holdings SA | Greece | 2004 | 2024 | 21 |
| OTPB.BU | OTP Bank Nyrt | Hungary | 2004 | 2024 | 21 |
| AIBG.I | AIB Group PLC | Ireland | 2004 | 2024 | 21 |
| BIRG.I | Bank of Ireland Group PLC | Ireland | 2004 | 2024 | 21 |
| PTSB.I | Permanent TSB Group Holdings PLC | Ireland | 2004 | 2024 | 21 |
| EMII.MI | BPER Banca SpA | Italy | 2004 | 2024 | 21 |
| BGN.MI | Banca Generali SpA | Italy | 2007 | 2024 | 18 |
| BMPS.MI | Banca Monte dei Paschi di Siena SpA | Italy | 2004 | 2024 | 21 |
| BPSI.MI | Banca Popolare di Sondrio SpA | Italy | 2004 | 2024 | 21 |
| PRO.MI | Banca Profilo SpA | Italy | 2004 | 2024 | 21 |
| BAMI.MI | Banco BPM SpA | Italy | 2004 | 2024 | 21 |
| DESI.MI | Banco di Desio e della Brianza SpA | Italy | 2004 | 2024 | 21 |
| EMBI.MI | Credito Emiliano SpA | Italy | 2004 | 2024 | 21 |
| ISP.MI | Intesa Sanpaolo SpA | Italy | 2004 | 2024 | 21 |

| EIKON Ticker | Bank Name | Country | Start | End | Obs. |
|---|---|---|---|---|---|
| CRDI.MI | UniCredit SpA | Italy | 2004 | 2024 | 21 |
| ROE1L.VL | Artea bankas AB | Lithuania | 2004 | 2024 | 21 |
| INGA.AS | ING Groep N.V. | Netherlands | 2004 | 2024 | 21 |
| VLAN.AS | Van Lanschot Kempen NV | Netherlands | 2004 | 2024 | 21 |
| AURG.OL | Aurskog Sparebank | Norway | 2004 | 2024 | 21 |
| DNB.OL | DNB ASA | Norway | 2004 | 2024 | 21 |
| HSPG.OL | Holand og Setskog Sparebank | Norway | 2004 | 2024 | 21 |
| JAREN.OL | Jaeren Sparebank | Norway | 2008 | 2024 | 17 |
| MELG.OL | Melhus Sparebank | Norway | 2004 | 2024 | 21 |
| ROGS.OL | Rogaland Sparebank | Norway | 2004 | 2024 | 21 |
| SKUE.OL | Skue Sparebank | Norway | 2004 | 2024 | 21 |
| SOGNS.OL | Sogn Sparebank | Norway | 2004 | 2024 | 21 |
| SB1NO.OL | SpareBank 1 Nord-Norge | Norway | 2004 | 2024 | 21 |
| MING.OL | SpareBank 1 SMN | Norway | 2004 | 2024 | 21 |
| HELG.OL | Sparebank 1 Helgeland | Norway | 2004 | 2024 | 21 |
| NONG.OL | Sparebank 1 Nord-Norge | Norway | 2004 | 2024 | 21 |
| SOAG.OL | Sparebank 1 Ostfold Akershus | Norway | 2006 | 2024 | 19 |
| RING.OL | Sparebank 1 Ringerike Hadeland | Norway | 2004 | 2024 | 21 |
| MORGS.OL | Sparebanken More | Norway | 2004 | 2024 | 21 |
| SBNOR.OL | Sparebanken Norge | Norway | 2004 | 2024 | 21 |
| SPOG.OL | Sparebanken Ost | Norway | 2004 | 2024 | 21 |
| VVL.OL | Voss Veksel og Landmandsbank ASA | Norway | 2004 | 2024 | 21 |
| BHW.WA | Bank Handlowy w Warszawie SA | Poland | 2004 | 2024 | 21 |
| MILP.WA | Bank Millennium SA | Poland | 2004 | 2024 | 21 |
| BOSP.WA | Bank Ochrony Srodowiska SA | Poland | 2004 | 2024 | 21 |
| PEO.WA | Bank Pekao SA | Poland | 2004 | 2024 | 21 |
| GTN.WA | Getin Holding SA | Poland | 2004 | 2024 | 21 |
| INGP.WA | ING Bank Slaski SA | Poland | 2004 | 2024 | 21 |
| PKO.WA | PKO Bank Polski SA | Poland | 2005 | 2024 | 20 |
| SPL1.WA | Santander Bank Polska SA | Poland | 2004 | 2024 | 21 |
| MBK.WA | mBank SA | Poland | 2004 | 2024 | 21 |
| BCP.LS | Banco Comercial Português SA (Millennium) | Portugal | 2004 | 2024 | 21 |
| BBVA.MC | Banco Bilbao Vizcaya Argentaria SA | Spain | 2004 | 2024 | 21 |
| SAN.MC | Banco Santander SA | Spain | 2004 | 2024 | 21 |
| SABE.MC | Banco de Sabadell SA | Spain | 2004 | 2024 | 21 |
| BKT.MC | Bankinter SA | Spain | 2004 | 2024 | 21 |
| CABK.MC | CaixaBank SA | Spain | 2008 | 2024 | 17 |
| AVANZ.ST | Avanza Bank Holding AB | Sweden | 2004 | 2024 | 21 |
| SEBA.ST | Skandinaviska Enskilda Banken AB (SEB) | Sweden | 2004 | 2024 | 21 |
| SHBA.ST | Svenska Handelsbanken AB | Sweden | 2004 | 2024 | 21 |
| SWEDA.ST | Swedbank AB | Sweden | 2004 | 2024 | 21 |
| BCVN.S | Banque Cantonale Vaudoise | Switzerland | 2004 | 2024 | 21 |
| BCGE.S | Banque Cantonale de Genève | Switzerland | 2004 | 2024 | 21 |
| BCJ.S | Banque Cantonale du Jura SA | Switzerland | 2004 | 2024 | 21 |
| WKB.S | Banque Cantonale du Valais | Switzerland | 2004 | 2024 | 21 |

| EIKON Ticker | Bank Name | Country | Start | End | Obs. |
|---|---|---|---|---|---|
| BLKB.S | Basellandschaftliche Kantonalbank | Switzerland | 2004 | 2024 | 21 |
| BSKP.S | Basler Kantonalbank | Switzerland | 2004 | 2024 | 21 |
| BEKN.S | Berner Kantonalbank AG | Switzerland | 2004 | 2024 | 21 |
| EFGN.S | EFG International AG | Switzerland | 2006 | 2024 | 19 |
| GRKP.S | Graubündner Kantonalbank | Switzerland | 2004 | 2024 | 21 |
| HBLN.S | Hypothekarbank Lenzburg AG | Switzerland | 2004 | 2024 | 21 |
| LLBN.S | Liechtensteinische Landesbank AG | Switzerland | 2004 | 2024 | 21 |
| LUKN.S | Luzerner Kantonalbank AG | Switzerland | 2004 | 2024 | 21 |
| SNBN.S | Schweizerische Nationalbank | Switzerland | 2004 | 2024 | 21 |
| SGKN.S | St.Galler Kantonalbank AG | Switzerland | 2004 | 2024 | 21 |
| VPBN.S | VP Bank AG | Switzerland | 2004 | 2024 | 21 |
| VATN.S | Valiant Holding AG | Switzerland | 2004 | 2024 | 21 |
| VONN.S | Vontobel Holding AG | Switzerland | 2004 | 2024 | 21 |
| ZUGER.S | Zuger Kantonalbank | Switzerland | 2004 | 2024 | 21 |
| ARBB.L | Arbuthnot Banking Group PLC | United Kingdom | 2004 | 2024 | 21 |
| CBRO.L | Close Brothers Group PLC | United Kingdom | 2004 | 2024 | 21 |
| HSBA.L | HSBC Holdings PLC | United Kingdom | 2004 | 2024 | 21 |
| INVP.L | Investec PLC | United Kingdom | 2004 | 2024 | 21 |
| LLOY.L | Lloyds Banking Group PLC | United Kingdom | 2004 | 2024 | 21 |
| NWG.L | NatWest Group PLC | United Kingdom | 2004 | 2024 | 21 |
| STAN.L | Standard Chartered PLC | United Kingdom | 2004 | 2024 | 21 |

| Variable | N | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| Excess stock return | 2811 | 3.52 | 3.00 | 35.49 | -123.31 | 296.45 |
| Excess market return | 2811 | 4.86 | 5.94 | 23.44 | -87.64 | 389.99 |
| Loan Loss Provision / Equity | 2600 | 0.05 | 0.02 | 0.21 | -5.62 | 2.87 |
| Capital Adequacy (Total) | 2463 | 0.17 | 0.17 | 0.04 | -0.02 | 0.45 |
| Capital Adequacy (Tier 1) | 2341 | 0.15 | 0.15 | 0.05 | -0.06 | 0.45 |
| Non-Performing Loans / Net Loans | 1947 | 0.05 | 0.02 | 0.16 | 0.00 | 5.29 |
| Risk-Weighted Assets / Total Assets | 2130 | 0.49 | 0.49 | 0.19 | 0.00 | 2.95 |
| Debt-to-Equity | 2788 | 2.14 | 1.36 | 4.46 | -173.39 | 51.91 |
| Free Cash Flow / Bank Income | 2516 | 1.75 | 0.15 | 71.68 | -8.78 | 3595.00 |

Table 2. A2 — Descriptive Statistics of Key Variables

| Variable | Excess stock | Excess market | LLP/Equity | CAR (Total) | CAR (Tier 1) | NPL/Loans | RWA/Assets | Debt/Equity | FCF/Income |
|---|---|---|---|---|---|---|---|---|---|
| Excess stock | 1.00 | 0.60 | -0.03 | 0.09 | 0.10 | -0.05 | -0.00 | -0.01 | -0.03 |
| Excess market | 0.60 | 1.00 | -0.02 | 0.11 | 0.12 | -0.03 | 0.02 | -0.01 | -0.01 |
| LLP/Equity | -0.03 | -0.02 | 1.00 | -0.04 | -0.06 | 0.17 | 0.07 | 0.06 | -0.00 |
| CAR (Total) | 0.09 | 0.11 | -0.04 | 1.00 | 0.93 | -0.14 | -0.31 | -0.10 | 0.01 |
| CAR (Tier 1) | 0.10 | 0.12 | -0.06 | 0.93 | 1.00 | -0.12 | -0.27 | -0.18 | 0.02 |
| NPL/Loans | -0.05 | -0.03 | 0.17 | -0.14 | -0.12 | 1.00 | 0.36 | -0.12 | 0.01 |
| RWA/Assets | -0.00 | 0.02 | 0.07 | -0.31 | -0.27 | 0.36 | 1.00 | -0.29 | 0.03 |
| Debt/Equity | -0.01 | -0.01 | 0.06 | -0.10 | -0.18 | -0.12 | -0.29 | 1.00 | -0.02 |
| FCF/Income | -0.03 | -0.01 | -0.00 | 0.01 | 0.02 | 0.01 | 0.03 | -0.02 | 1.00 |

Table 3. A3 — Correlation Matrix (Pearson)

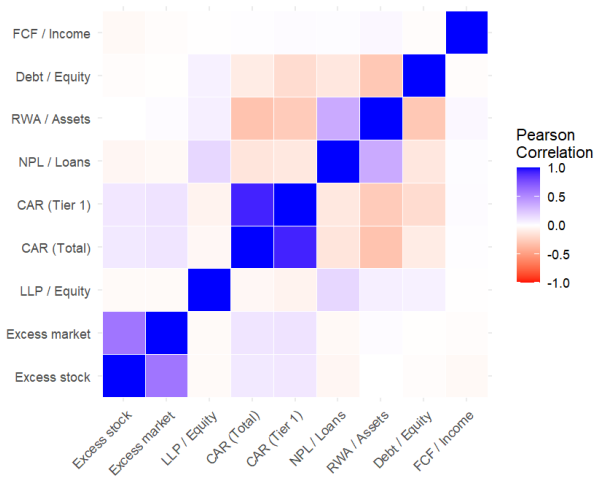



FIGURE 1. A4 - Heatmap of Pearson correlations among key variables

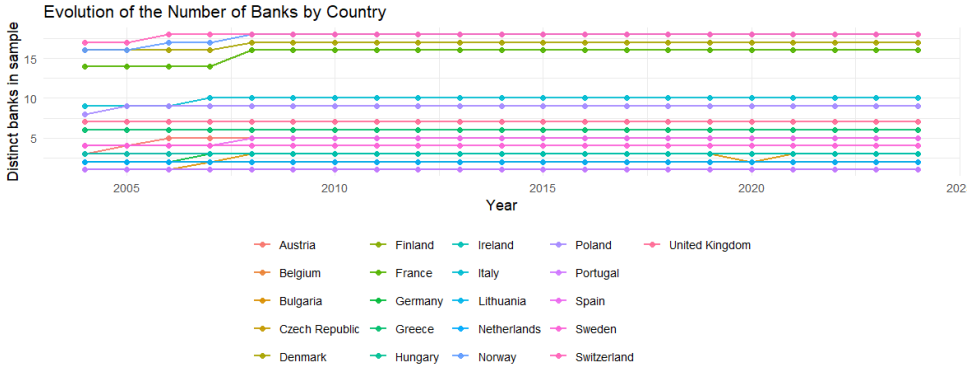



FIGURE 2. A5 - Evolution of the Number of Banks by Country

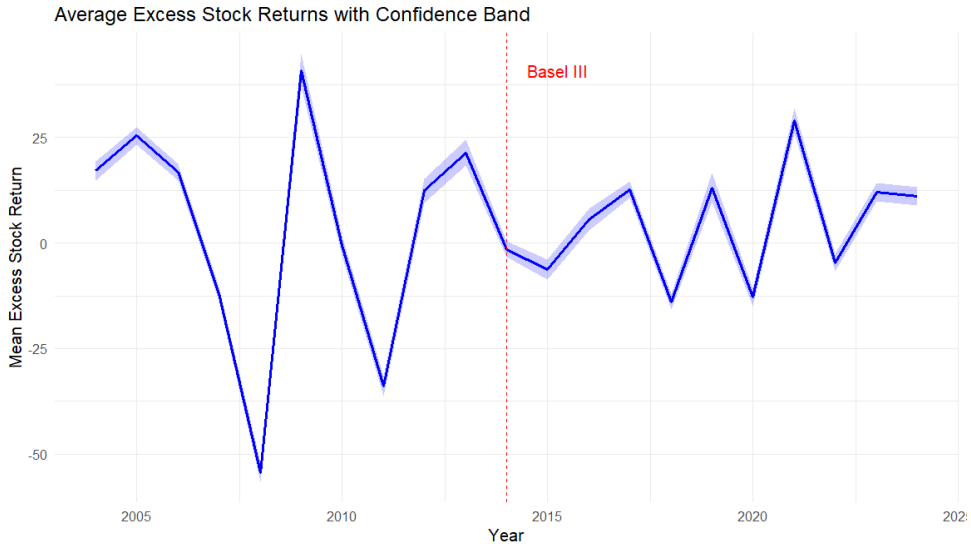



FIGURE 3. A6 - Annual Mean Cost of Equity (Proxy)

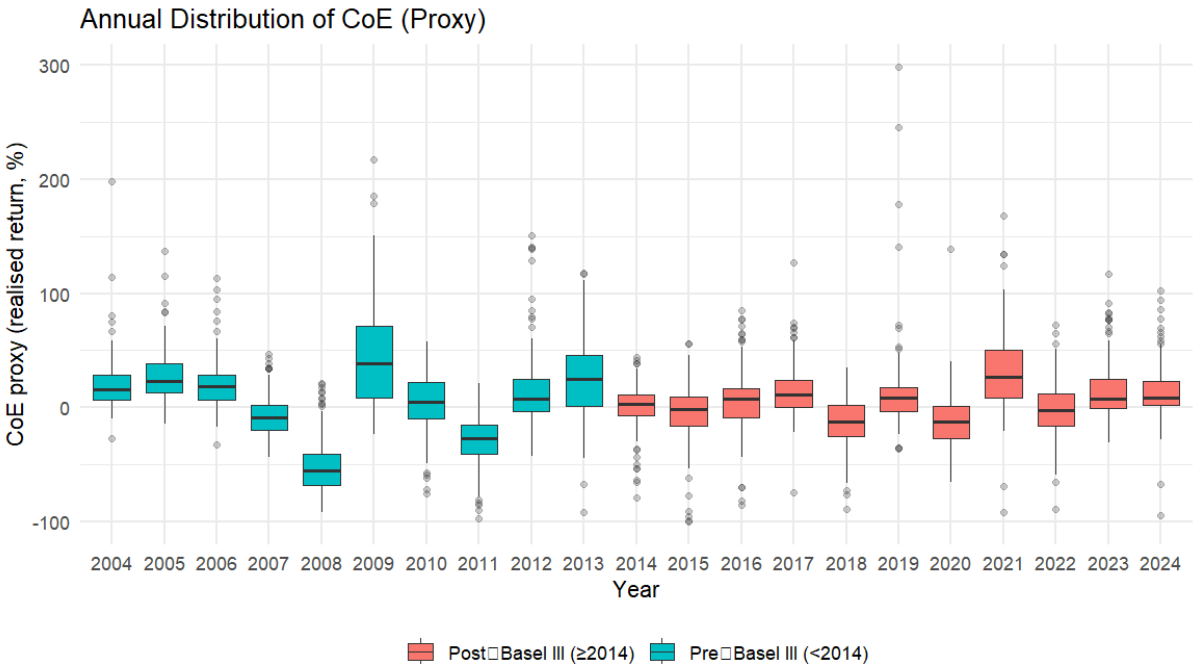



FIGURE 4. A7 - Annual Distribution of CoE (Proxy)

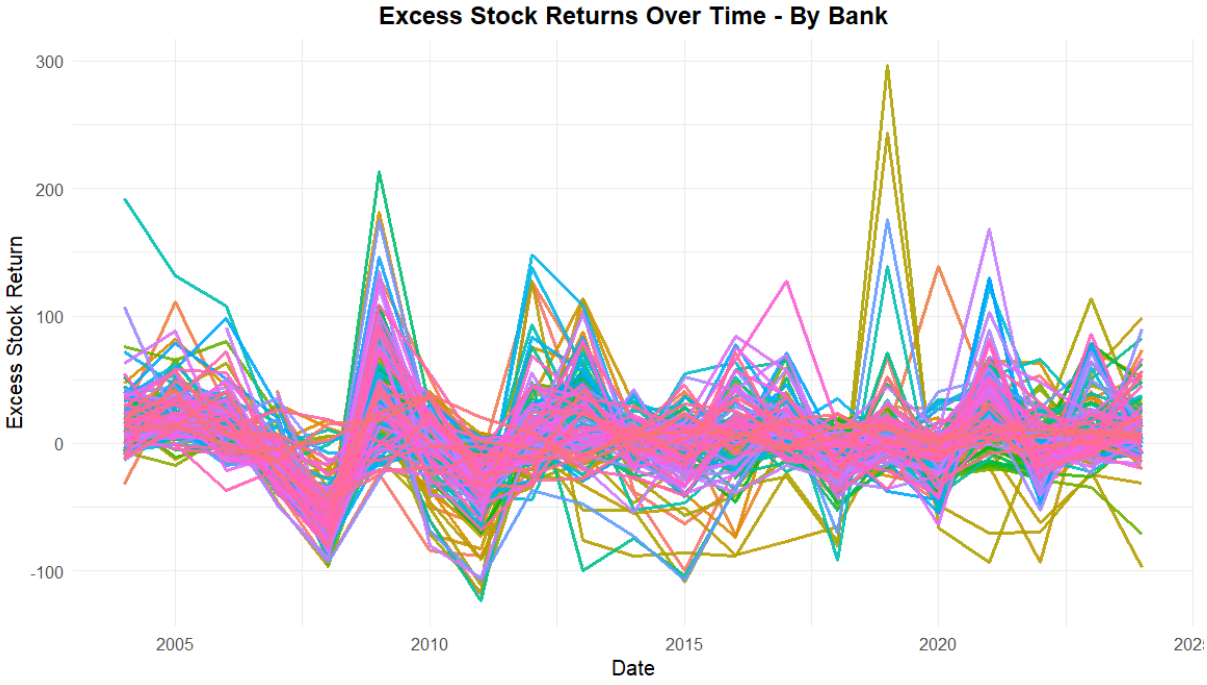



FIGURE 5. A8 - Excess Stock Returns Over Time - By Bank

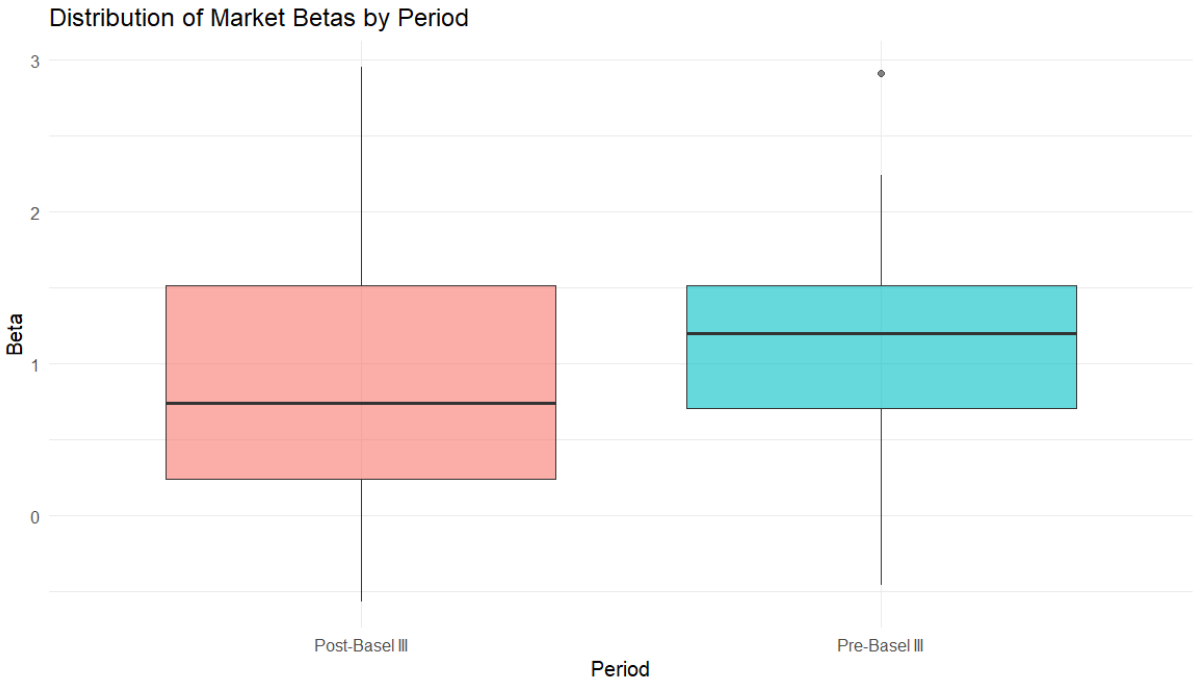



FIGURE 6. A9 - Boxplot of estimated market betas across banks, comparing the pre- and post-Basel III periods.

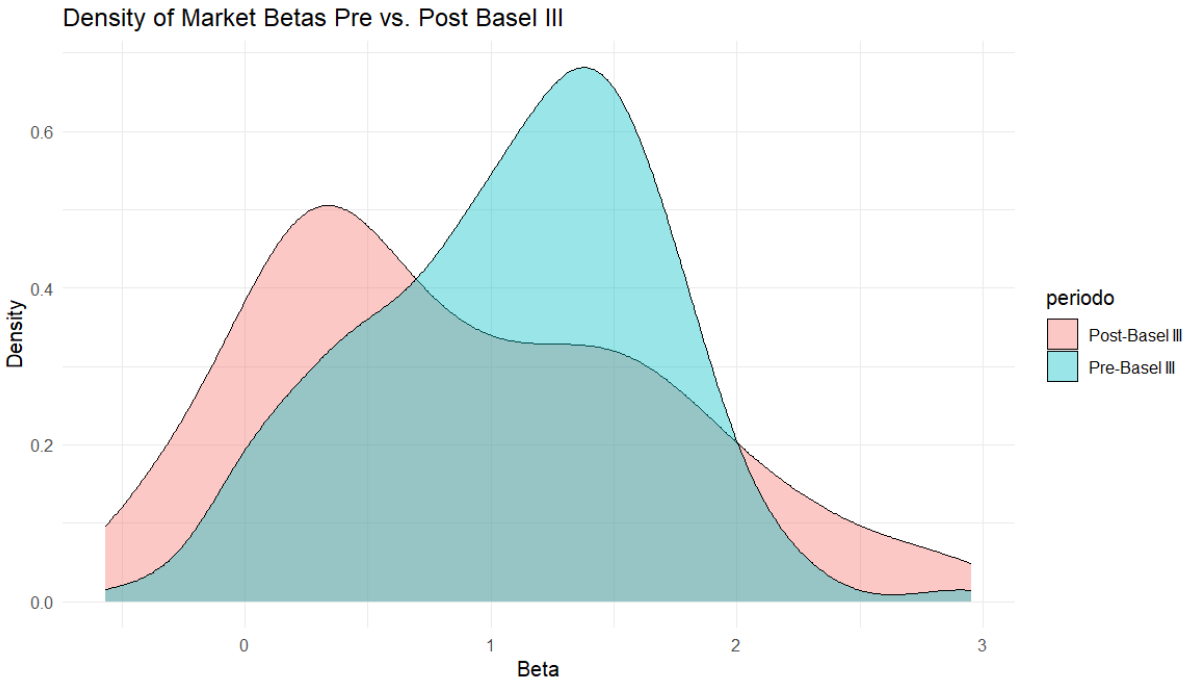



FIGURE 7. A10 - Kernel density estimates of market betas for banks before and after Basel III.

## B - Structural Breaks and Temporal Segmentation

This appendix expands on the analysis of structural breaks that was only briefly mentioned in the main body of the thesis. The purpose of this additional material is to provide full transparency regarding the statistical tests, graphical diagnostics, and alternative hypotheses for structural change. The analysis is based on the Bai and Perron methodology, which allows for the estimation of multiple breakpoints in linear regression models. Both a simple specification (only market returns) and a more complete specification (including bank-level fundamentals) were estimated in order to capture different possible drivers of instability.

### Overview of the Results

The results confirm the existence of multiple episodes of structural change over the sample period. However, the precise location of the breaks depends on the model specification:

- In the **simple model**, the strongest breaks appear around 2008 and 2012, coinciding with the Global Financial Crisis and the European Sovereign Debt Crisis. A further break is suggested in 2015–2017, which is broadly consistent with the start of Basel III implementation.
- In the **extended model**, which includes bank-level controls such as capital adequacy, loan quality and leverage, the breaks are estimated later, in 2015 and 2019. These dates correspond to the consolidation of Basel III regulation and the pre-COVID period, respectively.
- A **breakpoint around 2014** was also retained as a relevant reference. Although not explicitly highlighted by all model specifications, it coincides with the official entry into force of Basel III rules in Europe and therefore represents a natural institutional benchmark consistent with the regulatory context.

### Interpretation of Break Episodes

The identification of 2008 as a breakpoint is unsurprising. This date marks the collapse of Lehman Brothers and the intensification of the Global Financial Crisis, which had a profound effect on European banks' equity valuations. The estimated break around 2012 is consistent with the Sovereign Debt Crisis, particularly the turbulence in Southern Europe, which placed further pressure on the banking sector. These earlier breaks confirm that market-driven turmoil is strongly reflected in the cost of equity dynamics.

The later breaks around 2014–2015 can be interpreted in two complementary ways. On the one hand, they coincide with the introduction of Basel III capital requirements, signalling that regulatory tightening may have altered investors' risk assessments. On the other hand, the evidence of breaks around 2015–2017 also reflects a recovery phase, in which bank profitability and capital positions started to improve, changing the relationship between stock returns and market factors.

The 2019 breakpoint suggested by the extended model is more difficult to interpret. It may reflect early signals of macroeconomic slowdown in Europe and heightened uncertainty in financial markets, later amplified by the outbreak of COVID-19 in 2020. Although the pandemic itself falls outside the estimation window of some models, the structural change may already have been underway by late 2019.

### Model Dependence and Robustness

A key insight is that the exact location of structural breaks is not unique: the simple model, dominated by market dynamics, highlights crisis-driven episodes, whereas the extended model, which accounts for bank fundamentals, shifts attention towards regulatory and structural factors. This divergence suggests that the estimation of breakpoints is inherently model-dependent. The Bai and Perron method captures the presence of significant shifts but does not by itself identify their economic causes. As such, interpreting the breaks requires a combination of statistical evidence and contextual knowledge.

### Adopted Breakpoint for the Thesis

Given these alternative possibilities, and in order to maintain coherence with the main research question on the effects of Basel III, the thesis adopts 2014–2015 as the structural breakpoint. This choice balances the statistical evidence (which places breaks within this window in both specifications) with the institutional reality of regulatory implementation. The earlier breaks are acknowledged as important episodes of financial instability, but they are not the primary focus of the thesis, which is centred on the regulatory framework.

### Complete Results

The full outputs of the breakpoint analysis, including F-statistics, confidence intervals, information criteria, regression estimates by segment, and graphical diagnostics, are reported in the following tables and figures. These results allow readers to assess the robustness of the estimated breakpoints and to compare the implications of different specifications.

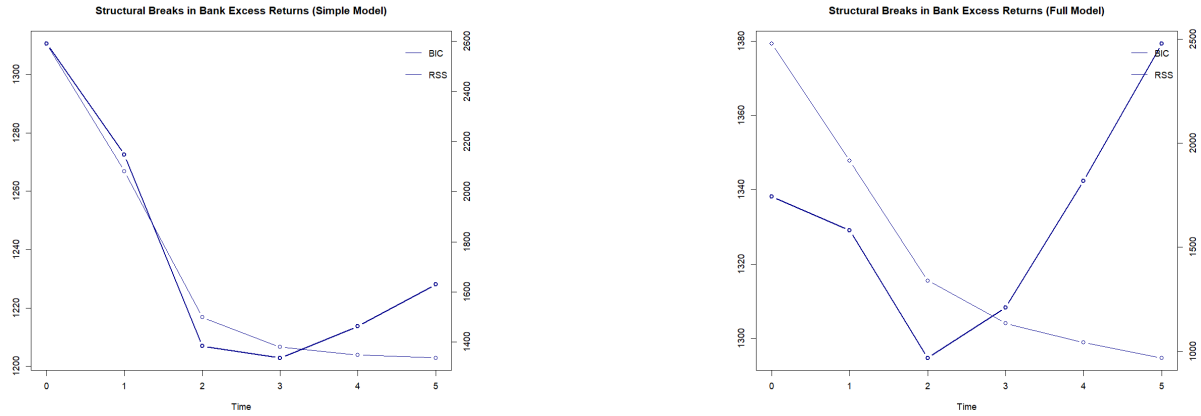



FIGURE 8. B1 - Bayesian Information Criterion (BIC) and Residual Sum of Squares (RSS) for candidate breakpoints.

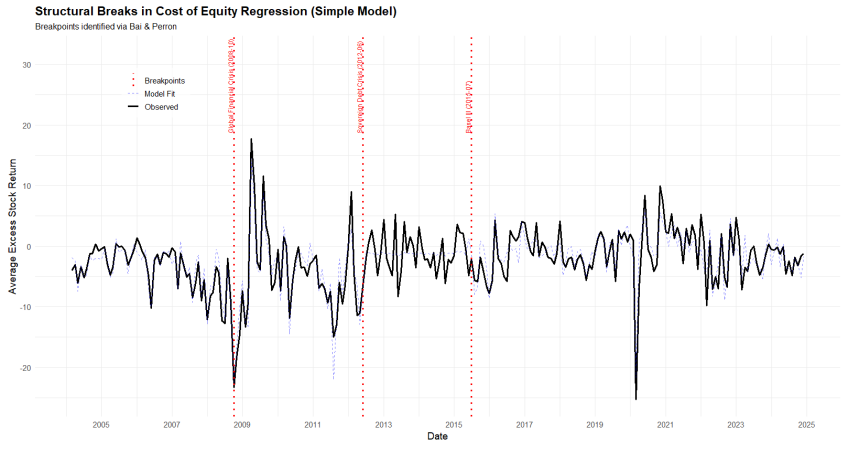



FIGURE 9. B2 - Structural breaks in the cost of equity regression (Simple Model

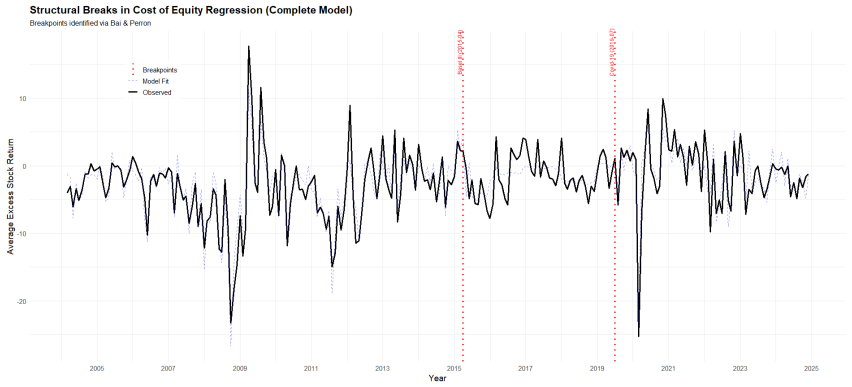



FIGURE 10. B3 - Structural breaks in the cost of equity regression (Complet Model

| Break Date | BIC | Adj. $R^2$ | Model | Breaks |
|---|---|---|---|---|
| 2015-04, 2019-07 | 1247 | 0.766 | Full | Full Model |
| 2008-10, 2012-06, 2015-07 | 1219 | 0.768 | Full | Simple Model |
| 2014-01 | 1306 | 0.669 | Full | Manual Cut |
| 2008-10, 2012-06, 2015-07 | 1165 | 0.762 | Simple | Simple Model |
| 2015-04, 2019-07 | 1198 | 0.750 | Simple | Full Model |
| 2014-01 | 1255 | 0.661 | Simple | Manual Cut |

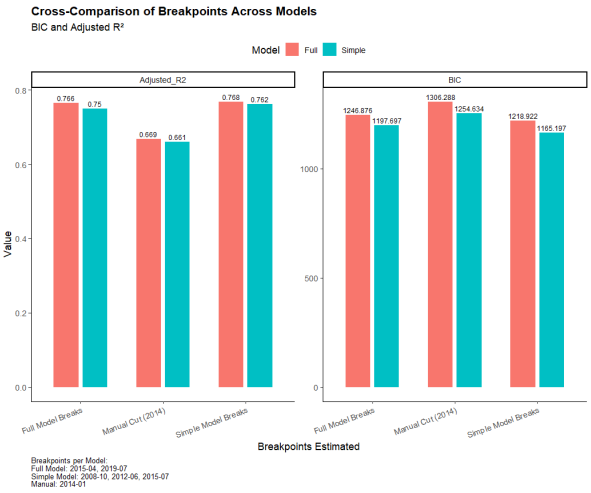



FIGURE 11. B4 - Comparison of diferent structural break specifications BIC and adjusted $R^2$ for different models.

TABLE 4. B5 - Panel regression results with pre- and post-2014 dummy (baseline and complete specifications)

| | | **OLS (pooled)** | | | **FE (within)** | | | **RE** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Period | Spec | Est. | Std. Err. | $p$-val | Est. | Std. Err. | $p$-val | Est. | Std. Err. | $p$-val |
| **Baseline** | Intercept | -0.427 | 0.745 | 0.566 | – | – | – | -0.447 | 0.785 | 0.569 |
| | Excess Market | 0.905 | $0.023 < 2.2 \times 10^{-16}$ | | 0.919 | $0.023 < 2.2 \times 10^{-16}$ | | 0.908 | $0.023 < 2.2 \times 10^{-16}$ | |
| | Dummy (pre=1) | -0.959 | 1.076 | 0.373 | -0.896 | 1.070 | 0.403 | -0.948 | 1.070 | 0.375 |
| | $R^2$ | | 0.357 | | | 0.369 | | | 0.360 | |
| | Adj. $R^2$ | | 0.357 | | | 0.337 | | | 0.359 | |
| | Global test | F=780.6, $p < 2.2 \times 10^{-16}$ | | | F=783.3, $p < 2.2 \times 10^{-16}$ | | | $\chi^2 = 1576.2$, $p < 2.2 \times 10^{-16}$ | | |
| **Complete** | Intercept | 5.985 | 5.432 | 0.271 | – | – | – | 5.985 | 5.432 | 0.271 |
| | Excess Market | 1.067 | $0.034 < 2.2 \times 10^{-16}$ | | 1.086 | $0.035 < 2.2 \times 10^{-16}$ | | 1.067 | $0.034 < 2.2 \times 10^{-16}$ | |
| | LLP / Equity | -2.972 | 3.797 | 0.434 | -6.054 | 4.062 | 0.136 | -2.972 | 3.797 | 0.434 |
| | Total Capital Adequacy | 66.086 | 51.236 | 0.197 | -14.903 | 70.884 | 0.834 | 66.086 | 51.236 | 0.197 |
| | Tier 1 Capital Adequacy | -82.326 | 47.522 | 0.083 | 95.087 | 73.790 | 0.198 | -82.326 | 47.522 | 0.083 |
| | NPL / Loans | -30.263 | 8.960 | 0.00075 | -37.287 | 11.769 | 0.00157 | -30.263 | 8.960 | 0.00073 |
| | RWA / Assets | -2.930 | 4.794 | 0.541 | 9.113 | 7.827 | 0.244 | -2.930 | 4.794 | 0.541 |
| | Debt / Equity | -1.149 | 0.322 | 0.00038 | -1.256 | 0.558 | 0.024 | -1.149 | 0.322 | 0.00037 |
| | FCF / Income | -0.0103 | 0.00765 | 0.177 | -0.0231 | 0.00892 | 0.0098 | -0.0103 | 0.00765 | 0.176 |
| | Dummy (pre=1) | -1.783 | 1.887 | 0.345 | 2.207 | 2.222 | 0.321 | -1.783 | 1.887 | 0.345 |
| | $R^2$ | | 0.397 | | | 0.417 | | | 0.397 | |
| | Adj. $R^2$ | | 0.394 | | | 0.368 | | | 0.394 | |
| | Global test | F=113.2, $p < 2.2 \times 10^{-16}$ | | | F=114.0, $p < 2.2 \times 10^{-16}$ | | | $\chi^2 = 1019.0$, $p < 2.2 \times 10^{-16}$ | | |

*Notes:* FE intercept absorbed by individual effects. LLP/Equity = Loan Loss Provision to Equity; NPL/Loans = Non-performing Loans to Net Loans; RWA/Assets = Risk-weighted Assets to Total Assets; FCF/Income = Free Cash Flow to Bank Income. Dummy = 1 for pre-2014, 0 otherwise.

## C - Results of Classical Models

TABLE 5. C1 - Regression results of baseline and extended CAPM models (OLS, Fixed Effects, Random Effects), pre-2014 and post-2014

| Model | Period | Param. | Estimate | Std. Err. | Stat. | $p$-val | $R^2$ | Adj. $R^2$ | TSS | RSS | Global Test | Var(idio.) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Baseline CAPM (Market Beta Only)** | | | | | | | | | | | | |
| OLS | Pre-2014 | Const. | -1.304 | 0.864 | -1.510 | 0.131 | 0.426 | 0.426 | 2,160,400 | 1,239,300 | $F(1, 1304) = 969.3^{***}$ | — |
| | | Excess Mkt | 0.885 | 0.028 | 31.13 | $< 2e{-}16$ | | | | | | |
| OLS | Post-2014 | Const. | -0.759 | 0.717 | -1.059 | 0.290 | 0.244 | 0.243 | 1,352,400 | 1,023,000 | $F(1, 1482) = 477.2^{***}$ | — |
| | | Excess Mkt | 0.966 | 0.044 | 21.84 | $< 2e{-}16$ | | | | | | |
| Fixed | Pre-2014 | Const. | (absorbed) | — | — | — | 0.466 | 0.404 | 2,004,800 | 1,070,400 | $F(1, 1170) = 1021.3^{***}$ | — |
| | | Excess Mkt | 0.923 | 0.029 | 31.96 | $< 2.2e{-}16$ | | | | | | |
| Fixed | Post-2014 | Const. | (absorbed) | — | — | — | 0.253 | 0.179 | 1,262,900 | 942,870 | $F(1, 1348) = 457.6^{***}$ | — |
| | | Excess Mkt | 0.988 | 0.046 | 21.39 | $< 2.2e{-}16$ | | | | | | |
| Random | Pre-2014 | Const. | -1.318 | 0.932 | -1.414 | 0.157 | 0.432 | 0.432 | 2,135,000 | 1,212,300 | $\chi^2(1) = 992.6^{***}$ | 914.9 |
| | | Excess Mkt | 0.890 | 0.028 | 31.51 | $< 2e{-}16$ | | | | | | |
| Random | Post-2014 | Const. | -0.759 | 0.717 | -1.059 | 0.290 | 0.244 | 0.243 | 1,352,400 | 1,023,000 | $\chi^2(1) = 477.2^{***}$ | 699.5 |
| | | Excess Mkt | 0.966 | 0.044 | 21.84 | $< 2e{-}16$ | | | | | | |
| **Extended CAPM (Market Beta + Bank Fundamentals)** | | | | | | | | | | | | |
| OLS | Pre-2014 | Const. | 6.606 | 8.419 | 0.785 | 0.433 | 0.513 | 0.505 | 923,380 | 449,640 | $F(8, 508) = 66.9^{***}$ | — |
| | | Excess Mkt | 1.008 | 0.047 | 21.61 | $< 2.2e{-}16$ | | | | | | |
| | | LLP/Equity | -17.898 | 8.304 | -2.155 | 0.032* | | | | | | |
| | | Tot. Cap. Adeq. | 5.105 | 76.810 | 0.067 | 0.947 | | | | | | |
| | | Tier1 Adeq. | 0.975 | 69.515 | 0.014 | 0.989 | | | | | | |
| | | NPL/Loans | 13.411 | 16.667 | 0.805 | 0.421 | | | | | | |
| | | RWA/Assets | -9.013 | 7.449 | -1.210 | 0.227 | | | | | | |
| | | Debt/Equity | -1.389 | 0.505 | -2.749 | 0.006** | | | | | | |
| | | FCF/Income | 0.706 | 1.364 | 0.518 | 0.605 | | | | | | |
| OLS | Post-2014 | Const. | 2.612 | 6.731 | 0.388 | 0.698 | 0.307 | 0.301 | 985,830 | 683,550 | $F(8, 1018) = 56.3^{***}$ | — |
| | | Excess Mkt | 1.144 | 0.056 | 20.28 | $< 2.2e{-}16$ | | | | | | |
| | | LLP/Equity | 1.335 | 4.159 | 0.321 | 0.748 | | | | | | |
| | | Tot. Cap. Adeq. | 166.31 | 73.586 | 2.260 | 0.024* | | | | | | |
| | | Tier1 Adeq. | -198.31 | 68.786 | -2.883 | 0.004** | | | | | | |
| | | NPL/Loans | -54.878 | 10.781 | -5.091 | $< 1e{-}6$ *** | | | | | | |
| | | RWA/Assets | 6.668 | 6.469 | 1.031 | 0.303 | | | | | | |
| | | Debt/Equity | -0.852 | 0.436 | -1.953 | 0.051. | | | | | | |
| | | FCF/Income | -0.009 | 0.007 | -1.293 | 0.196 | | | | | | |
| Fixed | Pre-2014 | Const. | (absorbed) | — | — | — | 0.563 | 0.463 | 835,220 | 364,810 | $F(8, 420) = 67.7^{***}$ | — |
| | | Excess Mkt | 1.041 | 0.049 | 21.35 | $< 2.2e{-}16$ | | | | | | |
| | | LLP/Equity | -16.677 | 8.860 | -1.882 | 0.061. | | | | | | |
| | | Tot. Cap. Adeq. | -148.17 | 149.01 | -0.994 | 0.321 | | | | | | |
| | | Tier1 Adeq. | 291.21 | 137.28 | 2.121 | 0.034* | | | | | | |
| | | NPL/Loans | -2.217 | 21.021 | -0.106 | 0.916 | | | | | | |
| | | RWA/Assets | 12.827 | 13.065 | 0.982 | 0.327 | | | | | | |
| | | Debt/Equity | -0.092 | 0.984 | -0.093 | 0.926 | | | | | | |
| | | FCF/Income | -0.583 | 1.539 | -0.379 | 0.705 | | | | | | |
| Fixed | Post-2014 | Const. | (absorbed) | — | — | — | 0.327 | 0.239 | 934,620 | 629,440 | $F(8, 908) = 55.0^{***}$ | — |
| | | Excess Mkt | 1.168 | 0.060 | 19.63 | $< 2.2e{-}16$ | | | | | | |
| | | LLP/Equity | -3.061 | 4.723 | -0.648 | 0.517 | | | | | | |
| | | Tot. Cap. Adeq. | 228.48 | 134.41 | 1.700 | 0.089. | | | | | | |
| | | Tier1 Adeq. | -169.88 | 141.11 | -1.204 | 0.229 | | | | | | |
| | | NPL/Loans | -60.169 | 16.920 | -3.556 | 0.0004*** | | | | | | |
| | | RWA/Assets | 12.105 | 14.718 | 0.823 | 0.411 | | | | | | |
| | | Debt/Equity | -1.455 | 1.734 | -0.839 | 0.402 | | | | | | |
| | | FCF/Income | -0.022 | 0.009 | -2.497 | 0.013* | | | | | | |
| Random | Pre-2014 | Const. | 6.606 | 8.419 | 0.785 | 0.433 | 0.513 | 0.505 | 923,380 | 449,640 | $\chi^2(8) = 535.2^{***}$ | 868.6 |
| | | Excess Mkt | 1.008 | 0.047 | 21.61 | $< 2.2e{-}16$ | | | | | | |
| | | LLP/Equity | -17.898 | 8.304 | -2.155 | 0.031* | | | | | | |
| | | Tot. Cap. Adeq. | 5.105 | 76.810 | 0.067 | 0.947 | | | | | | |
| | | Tier1 Adeq. | 0.975 | 69.515 | 0.014 | 0.989 | | | | | | |
| | | NPL/Loans | 13.411 | 16.667 | 0.805 | 0.421 | | | | | | |
| | | RWA/Assets | -9.013 | 7.449 | -1.210 | 0.227 | | | | | | |
| | | Debt/Equity | -1.389 | 0.505 | -2.749 | 0.006** | | | | | | |
| | | FCF/Income | 0.706 | 1.364 | 0.518 | 0.605 | | | | | | |
| Random | Post-2014 | Const. | 2.612 | 6.731 | 0.388 | 0.698 | 0.307 | 0.301 | 985,830 | 683,550 | $\chi^2(8) = 450.2^{***}$ | 693.2 |
| | | Excess Mkt | 1.144 | 0.056 | 20.28 | $< 2.2e{-}16$ | | | | | | |
| | | LLP/Equity | 1.335 | 4.159 | 0.321 | 0.748 | | | | | | |
| | | Tot. Cap. Adeq. | 166.31 | 73.586 | 2.260 | 0.024* | | | | | | |
| | | Tier1 Adeq. | -198.31 | 68.786 | -2.883 | 0.004** | | | | | | |
| | | NPL/Loans | -54.878 | 10.781 | -5.091 | $< 1e{-}6$ *** | | | | | | |
| | | RWA/Assets | 6.668 | 6.469 | 1.031 | 0.303 | | | | | | |
| | | Debt/Equity | -0.852 | 0.436 | -1.953 | 0.051. | | | | | | |
| | | FCF/Income | -0.009 | 0.007 | -1.293 | 0.196 | | | | | | |

Notes: Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. LLP = Loan Loss Provisions. Tot. Cap. Adeq. = Total Capital Adequacy. Tier1 Adeq. = Tier 1 Capital Adequacy. NPL = Non-performing Loans. RWA = Risk-Weighted Assets. FCF = Free Cash Flow. In Fixed Effects models the intercept is absorbed. Random Effects include idiosyncratic variance (Var(idio.)).

TABLE 6. C2 - Time fixed-effects regressions (baseline and extended), pre-2014 and post-2014

| Model | Period | Param. | Estimate | Std. Err. | Stat. | $p$-val | $R^2$ | Adj. $R^2$ | TSS | RSS | Global $F$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Baseline with Time Fixed Effects** | | | | | | | | | | | |
| FE (time) | Pre-2014 | Excess Mkt | 0.473 | 0.048 | 9.810 | $< 2.2e{-}16 * **$ | 0.546 | 0.489 | 2,004,800 | 911,060 | $F(10, 1161) = 139.38^{***}$ |
| | | Date2005 | 0.255 | 3.693 | 0.069 | 0.945 | | | | | |
| | | Date2006 | -1.350 | 3.586 | -0.377 | 0.707 | | | | | |
| | | Date2007 | -20.429 | 3.674 | -5.560 | $3.35e{-}08 * **$ | | | | | |
| | | Date2008 | -41.685 | 4.671 | -8.924 | $< 2.2e{-}16 * **$ | | | | | |
| | | Date2009 | 13.574 | 3.672 | 3.697 | $0.00023^{***}$ | | | | | |
| | | Date2010 | -16.689 | 3.532 | -4.725 | $2.58e{-}06 * **$ | | | | | |
| | | Date2011 | -35.047 | 3.897 | -8.993 | $< 2.2e{-}16 * **$ | | | | | |
| | | Date2012 | -7.585 | 3.538 | -2.144 | $0.032*$ | | | | | |
| | | Date2013 | 5.437 | 3.532 | 1.539 | 0.124 | | | | | |
| FE (time) | Post-2014 | Excess Mkt | 0.871 | 0.060 | 14.445 | $< 2.2e{-}16 * **$ | 0.290 | 0.213 | 1,262,900 | 896,950 | $F(11, 1338) = 49.63^{***}$ |
| | | Date2015 | -0.248 | 3.166 | -0.078 | 0.938 | | | | | |
| | | Date2016 | 7.180 | 3.151 | 2.279 | $0.023*$ | | | | | |
| | | Date2017 | 5.369 | 3.210 | 1.673 | 0.095. | | | | | |
| | | Date2018 | 0.031 | 3.268 | 0.010 | 0.992 | | | | | |
| | | Date2019 | 2.347 | 3.266 | 0.719 | 0.473 | | | | | |
| | | Date2020 | -5.637 | 3.181 | -1.772 | 0.077. | | | | | |
| | | Date2021 | 15.104 | 3.316 | 4.555 | $5.71e{-}06 * **$ | | | | | |
| | | Date2022 | 7.871 | 3.240 | 2.430 | $0.015*$ | | | | | |
| | | Date2023 | 7.028 | 3.179 | 2.211 | $0.027*$ | | | | | |
| | | Date2024 | 12.657 | 3.151 | 4.016 | $6.24e{-}05 * **$ | | | | | |
| **Extended with Time Fixed Effects (Market + Bank Fundamentals)** | | | | | | | | | | | |
| FE (time) | Pre-2014 | Excess Mkt | 0.677 | 0.111 | 6.082 | $2.72e{-}09 * **$ | 0.604 | 0.502 | 835,220 | 331,020 | $F(17, 411) = 36.82^{***}$ |
| | | LLP/Equity | -22.762 | 8.933 | -2.548 | $0.011*$ | | | | | |
| | | Tot. Cap. Adeq. | -192.282 | 146.641 | -1.311 | 0.191 | | | | | |
| | | Tier1 Adeq. | 243.827 | 149.823 | 1.627 | 0.104 | | | | | |
| | | NPL/Loans | -5.219 | 20.572 | -0.254 | 0.800 | | | | | |
| | | RWA/Assets | 5.778 | 13.171 | 0.439 | 0.661 | | | | | |
| | | Debt/Equity | -0.223 | 0.975 | -0.229 | 0.819 | | | | | |
| | | FCF/Income | -0.429 | 1.497 | -0.287 | 0.774 | | | | | |
| | | Date2005 | 2.051 | 7.299 | 0.281 | 0.779 | | | | | |
| | | Date2006 | -4.172 | 7.182 | -0.581 | 0.562 | | | | | |
| | | Date2007 | -15.572 | 7.541 | -2.065 | $0.040*$ | | | | | |
| | | Date2008 | -26.580 | 10.389 | -2.559 | $0.011*$ | | | | | |
| | | Date2009 | 13.850 | 7.798 | 1.776 | 0.076. | | | | | |
| | | Date2010 | -9.440 | 7.076 | -1.334 | 0.183 | | | | | |
| | | Date2011 | -26.594 | 8.243 | -3.226 | $0.001**$ | | | | | |
| | | Date2012 | -0.935 | 7.354 | -0.127 | 0.899 | | | | | |
| | | Date2013 | 10.336 | 7.520 | 1.375 | 0.170 | | | | | |
| FE (time) | Post-2014 | Excess Mkt | 1.119 | 0.082 | 13.655 | $< 2.2e{-}16 * **$ | 0.356 | 0.264 | 934,620 | 602,220 | $F(18, 898) = 27.54^{***}$ |
| | | LLP/Equity | -1.418 | 4.701 | -0.302 | 0.763 | | | | | |
| | | Tot. Cap. Adeq. | 205.62 | 133.10 | 1.545 | 0.123 | | | | | |
| | | Tier1 Adeq. | -174.28 | 139.57 | -1.249 | 0.212 | | | | | |
| | | NPL/Loans | -53.768 | 16.853 | -3.191 | $0.001**$ | | | | | |
| | | RWA/Assets | 22.920 | 14.875 | 1.541 | 0.124 | | | | | |
| | | Debt/Equity | -1.028 | 1.730 | -0.594 | 0.553 | | | | | |
| | | FCF/Income | -0.019 | 0.009 | -2.185 | $0.029*$ | | | | | |
| | | Date2015 | -5.426 | 4.083 | -1.329 | 0.184 | | | | | |
| | | Date2016 | -2.596 | 4.172 | -0.622 | 0.534 | | | | | |
| | | Date2017 | -3.131 | 4.310 | -0.726 | 0.468 | | | | | |
| | | Date2018 | -3.834 | 4.235 | -0.905 | 0.366 | | | | | |
| | | Date2019 | -5.714 | 4.336 | -1.318 | 0.188 | | | | | |
| | | Date2020 | -11.799 | 4.466 | -2.642 | $0.008**$ | | | | | |
| | | Date2021 | 4.772 | 4.714 | 1.012 | 0.312 | | | | | |
| | | Date2022 | 4.453 | 4.605 | 0.967 | 0.334 | | | | | |
| | | Date2023 | 2.608 | 4.581 | 0.569 | 0.569 | | | | | |
| | | Date2024 | 7.372 | 4.643 | 1.588 | 0.113 | | | | | |

Notes: Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, "." $p < 0.15$. FE (time) = individual fixed effects with year dummies.

TABLE 7. Diagnostic tests for baseline and complete models with and without time dummies (pre-2014 and post-2014)

| Period | Spec | Model | Test | Statistic | df | p-value |
|---|---|---|---|---|---|---|
| Pre-2014 | Baseline | OLS | Breusch–Pagan | 198.83 | 1 | $< 2.2e{-}16$ |
| Pre-2014 | Baseline | OLS | Pesaran CD | 24.909 | – | $< 2.2e{-}16$ |
| Pre-2014 | Baseline | FE | Pesaran CD | 22.805 | – | $< 2.2e{-}16$ |
| Pre-2014 | Baseline | RE | Pesaran CD | 24.571 | – | $< 2.2e{-}16$ |
| Pre-2014 | Baseline | OLS | Durbin–Watson | 1.877 | – | 0.0130 |
| Pre-2014 | Baseline | FE | Durbin–Watson | 2.136 | – | 0.994 |
| Pre-2014 | Baseline | RE | Durbin–Watson | 1.913 | – | 0.059 |
| Pre-2014 | Baseline | FE vs RE | Hausman | 29.972 | 1 | $4.38e{-}08$ |
| Pre-2014 | Baseline | FE (time dummies) | Breusch–Pagan | 197.16 | 10 | $< 2.2e{-}16$ |
| Pre-2014 | Baseline | FE (time dummies) | Pesaran CD | -1.392 | – | 0.164 |
| Pre-2014 | Baseline | FE (time dummies) | Durbin–Watson | 2.128 | – | 0.991 |
| Pre-2014 | Baseline | FE (time dummies) | Joint F-test time dummies | 22.564 | 9 | $< 2.2e{-}16$ |
| Pre-2014 | Complete | OLS | Breusch–Pagan | 82.22 | 8 | $1.75e{-}14$ |
| Pre-2014 | Complete | OLS | Pesaran CD | 8.105 | – | $5.27e{-}16$ |
| Pre-2014 | Complete | FE | Pesaran CD | 6.759 | – | $1.39e{-}11$ |
| Pre-2014 | Complete | RE | Pesaran CD | 8.105 | – | $5.27e{-}16$ |
| Pre-2014 | Complete | OLS | Durbin–Watson | 2.021 | – | 0.544 |
| Pre-2014 | Complete | FE | Durbin–Watson | 2.280 | – | 0.999 |
| Pre-2014 | Complete | RE | Durbin–Watson | 2.021 | – | 0.544 |
| Pre-2014 | Complete | FE vs RE | Hausman | 31.714 | 8 | 0.000105 |
| Pre-2014 | Complete | FE (time dummies) | Breusch–Pagan | 119.43 | 17 | $< 2.2e{-}16$ |
| Pre-2014 | Complete | FE (time dummies) | Pesaran CD | -1.112 | – | 0.266 |
| Pre-2014 | Complete | FE (time dummies) | Durbin–Watson | 2.268 | – | 0.999 |
| Pre-2014 | Complete | FE (time dummies) | Joint F-test time dummies | 4.662 | 9 | $6.75e{-}06$ |
| Post-2014 | Baseline | OLS | Breusch–Pagan | 19.493 | 1 | $1.01e{-}05$ |
| Post-2014 | Baseline | OLS | Pesaran CD | 16.100 | – | $< 2.2e{-}16$ |
| Post-2014 | Baseline | FE | Pesaran CD | 16.001 | – | $< 2.2e{-}16$ |
| Post-2014 | Baseline | RE | Pesaran CD | 16.100 | – | $< 2.2e{-}16$ |
| Post-2014 | Baseline | OLS | Durbin–Watson | 1.909 | – | 0.040 |
| Post-2014 | Baseline | FE | Durbin–Watson | 2.059 | – | 0.881 |
| Post-2014 | Baseline | RE | Durbin–Watson | 1.909 | – | 0.040 |
| Post-2014 | Baseline | FE vs RE | Hausman | 2.593 | 1 | 0.107 |
| Post-2014 | Baseline | FE (time dummies) | Breusch–Pagan | 37.747 | 11 | $8.63e{-}05$ |
| Post-2014 | Baseline | FE (time dummies) | Pesaran CD | 1.569 | – | 0.117 |
| Post-2014 | Baseline | FE (time dummies) | Durbin–Watson | 2.057 | – | 0.873 |
| Post-2014 | Baseline | FE (time dummies) | Joint F-test time dummies | 6.851 | 10 | $1.67e{-}10$ |
| Post-2014 | Complete | OLS | Breusch–Pagan | 113.17 | 8 | $< 2.2e{-}16$ |
| Post-2014 | Complete | OLS | Pesaran CD | 12.500 | – | $< 2.2e{-}16$ |
| Post-2014 | Complete | FE | Pesaran CD | 12.291 | – | $< 2.2e{-}16$ |
| Post-2014 | Complete | RE | Pesaran CD | 12.500 | – | $< 2.2e{-}16$ |
| Post-2014 | Complete | OLS | Durbin–Watson | 1.969 | – | 0.270 |
| Post-2014 | Complete | FE | Durbin–Watson | 2.083 | – | 0.904 |
| Post-2014 | Complete | RE | Durbin–Watson | 1.969 | – | 0.270 |
| Post-2014 | Complete | FE vs RE | Hausman | 16.655 | 8 | 0.0339 |
| Post-2014 | Complete | FE (time dummies) | Breusch–Pagan | 141.13 | 18 | $< 2.2e{-}16$ |
| Post-2014 | Complete | FE (time dummies) | Pesaran CD | 0.951 | – | 0.342 |
| Post-2014 | Complete | FE (time dummies) | Durbin–Watson | 2.135 | – | 0.984 |
| Post-2014 | Complete | FE (time dummies) | Joint F-test time dummies | 4.059 | 10 | $1.78e{-}05$ |

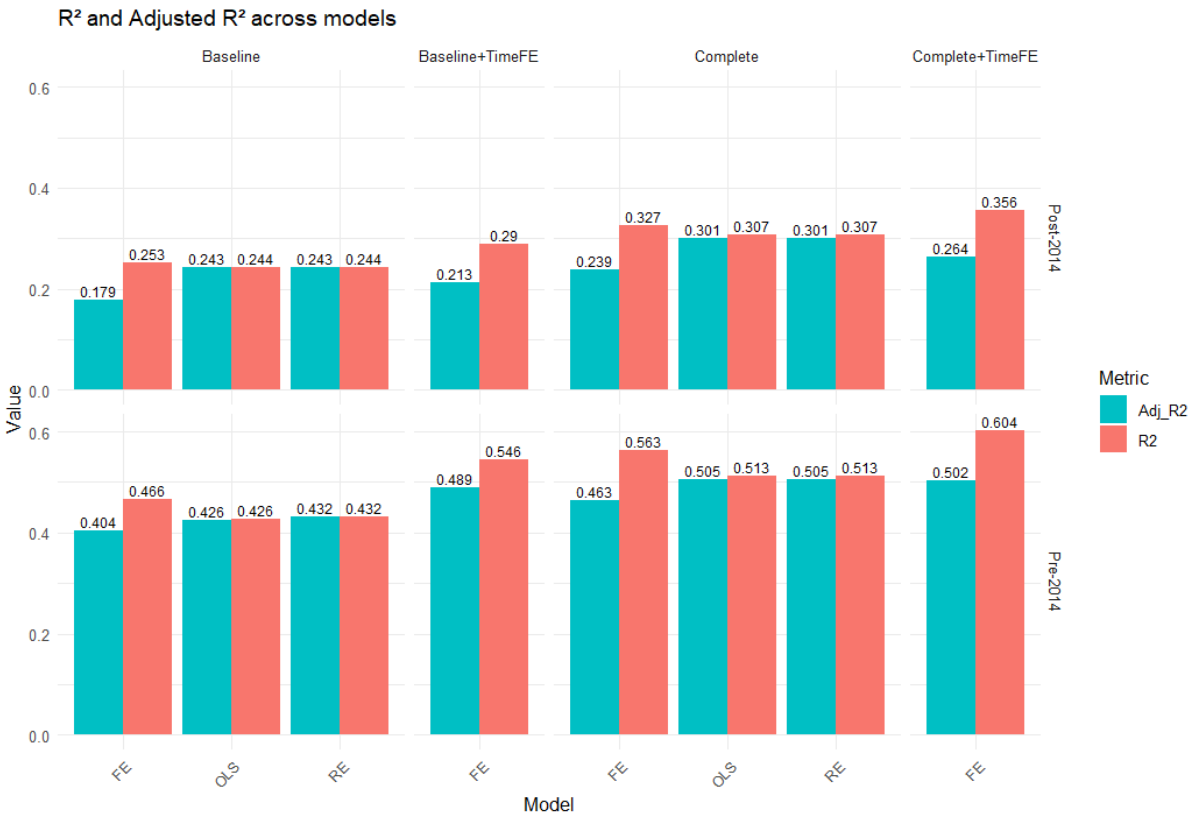



FIGURE 12. Coefficients of determination ($R^2$) and adjusted $R^2$ for pooled OLS, fixed effects, random effects, and time–fixed effects specifications, across baseline and complete models in the pre-2014 and post-2014 periods

**D - Results of Dynamic Panel Models**

TABLE 8. D1 - Dynamic FE and RE estimations

| Variable | Estimate | Std. Error | p-value |
|---|---|---|---|
| **Post-2014 — Baseline — FE (dynamic)** | $R^2 = 0.2612$, Adj.$R^2 = 0.1782$, $N = 1214$ | | |
| MKT | 1.022234 | 0.05170646 | 1.29e-75 |
| L.excess | -0.0008398048 | 0.02617622 | 0.9744114 |
| **Post-2014 — Baseline — RE (dynamic)** | $R^2 = 0.2509$, Adj.$R^2 = 0.2498$, $N = 1349$ | | |
| (Intercept) | -0.8304548 | 0.7826929 | 0.2886797 |
| MKT | 1.026554 | 0.04897055 | 1.44e-97 |
| L.excess | 0.05298764 | 0.02464916 | 0.03158105 |
| **Post-2014 — Complete — FE (dynamic)** | $R^2 = 0.3270$, Adj.$R^2 = 0.2318$, $N = 830$ | | |
| CAR(T1) | -215.7481 | 161.8878 | 0.1830001 |
| CAR(Tot) | 308.3099 | 153.1591 | 0.0444406 |
| D/E | -1.706126 | 1.951901 | 0.3823285 |
| FCF/Inc | -0.02422661 | 0.009345823 | 0.009705072 |
| LLP/Eq | -3.144482 | 5.0+21806 | 0.5313806 |
| NPL/Loans | -65.33589 | 20.37532 | 0.001395112 |
| RWA/TA | 27.06719 | 21.06002 | 0.1990712 |
| MKT | 1.181536 | 0.06681873 | 1.60e-59 |
| L.excess | 0.009014167 | 0.03457821 | 0.7943976 |
| **Post-2014 — Complete — RE (dynamic)** | $R^2 = 0.3113$, Adj.$R^2 = 0.3046$, $N = 938$ | | |
| (Intercept) | 1.600563 | 7.191224 | 0.8238689 |
| CAR(T1) | -231.2331 | 75.09211 | 0.002074697 |
| CAR(Tot) | 195.7579 | 80.21837 | 0.01467454 |
| D/E | -0.9345437 | 0.4717576 | 0.04759319 |
| FCF/Inc | -0.01048996 | 0.007521821 | 0.1631355 |
| LLP/Eq | 1.439585 | 4.327158 | 0.7393712 |
| NPL/Loans | -57.28631 | 12.49498 | 4.55e-06 |
| RWA/TA | 9.119718 | 7.270597 | 0.2097225 |
| MKT | 1.183995 | 0.06220791 | 9.11e-81 |
| L.excess | 0.03448069 | 0.03155994 | 0.2745930 |
| **Pre-2014 — Baseline — FE (dynamic)** | $R^2 = 0.4801$, Adj.$R^2 = 0.4117$, $N = 1037$ | | |
| MKT | 0.9167690 | 0.03012211 | 8.59e-146 |
| L.excess | -0.07542176 | 0.02299207 | 0.001071447 |
| **Pre-2014 — Baseline — RE (dynamic)** | $R^2 = 0.4338$, Adj.$R^2 = 0.4328$, $N = 1172$ | | |
| (Intercept) | -2.017148 | 0.9228543 | 0.2883235 |
| MKT | 0.8865806 | 0.02970439 | 9.66e-196 |
| L.excess | -0.01528767 | 0.02248874 | 0.4966359 |
| **Pre-2014 — Complete — FE (dynamic)** | $R^2 = 0.5702$, Adj.$R^2 = 0.4650$, $N = 398$ | | |
| CAR(T1) | 290.4006 | 146.0993 | 0.04754807 |
| CAR(Tot) | -134.0155 | 158.4885 | 0.3983053 |
| D/E | -0.2310734 | 1.062912 | 0.8280137 |
| FCF/Inc | -0.4838834 | 1.620755 | 0.7654400 |
| LLP/Eq | -18.01598 | 9.186343 | 0.05057406 |
| NPL/Loans | -2.393064 | 26.91980 | 0.9292104 |

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| Variable | Estimate | Std. Error | p-value |
|---|---|---|---|
| RWA/TA | 15.28986 | 13.97955 | 0.2747519 |
| MKT | 1.031003 | 0.05096875 | 1.21e-62 |
| L.excess | -0.07190953 | 0.03511279 | 0.4123674 |
| **Pre-2014 — Complete — RE (dynamic)** | $R^2 = 0.5173$, Adj.$R^2 = 0.5082$, $N = 485$ | | |
| (Intercept) | 4.676882 | 8.852535 | 0.5972842 |
| CAR(T1) | 4.068668 | 74.62388 | 0.9565190 |
| CAR(Tot) | 16.24905 | 82.35560 | 0.8435900 |
| D/E | -1.282317 | 0.5313842 | 0.1581473 |
| FCF/Inc | 0.6755117 | 1.421086 | 0.6345383 |
| LLP/Eq | -19.39147 | 8.668299 | 0.02528268 |
| NPL/Loans | 14.64048 | 20.35198 | 0.4719168 |
| RWA/TA | -9.754782 | 7.928802 | 0.2185859 |
| MKT | 1.006610 | 0.04858811 | 2.42e-95 |
| L.excess | -0.03610140 | 0.03369930 | 0.2840434 |

TABLE 9. D2 - Arellano–Bond Difference GMM (2-step)

| Variable | Estimate | Std. Error | p-value |
|---|---|---|---|
| **Post-2014 — Baseline — AB Diff GMM** | | | |
| MKT | 1.031763 | 0.06613621 | 7.21e-55 |
| L.excess | 0.03139454 | 0.02936569 | 0.2850295 |
| **Post-2014 — Baseline — AB Diff GMM [collapsed]** | | | |
| MKT | 1.107050 | 0.1009743 | 5.71e-28 |
| L.excess | 0.04294127 | 0.04550619 | 0.3453557 |
| **Post-2014 — Complete — AB Diff GMM** | | | |
| CAR(T1) | 99.53843 | 245.2677 | 0.6848632 |
| CAR(Tot) | -22.40958 | 205.1154 | 0.9130014 |
| D/E | 1.517821 | 2.480329 | 0.5405750 |
| FCF/Inc | -0.06285478 | 0.005997655 | 1.07e-25 |
| LLP/Eq | -15.27333 | 4.676749 | 0.001091555 |
| NPL/Loans | -11.25855 | 10.65628 | 0.2907315 |
| RWA/TA | -9.898631 | 23.56414 | 0.6744330 |
| MKT | 1.250503 | 0.05950652 | 4.83e-98 |
| L.excess | 0.1031956 | 0.03580821 | 0.003952897 |
| **Post-2014 — Complete — AB Diff GMM [collapsed]** | | | |
| CAR(T1) | -64.28314 | 342.5713 | 0.8511519 |
| CAR(Tot) | 257.3304 | 267.0917 | 0.3353200 |
| D/E | 3.403454 | 3.193679 | 0.2865664 |
| FCF/Inc | -0.06927889 | 0.009438227 | 2.13e-13 |
| LLP/Eq | -19.26425 | 7.719463 | 0.01257647 |
| NPL/Loans | 5.919326 | 20.35490 | 0.7711997 |
| RWA/TA | 30.86940 | 46.06381 | 0.5027658 |
| MKT | 1.295095 | 0.09161714 | 2.28e-45 |
| L.excess | 0.1166187 | 0.04907447 | 0.1748426 |

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| Variable | Estimate | Std. Error | p-value |
|---|---|---|---|
| **Pre-2014 — Baseline — AB Diff GMM** | | | |
| MKT | 0.9928033 | 0.04377014 | 6.71e-114 |
| L.excess | -0.02355673 | 0.01457651 | 0.1060780 |
| **Pre-2014 — Baseline — AB Diff GMM [collapsed]** | | | |
| MKT | 1.124834 | 0.1172839 | 8.75e-22 |
| L.excess | 0.01046005 | 0.02610920 | 0.6886948 |
| **Pre-2014 — Complete — AB Diff GMM** | | | |
| CAR(T1) | -77.49023 | 162.4075 | 0.6332664 |
| CAR(Tot) | 286.9988 | 161.4051 | 0.0753830 |
| D/E | 0.9737844 | 1.107249 | 0.3791502 |
| FCF/Inc | -4.711981 | 2.153319 | 0.2865203 |
| LLP/Eq | -22.92789 | 3.545983 | 1.01e-10 |
| NPL/Loans | 30.11020 | 22.46753 | 0.1801916 |
| RWA/TA | 13.19416 | 15.71061 | 0.4010068 |
| MKT | 1.008231 | 0.05703575 | 6.29e-70 |
| L.excess | -0.05782833 | 0.02139700 | 0.006879180 |
| **Pre-2014 — Complete — AB Diff GMM [collapsed]** | | | |
| CAR(T1) | 94.42629 | 221.8300 | 0.6703486 |
| CAR(Tot) | 152.8420 | 200.2665 | 0.4453483 |
| D/E | 0.6294305 | 1.427782 | 0.6593253 |
| FCF/Inc | -4.204429 | 2.464113 | 0.4736523 |
| LLP/Eq | -14.89872 | 9.042393 | 0.09942413 |
| NPL/Loans | -8.818345 | 28.54916 | 0.7574107 |
| RWA/TA | 6.961700 | 18.08618 | 0.7002980 |
| MKT | 1.016724 | 0.08949189 | 6.53e-30 |
| L.excess | -0.001926022 | 0.04262131 | 0.9639565 |

TABLE 10. D3 - Blundell–Bond System GMM (2-step)

| Variable | Estimate | Std. Error | p-value |
|---|---|---|---|
| **Post-2014 — Baseline — Blundell–Bond Sys GMM** | | | |
| MKT | 0.9678260 | 0.05851928 | 1.94e-61 |
| L.excess | 0.05246413 | 0.01540814 | 0.0006617303 |
| **Post-2014 — Baseline — Blundell–Bond Sys GMM [collapsed]** | | | |
| MKT | 0.9933583 | 0.08322749 | 7.73e-33 |
| L.excess | -0.007954647 | 0.03708919 | 0.8301779 |
| **Post-2014 — Complete — Blundell–Bond Sys GMM** | | | |
| CAR(T1) | -208.0728 | 33.65227 | 6.29e-10 |
| CAR(Tot) | 180.4427 | 31.53818 | 1.06e-08 |
| D/E | -0.6643187 | 0.1999808 | 0.0008940265 |
| FCF/Inc | -0.01191169 | 0.0006571953 | 2.02e-73 |
| LLP/Eq | 0.9394285 | 0.4880808 | 0.05426192 |
| NPL/Loans | -51.15135 | 3.580889 | 2.73e-46 |
| RWA/TA | 7.706775 | 2.659160 | 0.003753118 |

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| Variable | Estimate | Std. Error | p-value |
|---|---|---|---|
| MKT | 1.146765 | 0.03197443 | 1.07e-281 |
| L.excess | 0.07007093 | 0.01643806 | 0.0000201949 |
| **Post-2014 — Complete — Blundell–Bond Sys GMM [collapsed]** | | | |
| CAR(T1) | -209.7824 | 47.74379 | 1.11e-05 |
| CAR(Tot) | 181.6071 | 44.45152 | 4.40e-05 |
| D/E | -0.4557452 | 0.2743184 | 0.09663854 |
| FCF/Inc | -0.01238647 | 0.001198462 | 4.88e-25 |
| LLP/Eq | -1.962595 | 1.568463 | 0.2108304 |
| NPL/Loans | -41.20532 | 8.023346 | 2.81e-07 |
| RWA/TA | 7.200641 | 3.774555 | 0.05643270 |
| MKT | 1.086951 | 0.07405263 | 8.91e-49 |
| L.excess | 0.06749592 | 0.03119322 | 0.3047964 |
| **Pre-2014 — Baseline — Blundell–Bond Sys GMM** | | | |
| MKT | 0.9389205 | 0.03377928 | 4.88e-170 |
| L.excess | -0.04042805 | 0.01127238 | 0.0003351828 |
| **Pre-2014 — Baseline — Blundell–Bond Sys GMM [collapsed]** | | | |
| MKT | 1.115173 | 0.1089308 | 1.35e-24 |
| L.excess | 0.01297621 | 0.02521576 | 0.6068276 |
| **Pre-2014 — Complete — Blundell–Bond Sys GMM** | | | |
| CAR(T1) | 33.23145 | 49.35651 | 0.5007602 |
| CAR(Tot) | 1.810547 | 48.92630 | 0.9704805 |
| D/E | -1.056154 | 0.3165223 | 0.0008476610 |
| FCF/Inc | 1.015626 | 1.003401 | 0.3114504 |
| LLP/Eq | -24.61536 | 2.555034 | 5.74e-22 |
| NPL/Loans | 22.60600 | 15.54604 | 0.1459097 |
| RWA/TA | -4.831118 | 3.320375 | 0.1456716 |
| MKT | 0.9617882 | 0.04567432 | 1.95e-98 |
| L.excess | -0.02342529 | 0.01657975 | 0.1576893 |
| **Pre-2014 — Complete — Blundell–Bond Sys GMM [collapsed]** | | | |
| CAR(T1) | 39.60525 | 57.87034 | 0.4937358 |
| CAR(Tot) | 2.471007 | 59.69472 | 0.9669817 |
| D/E | -0.9699709 | 0.3524341 | 0.005919538 |
| FCF/Inc | 1.042467 | 1.454843 | 0.4736523 |
| LLP/Eq | -21.62183 | 4.594423 | 2.52e-06 |
| NPL/Loans | 19.80783 | 24.60140 | 0.4207330 |
| RWA/TA | -6.297707 | 4.734954 | 0.1835031 |
| MKT | 1.000764 | 0.07513165 | 1.77e-40 |
| L.excess | 0.01480158 | 0.03482865 | 0.6708491 |

TABLE 11. D4 - Arellano–Bond Difference GMM (2-step) diagnostics.

| Model | AR1 stat | AR1 p | AR2 stat | AR2 p | Hansen J | df | Hansen p |
|---|---|---|---|---|---|---|---|
| **Post-2014 — Baseline** | | | | | | | |
| AB Diff GMM | -5.43 | 5.7e-08 | -0.086 | 0.931 | 60.47 | 16 | 4.36e-07 |
| AB Diff GMM (coll.) | -6.12 | 9.3e-10 | -0.082 | 0.934 | 0.015 | 1 | 0.902 |
| **Post-2014 — Complete** | | | | | | | |
| AB Diff GMM | -5.17 | 2.3e-07 | 0.902 | 0.367 | 43.08 | 16 | 2.72e-04 |
| AB Diff GMM (coll.) | -5.86 | 4.7e-09 | 1.090 | 0.276 | 0.119 | 1 | 0.731 |
| **Pre-2014 — Baseline** | | | | | | | |
| AB Diff GMM | -4.48 | 7.5e-06 | -2.69 | 0.007 | 62.52 | 14 | 4.23e-08 |
| AB Diff GMM (coll.) | -4.94 | 7.9e-07 | -2.83 | 0.005 | 22.06 | 1 | 2.64e-06 |
| **Pre-2014 — Complete** | | | | | | | |
| AB Diff GMM | -4.47 | 7.9e-06 | -2.11 | 0.035 | 28.20 | 14 | 0.0134 |
| AB Diff GMM (coll.) | -4.76 | 1.9e-06 | -2.02 | 0.044 | 11.13 | 1 | 8.49e-04 |

TABLE 12. D5 - Blundell–Bond System GMM (2-step) diagnostics.

| Model | AR1 stat | AR1 p | AR2 stat | AR2 p | Hansen J | df | Hansen p |
|---|---|---|---|---|---|---|---|
| **Post-2014 — Baseline** | | | | | | | |
| BB Sys GMM | -3.20 | 1.38e-03 | 0.203 | 0.839 | 75.02 | 26 | 1.20e-06 |
| BB Sys GMM (coll.) | -7.67 | 1.71e-14 | -0.352 | 0.725 | 5.25 | 3 | 0.155 |
| **Post-2014 — Complete** | | | | | | | |
| BB Sys GMM | -3.06 | 2.24e-03 | 0.406 | 0.685 | 57.89 | 33 | 0.00472 |
| BB Sys GMM (coll.) | -3.54 | 4.02e-04 | 0.593 | 0.553 | 17.61 | 10 | 0.0618 |
| **Pre-2014 — Baseline** | | | | | | | |
| BB Sys GMM | -5.53 | 3.14e-08 | -2.74 | 0.006 | 70.63 | 23 | 9.73e-07 |
| BB Sys GMM (coll.) | -28.45 | 5.3e-178 | – | – | 23.62 | 3 | 2.99e-05 |
| **Pre-2014 — Complete** | | | | | | | |
| BB Sys GMM | -4.46 | 8.27e-06 | -2.67 | 0.0076 | 45.25 | 30 | 0.0366 |
| BB Sys GMM (coll.) | -4.73 | 2.20e-06 | -2.09 | 0.0366 | 20.44 | 10 | 0.0254 |

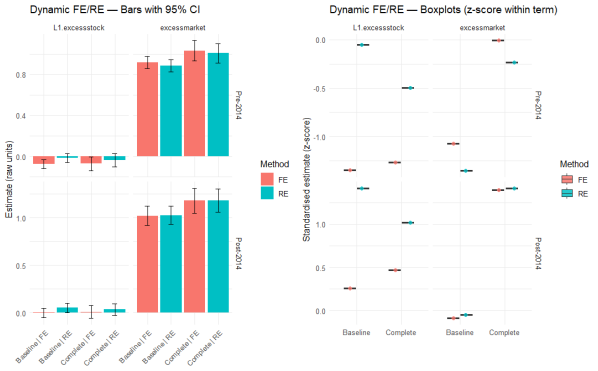



FIGURE 13. D6 - Comparison of dynamic Fixed Effects (FE) and Random Effects (RE) models, showing key coefficients (*L1.excessstock*, *excessmarket*) before and after 2014.

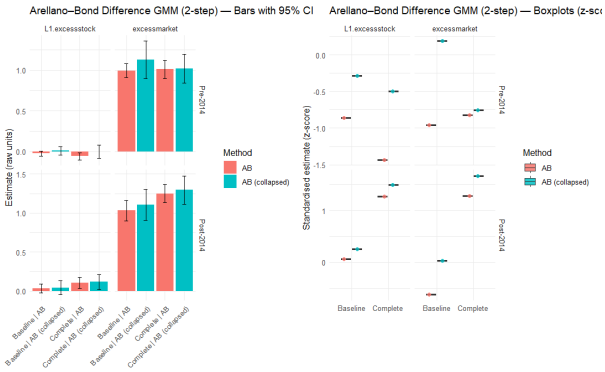



FIGURE 14. D7 - Arellano–Bond Difference GMM (2-step) estimations for baseline and complete specifications, with and without collapsed instruments, before and after 2014.

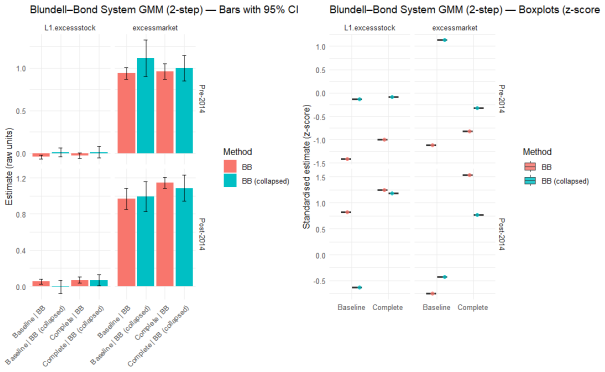
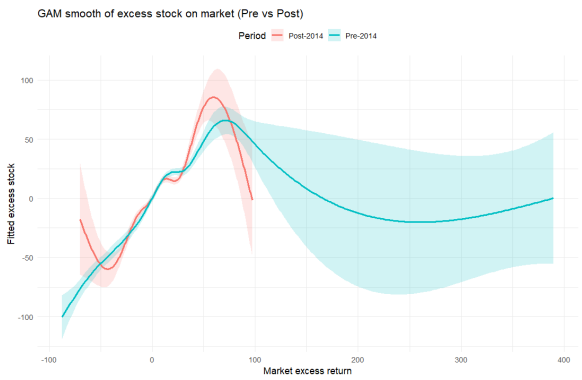



FIGURE 15. D8 - Blundell–Bond System GMM (2-step) results for baseline and complete specifications, with and without collapsed instruments, before and after 2014.

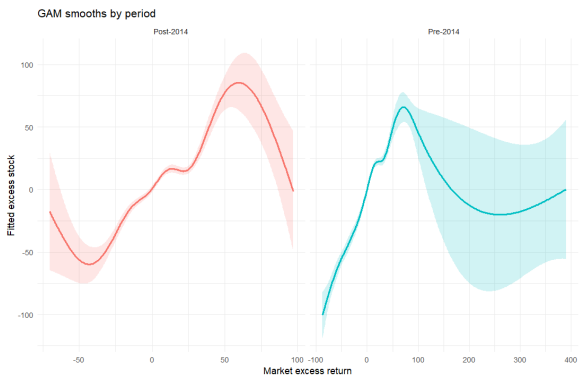
**E - Advanced Models**

TABLE 13. E1 - Summary of GAM models for Pre-2014 and Post-2014 periods

| | **Pre-2014** | | **Post-2014** | |
|---|---|---|---|---|
| | Estimate | Std. Error | Estimate | Std. Error |
| **Parametric coefficient** | | | | |
| Intercept | 2.9110*** | 0.7865 | 4.0672*** | 0.6619 |
| **Smooth term: s(excessmarket)** | | | | |
| edf | 8.465 | | 8.245 | |
| Ref.df | 8.910 | | 8.838 | |
| F-statistic | 154.00*** | | 67.82*** | |
| **Model fit** | | | | |
| Adj. $R^2$ | 0.512 | | 0.287 | |
| Deviance explained (%) | 51.5 | | 29.1 | |
| GCV | 813.74 | | 654.21 | |
| Scale est. | 807.85 | | 650.13 | |
| Observations ($n$) | 1306 | | 1484 | |




(A) GAM smooth of excess stock returns on market excess returns, Pre-2014 vs Post-2014.




(B) GAM smooths estimated separately for the Pre-2014 and Post-2014 samples.

FIGURE 16. E2 - Comparison of GAM smooths of excess stock returns on market excess returns across Pre-2014 and Post-2014 periods.

TABLE 14. E3 - Mean Group (MG) estimator of bank-level market betas on excess market returns.

| Period | MG $\beta$ mean | SE($\beta$) | N. Banks | CI Low | CI High |
|---|---|---|---|---|---|
| Post-2014 | 0.889 | 0.070 | 135 | 0.751 | 1.028 |
| Pre-2014 | 1.092 | 0.051 | 135 | 0.993 | 1.191 |

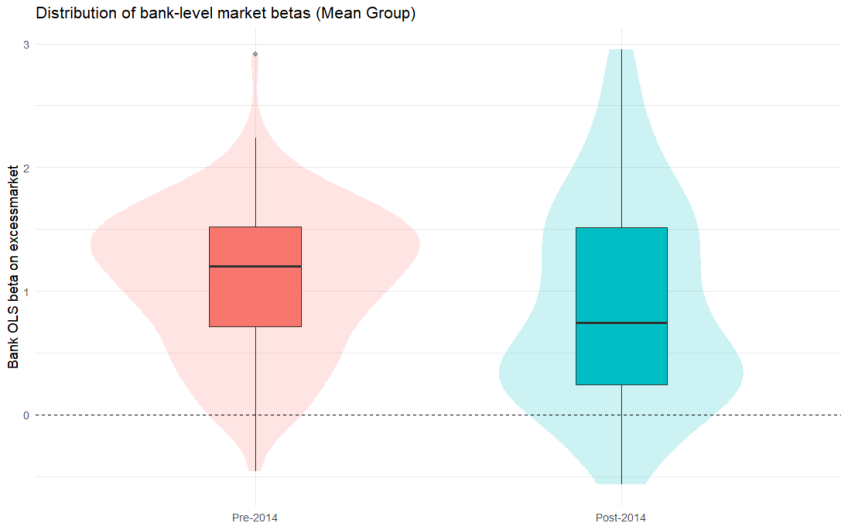



FIGURE 17. E4 - Distribution of bank-level market betas (Mean Group estimator) before and after 2014.

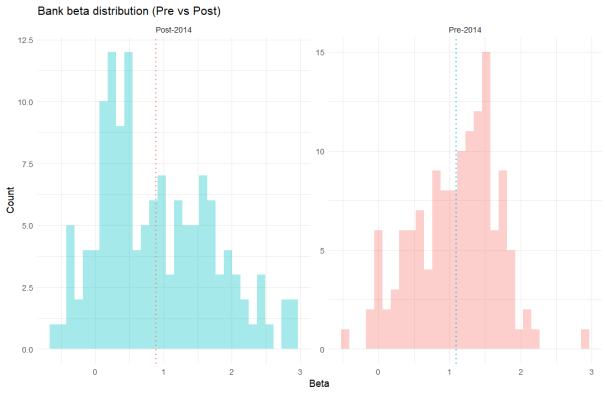



FIGURE 18. E5 - Histograms of estimated bank-level market betas in the Pre-2014 and Post-2014 periods.

TABLE 15. E6 - Bayesian model results (Pre- and Post-2014; Simple and Complete)

| Parameter | Estimate | Std.Error | l-95% | u-95% | Rhat | Bulk ESS | Tail ESS |
|---|---|---|---|---|---|---|---|
| **Pre-2014 (Simple)** | | | | | | | |
| sd(Intercept) | 20.11 | 5.74 | 11.87 | 34.06 | 1.00 | 758 | 1399 |
| Intercept | 0.95 | 6.43 | −11.81 | 14.26 | 1.01 | 594 | 688 |
| Excess Market | 0.47 | 0.04 | 0.39 | 0.56 | 1.00 | 2593 | 2347 |
| $\sigma$ | 28.61 | 0.55 | 27.56 | 29.71 | 1.00 | 2586 | 2477 |
| **Post-2014 (Simple)** | | | | | | | |
| sd(Intercept) | 6.53 | 1.89 | 3.77 | 11.04 | 1.00 | 1106 | 1562 |
| Intercept | −0.36 | 2.16 | −4.59 | 4.21 | 1.01 | 1001 | 1245 |
| Excess Market | 0.87 | 0.06 | 0.76 | 0.98 | 1.00 | 2819 | 2258 |
| $\sigma$ | 25.76 | 0.49 | 24.80 | 26.75 | 1.00 | 4951 | 2310 |
| **Pre-2014 (Complete)** | | | | | | | |
| sd(Intercept) | 14.90 | 5.06 | 7.49 | 27.52 | 1.00 | 1168 | 1831 |
| Intercept | 15.29 | 9.76 | −3.35 | 35.37 | 1.00 | 2575 | 2783 |
| Excess Market | 0.72 | 0.10 | 0.53 | 0.90 | 1.00 | 2297 | 2457 |
| Loan Loss / Equity | −25.42 | 8.51 | −42.21 | −8.78 | 1.00 | 4254 | 2860 |
| Total Capital Adequacy | −38.73 | 72.20 | −180.92 | 103.24 | 1.00 | 3124 | 3121 |
| Tier 1 Capital Adequacy | −15.21 | 69.35 | −150.60 | 121.50 | 1.00 | 2892 | 2857 |
| NPL / Net Loans | 1.79 | 16.67 | −31.15 | 34.42 | 1.00 | 4939 | 2757 |
| RWA / Assets | −10.14 | 7.23 | −24.28 | 3.90 | 1.00 | 3967 | 2313 |
| Debt / Equity | −1.02 | 0.50 | −1.99 | −0.05 | 1.00 | 3886 | 2635 |
| FCF / Income | 0.65 | 1.33 | −1.87 | 3.17 | 1.00 | 4539 | 3296 |
| $\sigma$ | 28.39 | 0.90 | 26.68 | 30.22 | 1.00 | 4414 | 2854 |
| **Post-2014 (Complete)** | | | | | | | |
| sd(Intercept) | 6.01 | 1.90 | 3.20 | 10.52 | 1.00 | 1453 | 2703 |
| Intercept | 4.12 | 6.93 | −9.23 | 17.96 | 1.00 | 3060 | 3216 |
| Excess Market | 1.08 | 0.07 | 0.94 | 1.22 | 1.00 | 2900 | 3149 |
| Loan Loss / Equity | 2.47 | 3.99 | −5.58 | 10.37 | 1.00 | 4161 | 2995 |
| Total Capital Adequacy | 139.86 | 72.97 | −2.88 | 283.26 | 1.00 | 2608 | 2838 |
| Tier 1 Capital Adequacy | −185.53 | 67.70 | −314.90 | −54.57 | 1.00 | 2591 | 2754 |
| NPL / Net Loans | −52.65 | 10.93 | −74.05 | −30.95 | 1.00 | 4002 | 2972 |
| RWA / Assets | 8.75 | 6.38 | −3.83 | 20.92 | 1.00 | 3549 | 2836 |
| Debt / Equity | −0.63 | 0.44 | −1.52 | 0.22 | 1.00 | 3653 | 3331 |
| FCF / Income | −0.01 | 0.01 | −0.02 | 0.01 | 1.00 | 5164 | 3217 |
| $\sigma$ | 25.47 | 0.57 | 24.40 | 26.60 | 1.00 | 5376 | 3150 |

TABLE 16. E7 - Model diagnostics (Rhat, ESS, $R^2$, LOOIC, WAIC, Pareto-$k$)

| Period | Spec | Rhat_max | ESS_bulk_min | ESS_tail_min | $R^2$_mean | LOOIC | WAIC | Pareto_k_max |
|---|---|---|---|---|---|---|---|---|
| Post-2014 | Complete | 1.002 | 2590.687 | 2753.713 | 0.254 | 9608.294 | 9607.047 | 1.279 |
| Post-2014 | Simple | 1.005 | 1001.494 | 1245.083 | 0.210 | 13874.968 | 13875.024 | 0.775 |
| Pre-2014 | Complete | 1.003 | 2296.840 | 2313.462 | 0.421 | 4948.748 | 4948.420 | 0.599 |
| Pre-2014 | Simple | 1.005 | 593.807 | 688.309 | 0.382 | 12494.748 | 12498.096 | 1.374 |

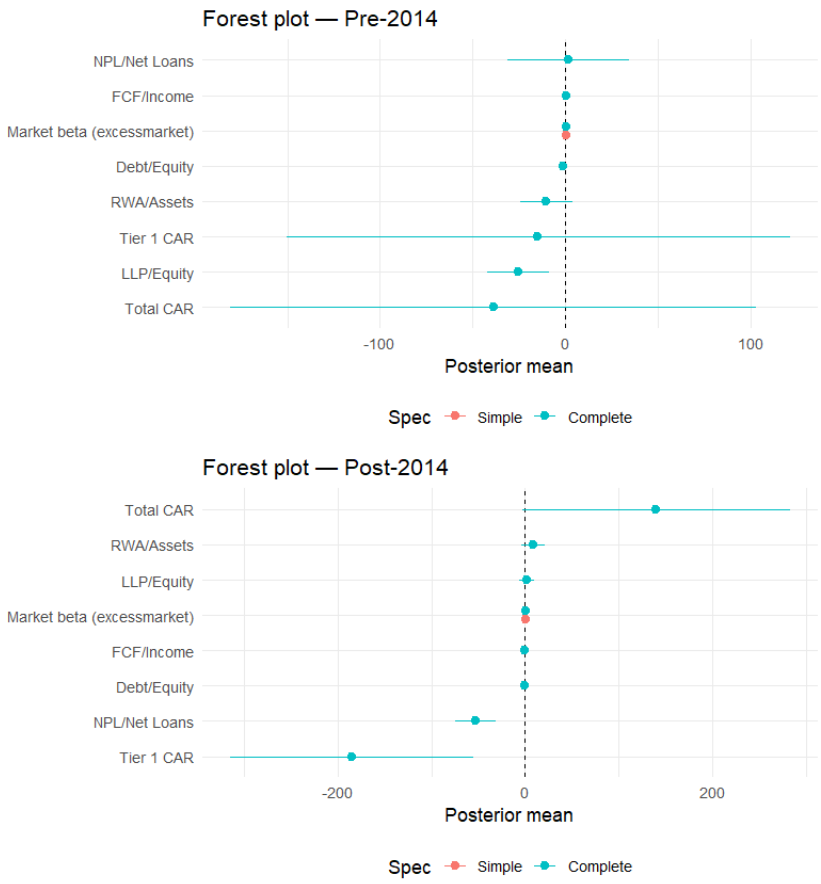



FIGURE 19. E8 - Forest plots of posterior means and 95% credible intervals for the estimated coefficients in the Bayesian CAPM models.




FIGURE 20. E9 - Comparison of year-specific random effects from the Bayesian hierarchical models: (a) caterpillar plot and (b) time evolution of combined intercepts.

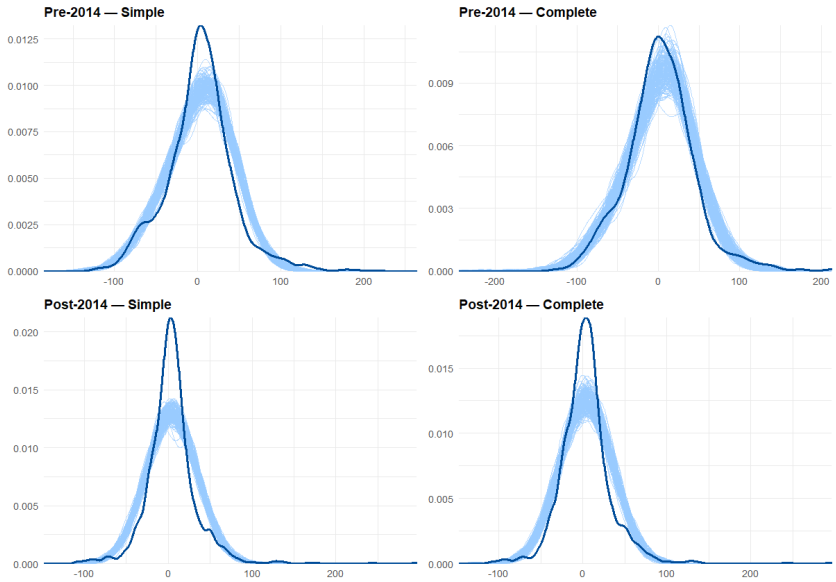



FIGURE 21. E10 - Posterior predictive checks (density overlay) for the Bayesian CAPM models.

TABLE 17. E11 - LOO model comparison for Bayesian CAPM specifications

| Model | elpd_diff | se_diff |
|---|---|---|
| **Pre-2014** | | |
| Simple | 0.0 | 0.0 |
| Complete | -2.5 | 6.7 |
| **Post-2014** | | |
| Simple | 0.0 | 0.0 |
| Complete | -29.7 | 31.8 |

TABLE 18. E12 - Top variables by $|\beta|$ within each model

| Period | Spec | Rank | Variable | Est. | 2.5% | 97.5% |
|---|---|---|---|---|---|---|
| Post-2014 | Comp. | 1 | Tier 1 CAR | -185.53 | -314.90 | -54.57 |
| Post-2014 | Comp. | 2 | Tot. CAR | 139.86 | -2.88 | 283.26 |
| Post-2014 | Comp. | 3 | NPL/Loans | -52.65 | -74.05 | -30.95 |
| Post-2014 | Comp. | 4 | RWA/Assets | 8.75 | -3.83 | 20.92 |
| Post-2014 | Comp. | 5 | LLP/Eq. | 2.47 | -5.58 | 10.37 |
| Post-2014 | Comp. | 6 | Mkt beta | 1.08 | 0.94 | 1.22 |
| Post-2014 | Comp. | 7 | D/E ratio | -0.63 | -1.52 | 0.22 |
| Post-2014 | Comp. | 8 | FCF/Inc. | -0.01 | -0.02 | 0.01 |
| Post-2014 | Simple | 1 | Mkt beta | 0.87 | 0.76 | 0.98 |
| Pre-2014 | Comp. | 1 | Tot. CAR | -38.73 | -180.92 | 103.24 |
| Pre-2014 | Comp. | 2 | LLP/Eq. | -25.42 | -42.21 | -8.78 |
| Pre-2014 | Comp. | 3 | Tier 1 CAR | -15.21 | -150.60 | 121.50 |
| Pre-2014 | Comp. | 4 | RWA/Assets | -10.14 | -24.28 | 3.90 |
| Pre-2014 | Comp. | 5 | NPL/Loans | 1.79 | -31.15 | 34.42 |
| Pre-2014 | Comp. | 6 | D/E ratio | -1.02 | -1.99 | -0.05 |
| Pre-2014 | Comp. | 7 | Mkt beta | 0.72 | 0.53 | 0.90 |
| Pre-2014 | Comp. | 8 | FCF/Inc. | 0.65 | -1.87 | 3.17 |
| Pre-2014 | Simple | 1 | Mkt beta | 0.47 | 0.39 | 0.56 |

TABLE 19. E13 - Random Forest performance metrics and summaries

| Specification | OOB RMSE | OOB $R^2$ | Test RMSE | Test MAE | Test $R^2$ | $\Delta R^2$ |
|---|---|---|---|---|---|---|
| Pre-2014 — Market only | 26.68 | 0.570 | 23.17 | 17.10 | 0.564 | — |
| Pre-2014 — Market + ratios | 26.50 | 0.576 | 13.77 | 9.99 | 0.846 | +0.282 |
| Post-2014 — Market only | 24.93 | 0.318 | 18.22 | 12.05 | 0.496 | — |
| Post-2014 — Market + ratios | 24.48 | 0.342 | 9.26 | 6.10 | 0.870 | +0.374 |
| *Market factor importance (%IncMSE, full model)* | | | | | | |
| Pre-2014: 205.28 Post-2014: 91.96 Variation: −55.2% | | | | | | |

TABLE 20. E14 - Variable importance (%IncMSE) by period and specification

| Variable | Pre-2014 (Full) | Post-2014 (Full) | Pre-2014 (Market only) | Post-2014 (Market only) |
|---|---|---|---|---|
| excessmarket | 205.28 | 91.96 | 325.07 | 208.29 |
| Loan Loss / Equity | 24.59 | 31.22 | – | – |
| Tier 1 Capital Adequacy | 24.36 | 19.00 | – | – |
| Total Capital Adequacy | 23.74 | 17.82 | – | – |
| NPL / Net Loans | 16.66 | 17.13 | – | – |
| RWA / Assets | 16.37 | 9.11 | – | – |
| Debt / Equity | 15.68 | 12.83 | – | – |
| FCF / Income | 5.40 | 2.37 | – | – |
| *Top-3 ratios (excluding market factor)* | | | | |
| Pre-2014: Loan Loss / Equity (24.59), Tier 1 CAR (24.36), Total CAR (23.74) | | | | |
| Post-2014: Loan Loss / Equity (31.22), Tier 1 CAR (19.00), Total CAR (17.82) | | | | |

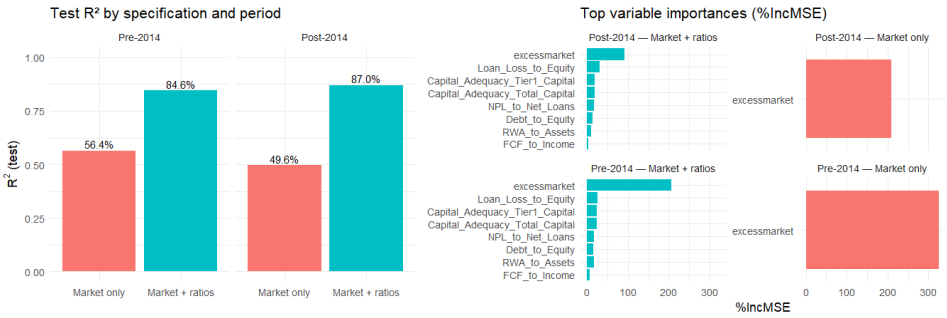



FIGURE 22. E15 - Test $R^2$ values and variable importance across specifications and periods.

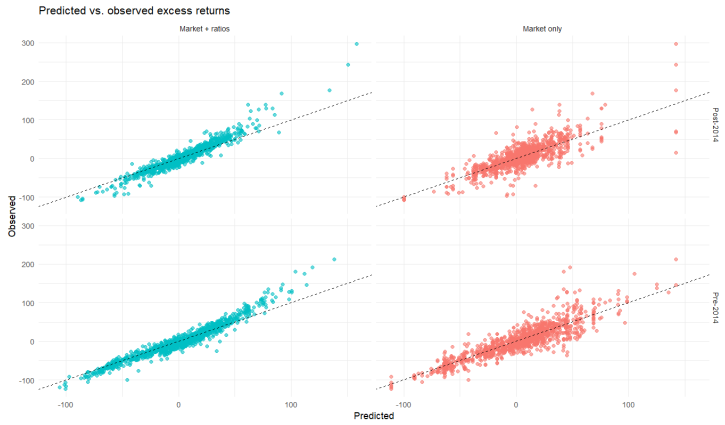



FIGURE 23. E16 - Predicted versus observed excess returns for Random Forest models.

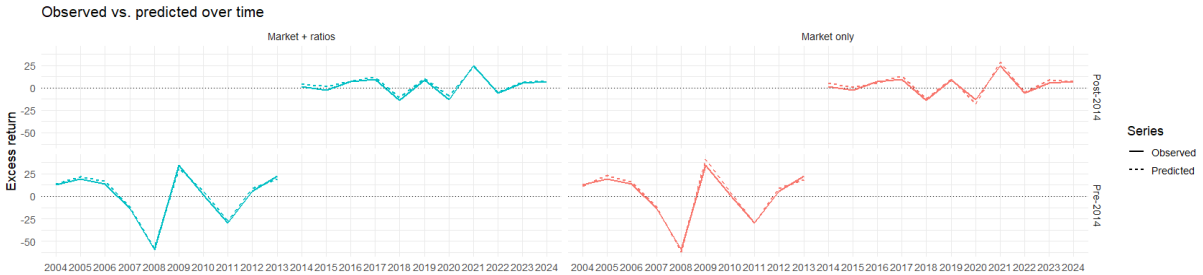
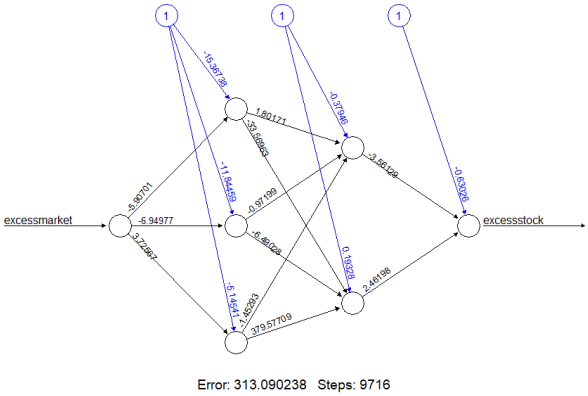
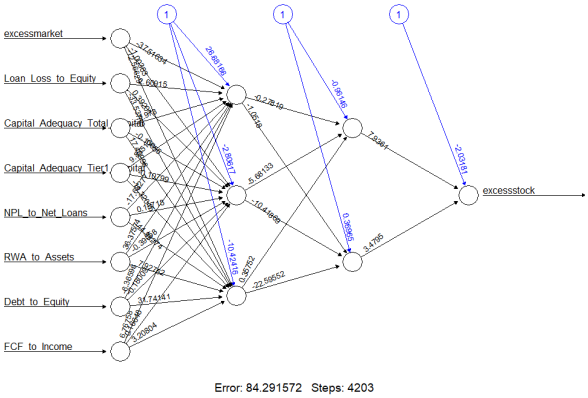


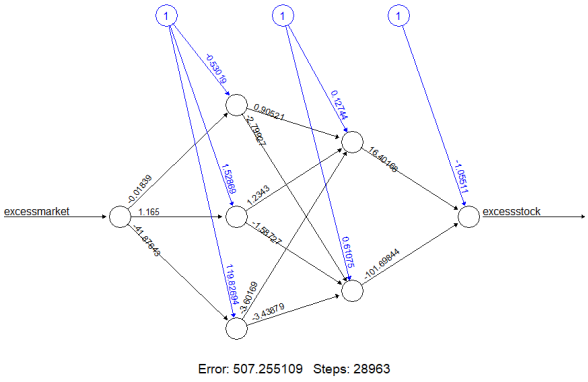

FIGURE 24. E17 - Observed versus predicted excess returns over time for Random Forest models.



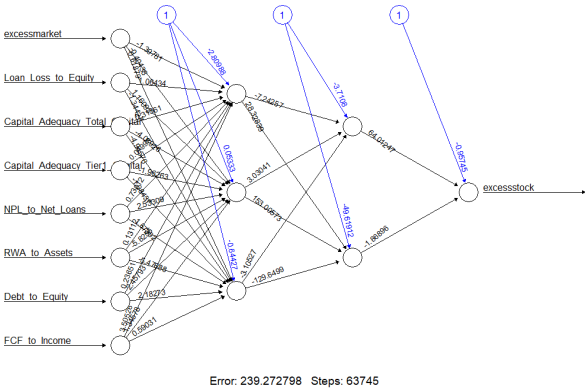

(A) Neural network architecture — Pre-2014 (Simple)




(B) Neural network architecture — Pre-2014 (Full)




(C) Neural network architecture — Post-2014 (Simple)




(D) Neural network architecture — Post-2014 (Full)

FIGURE 25. E18 - Neural network architecture diagrams.

TABLE 21. E19 - Neural network training summary (error, threshold, steps)

| Period | Specification | Model tag | Error (SSE) | Reached threshold | Steps |
|---|---|---|---|---|---|
| Pre-2014 | Simple | nn_model_pre | 313.09023764 | 0.04345763 | 9716 |
| Pre-2014 | Full | nn_model_pre_complet | 84.29157240 | 0.04348273 | 4203 |
| Post-2014 | Simple | nn_model_post | 507.25510921 | 0.04844526 | 28963 |
| Post-2014 | Full | nn_model_post_complet | 239.27279848 | 0.04973165 | 63745 |

TABLE 22. E20 - Neural network weights by connection (compressed to one page)

| Period | Specification | Layer | From | To:Weight list |
|---|---|---|---|---|
| Pre-2014 | Simple | Input→Hidden1 | Intercept | {1layhid1: -15.36737782, 1layhid2: -11.84458865, 1layhid3: -5.14541427} |
| Pre-2014 | Simple | Input→Hidden1 | excessmarket | {1layhid1: -5.90700974, 1layhid2: -6.94977291, 1layhid3: 3.72566664} |
| Pre-2014 | Simple | Hidden1→Hidden2 | Intercept | {2layhid1: -0.37945917, 2layhid2: 0.19328098} |
| Pre-2014 | Simple | Hidden1→Hidden2 | 1layhid1 | {2layhid1: 1.80170652, 2layhid2: -33.56962740} |
| Pre-2014 | Simple | Hidden1→Hidden2 | 1layhid2 | {2layhid1: -0.97199142, 2layhid2: -6.49027906} |
| Pre-2014 | Simple | Hidden1→Hidden2 | 1layhid3 | {2layhid1: -1.45293057, 2layhid2: 379.57709024} |
| Pre-2014 | Simple | Hidden2→Output | Intercept | {excessstock: -0.63025926} |
| Pre-2014 | Simple | Hidden2→Output | 2layhid1 | {excessstock: -3.56128737} |
| Pre-2014 | Simple | Hidden2→Output | 2layhid2 | {excessstock: 2.46198003} |
| Pre-2014 | Full | Input→Hidden1 | Intercept | {1layhid1: 26.68165834, 1layhid2: -2.80616719, 1layhid3: -10.42416020} |
| Pre-2014 | Full | Input→Hidden1 | excessmarket | {1layhid1: -37.51633851, 1layhid2: -1.00382663, 1layhid3: -12.56628864} |
| Pre-2014 | Full | Input→Hidden1 | Loan_Loss_to_Equity | {1layhid1: 2.60914929, 1layhid2: 0.39200906, 1layhid3: -33.53712881} |
| Pre-2014 | Full | Input→Hidden1 | Capital_Adequacy_Total_Capital | {1layhid1: -4.97800350, 1layhid2: -0.10654764, 1layhid3: 17.40996417} |
| Pre-2014 | Full | Input→Hidden1 | Capital_Adequacy_Tier1_Capital | {1layhid1: 9.84511674, 1layhid2: -0.10799143, 1layhid3: -11.32044514} |
| Pre-2014 | Full | Input→Hidden1 | NPL_to_Net_Loans | {1layhid1: -17.68277251, 1layhid2: 0.13717793, 1layhid3: -44.82273940} |
| Pre-2014 | Full | Input→Hidden1 | RWA_to_Assets | {1layhid1: 36.37574492, 1layhid2: -0.39058060, 1layhid3: 7.92762495} |
| Pre-2014 | Full | Input→Hidden1 | Debt_to_Equity | {1layhid1: -6.36596070, 1layhid2: -0.18008926, 1layhid3: 31.74141120} |
| Pre-2014 | Full | Input→Hidden1 | FCF_to_Income | {1layhid1: 6.76757959, 1layhid2: -0.16648155, 1layhid3: 3.20803780} |
| Pre-2014 | Full | Hidden1→Hidden2 | Intercept | {2layhid1: -0.96146313, 2layhid2: 0.36965237} |
| Pre-2014 | Full | Hidden1→Hidden2 | 1layhid1 | {2layhid1: -0.27818534, 2layhid2: -1.05180103} |
| Pre-2014 | Full | Hidden1→Hidden2 | 1layhid2 | {2layhid1: -5.68132742, 2layhid2: -10.41869022} |
| Pre-2014 | Full | Hidden1→Hidden2 | 1layhid3 | {2layhid1: 0.35752042, 2layhid2: -22.59551786} |
| Pre-2014 | Full | Hidden2→Output | Intercept | {excessstock: -2.03181041} |
| Pre-2014 | Full | Hidden2→Output | 2layhid1 | {excessstock: 7.93609769} |
| Pre-2014 | Full | Hidden2→Output | 2layhid2 | {excessstock: 3.47949747} |
| Post-2014 | Simple | Input→Hidden1 | Intercept | {1layhid1: -0.53018717, 1layhid2: 1.52869046, 1layhid3: 119.82694264} |
| Post-2014 | Simple | Input→Hidden1 | excessmarket | {1layhid1: -0.01839140, 1layhid2: 1.16500402, 1layhid3: -41.87642901} |
| Post-2014 | Simple | Hidden1→Hidden2 | Intercept | {2layhid1: 0.12743572, 2layhid2: 0.61075071} |
| Post-2014 | Simple | Hidden1→Hidden2 | 1layhid1 | {2layhid1: 0.90521201, 2layhid2: -2.79926644} |
| Post-2014 | Simple | Hidden1→Hidden2 | 1layhid2 | {2layhid1: 1.23430265, 2layhid2: -1.58726762} |
| Post-2014 | Simple | Hidden1→Hidden2 | 1layhid3 | {2layhid1: -3.60168744, 2layhid2: -3.43879012} |
| Post-2014 | Simple | Hidden2→Output | Intercept | {excessstock: -1.05511045} |
| Post-2014 | Simple | Hidden2→Output | 2layhid1 | {excessstock: 16.40167528} |
| Post-2014 | Simple | Hidden2→Output | 2layhid2 | {excessstock: -101.69843604} |
| Post-2014 | Full | Input→Hidden1 | Intercept | {1layhid1: -2.80987823, 1layhid2: 0.05333016, 1layhid3: -0.64426515} |
| Post-2014 | Full | Input→Hidden1 | excessmarket | {1layhid1: -1.39781429, 1layhid2: -0.40437711, 1layhid3: -0.61878531} |
| Post-2014 | Full | Input→Hidden1 | Loan_Loss_to_Equity | {1layhid1: 1.06433812, 1layhid2: 1.16093437, 1layhid3: -1.34426734} |
| Post-2014 | Full | Input→Hidden1 | Capital_Adequacy_Total_Capital | {1layhid1: 0.31361392, 1layhid2: -4.08926102, 1layhid3: -4.94576246} |
| Post-2014 | Full | Input→Hidden1 | Capital_Adequacy_Tier1_Capital | {1layhid1: 0.07993115, 1layhid2: -1.96263278, 1layhid3: -1.08437332} |
| Post-2014 | Full | Input→Hidden1 | NPL_to_Net_Loans | {1layhid1: 0.73011742, 1layhid2: 2.53308839, 1layhid3: 1.67392074} |
| Post-2014 | Full | Input→Hidden1 | RWA_to_Assets | {1layhid1: 0.13112067, 1layhid2: -5.82550263, 1layhid3: -5.47688195} |
| Post-2014 | Full | Input→Hidden1 | Debt_to_Equity | {1layhid1: 0.23650825, 1layhid2: 2.45792639, 1layhid3: 2.18273194} |
| Post-2014 | Full | Input→Hidden1 | FCF_to_Income | {1layhid1: 3.50525853, 1layhid2: 1.34577823, 1layhid3: 0.59030753} |
| Post-2014 | Full | Hidden1→Hidden2 | Intercept | {2layhid1: -3.71080242, 2layhid2: -49.61911552} |
| Post-2014 | Full | Hidden1→Hidden2 | 1layhid1 | {2layhid1: -7.24256863, 2layhid2: 28.32839213} |
| Post-2014 | Full | Hidden1→Hidden2 | 1layhid2 | {2layhid1: 3.03040652, 2layhid2: 153.00572998} |
| Post-2014 | Full | Hidden1→Hidden2 | 1layhid3 | {2layhid1: -3.10526809, 2layhid2: -129.64990317} |
| Post-2014 | Full | Hidden2→Output | Intercept | {excessstock: -0.95745204} |
| Post-2014 | Full | Hidden2→Output | 2layhid1 | {excessstock: 64.01246508} |
| Post-2014 | Full | Hidden2→Output | 2layhid2 | {excessstock: -1.86895869} |

TABLE 23. E21 - Neural network performance (in- and out-of-sample): $R^2$, RMSE, MAE

| Period | Specification | Model tag | Set | $R^2$ | RMSE | MAE |
|---|---|---|---|---|---|---|
| Pre-2014 | Simple | NN PRE SIMPLE | in | 0.5990862800 | 0.6457107 | 0.4573157 |
| Pre-2014 | Simple | NN PRE SIMPLE | out | 0.0069717120 | 0.8535795 | 0.6587241 |
| Pre-2014 | Full | NN PRE FULL | in | 0.4589677423 | 0.8230238 | 0.6241829 |
| Pre-2014 | Full | NN PRE FULL | out | 0.0003934496 | 0.9031637 | 0.6602446 |
| Post-2014 | Simple | NN POST SIMPLE | in | 0.3340706000 | 0.8455542 | 0.5783208 |
| Post-2014 | Simple | NN POST SIMPLE | out | 0.1765970000 | 0.7472746 | 0.5039101 |
| Post-2014 | Full | NN POST FULL | in | 0.0203504190 | 1.9083750 | 1.4786520 |
| Post-2014 | Full | NN POST FULL | out | 0.0026910290 | 1.6132680 | 1.1494310 |

TABLE 24. E22 - Permutation importance ($\Delta R^2$) — Neural Networks FULL

| Variable | Pre-2014 Full | | Post-2014 Full | |
|---|---|---|---|---|
| | $\Delta R^2$ mean | $\Delta R^2$ sd | $\Delta R^2$ mean | $\Delta R^2$ sd |
| excessmarket | 0.3689205390 | 0.002413568 | 0.02299436124 | 0.0003394313 |
| Loan_Loss_to_Equity | 0.0156527811 | 0.007483553 | 0.00300320738 | 0.0008739073 |
| RWA_to_Assets | 0.0073425482 | 0.007538125 | 0.00139617302 | 0.0023669991 |
| Capital_Adequacy_Total_Capital | -0.0003749849 | 0.002322585 | -0.00069821089 | 0.0008226309 |
| FCF_to_Income | -0.0020048049 | 0.008061905 | 0.00593938596 | 0.0092449537 |
| Capital_Adequacy_Tier1_Capital | -0.0024941555 | 0.001320478 | -0.00008850501 | 0.0005922599 |
| NPL_to_Net_Loans | -0.0066728435 | 0.004270330 | 0.00203287109 | 0.0007350268 |
| Debt_to_Equity | -0.0202660499 | 0.026103955 | -0.00149604327 | 0.0041126543 |

*Note:* $\Delta R^2$ mean is the average change in $R^2$ after permuting the variable.

TABLE 25. E23 - Garson vs. Permutation importance — Neural Networks FULL

| Period | Variable | Garson rel. imp. | $\Delta R^2$ mean | $\Delta R^2$ sd | Rank (G) | Rank (P) |
|---|---|---|---|---|---|---|
| POST | excessmarket | 0.04702 | 0.0230207 | 0.0002751 | 6 | 1 |
| POST | FCF_to_Income | 0.02236 | 0.0032009 | 0.0078376 | 7 | 2 |
| POST | Loan_Loss_to_Equity | 0.34395 | 0.0028111 | 0.0009481 | 1 | 3 |
| POST | NPL_to_Net_Loans | 0.23160 | 0.0018765 | 0.0007156 | 2 | 4 |
| POST | RWA_to_Assets | 0.16948 | 0.0014136 | 0.0022622 | 3 | 5 |
| POST | Capital_Adequacy_Tier1_Capital | 0.09995 | -0.0001633 | 0.0005436 | 4 | 6 |
| POST | Capital_Adequacy_Total_Capital | 0.07084 | -0.0007867 | 0.0007522 | 5 | 7 |
| POST | Debt_to_Equity | 0.01480 | -0.0012353 | 0.0033494 | 8 | 8 |
| PRE | excessmarket | 0.062839 | 0.3686567 | 0.003212 | 6 | 1 |
| PRE | Loan_Loss_to_Equity | 0.131166 | 0.0137821 | 0.009367 | 4 | 2 |
| PRE | RWA_to_Assets | 0.188669 | 0.0079789 | 0.009247 | 3 | 3 |
| PRE | Capital_Adequacy_Total_Capital | 0.097033 | -0.0002357 | 0.001953 | 5 | 4 |
| PRE | Capital_Adequacy_Tier1_Capital | 0.228503 | -0.0028347 | 0.001889 | 2 | 5 |
| PRE | FCF_to_Income | 0.007189 | -0.0038683 | 0.007791 | 8 | 6 |
| PRE | NPL_to_Net_Loans | 0.277238 | -0.0068620 | 0.004845 | 1 | 7 |
| PRE | Debt_to_Equity | 0.007363 | -0.0294435 | 0.023414 | 7 | 8 |

*Notes:* Spearman $\rho$ (rank Garson vs Permutation): POST = 0.167, PRE = 0.048.

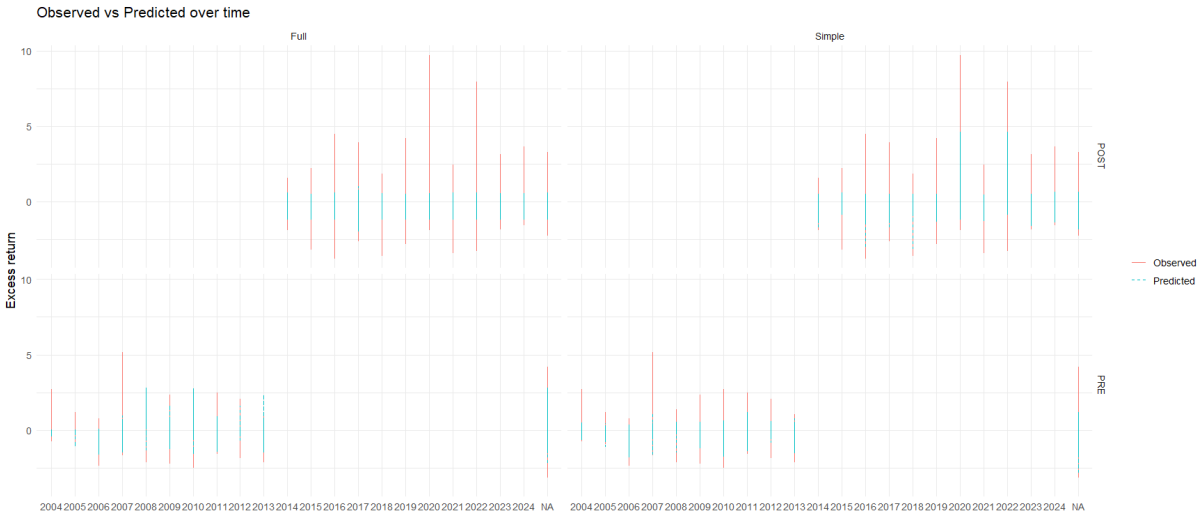



FIGURE 26. E24 - Time series of observed and predicted excess returns, faceted by period and specification (Simple/Full).

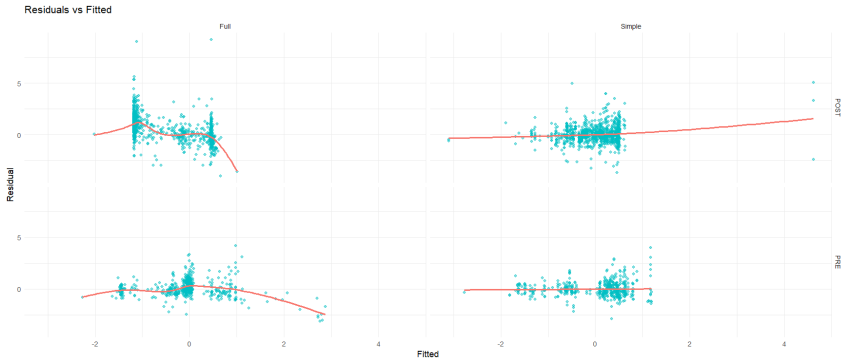



FIGURE 27. E25 - Residuals versus fitted values

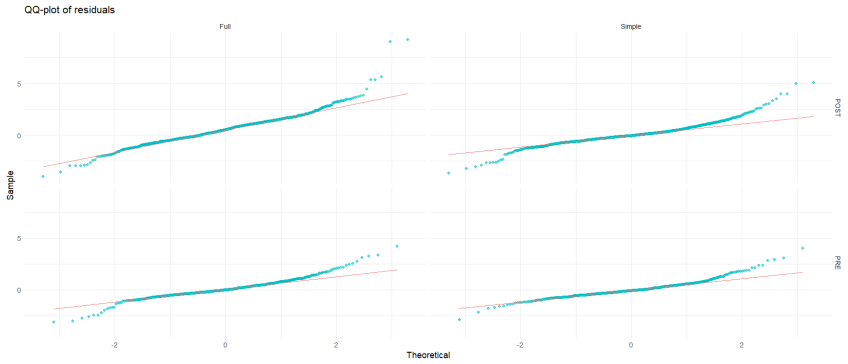



FIGURE 28. E26 - QQ plots of residuals against the theoretical normal

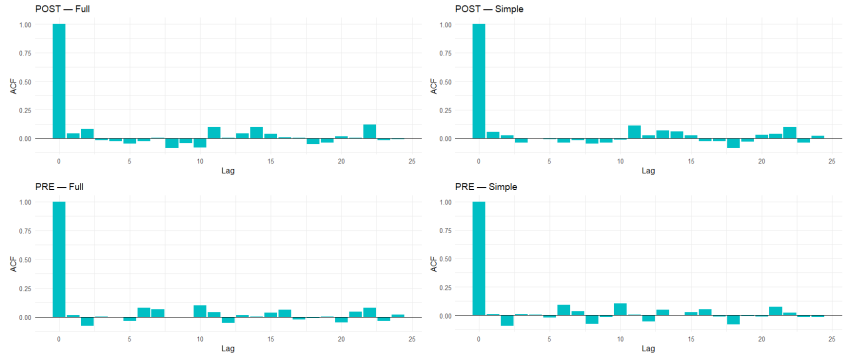



FIGURE 29. E27 - Residual autocorrelation up to 24 lags

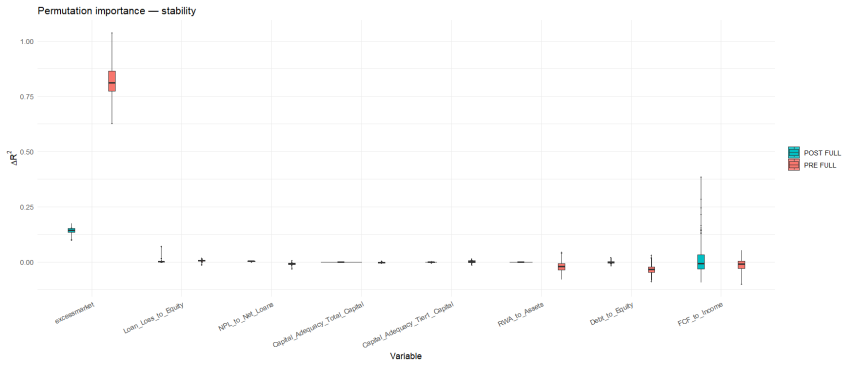



FIGURE 30. E28 - Permutation-importance ($\Delta R^2$) distributions by feature across repeated permutations

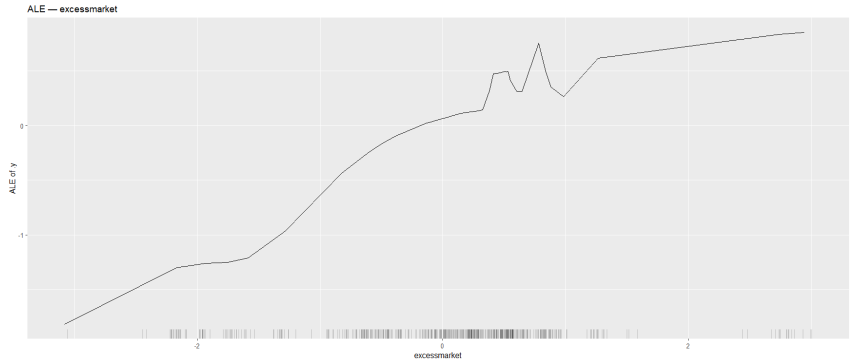



FIGURE 31. E29 - Accumulated Local Effects (ALE) of `excessmarket` for the NN (Full specification)

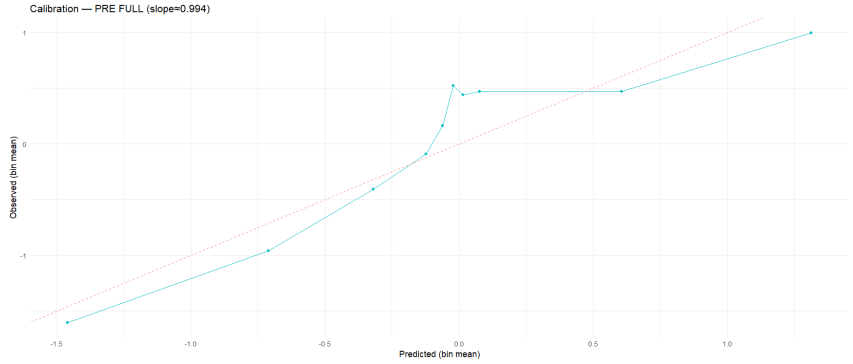



FIGURE 32. E32 - Calibration curve for the NN (PRE, Full).

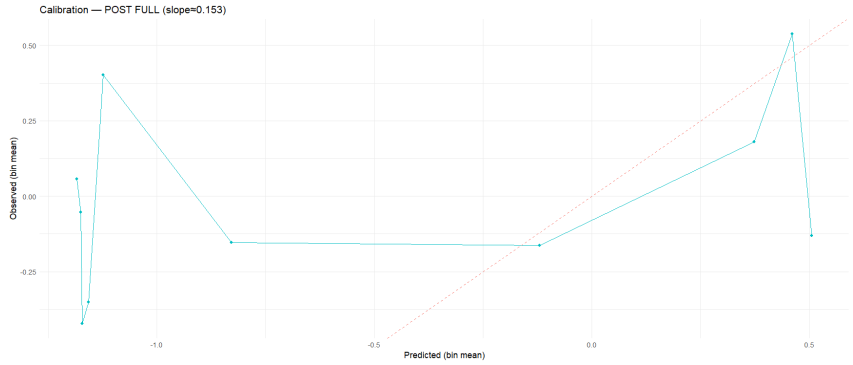



FIGURE 33. E33 - Calibration curve for the NN (POST, Full)

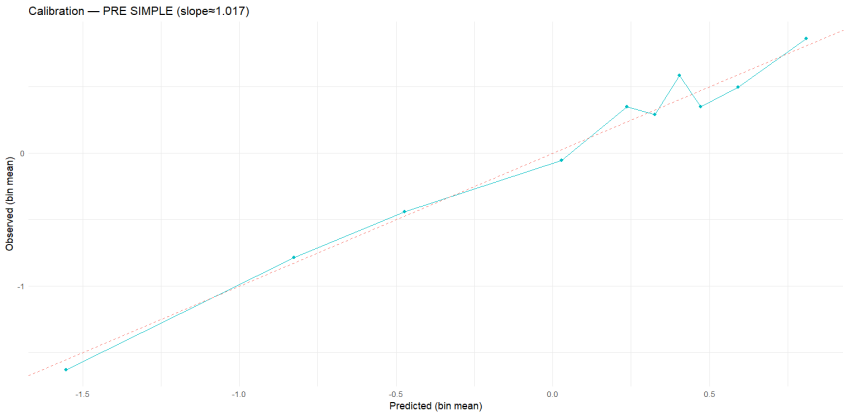



FIGURE 34. E34 - Calibration curve for the NN (PRE, Simple)

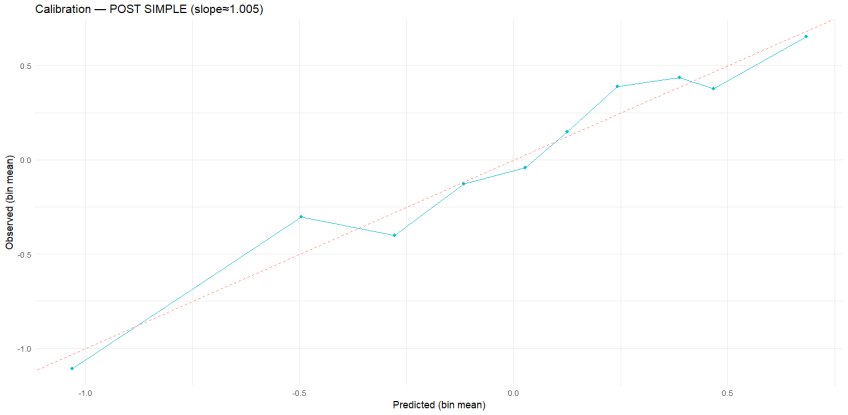



FIGURE 35. E35 - Calibration curve for the NN (POST, Simple)

Table 26. E36 - Model selection by BIC (combined view)

| Spec | Period | $k$=1 | $k$=2 | $k$=3 | $k$=4 | $k$=5 | $k$=6 |
|---|---|---|---|---|---|---|---|
| Simple | PRE | 12680.82 | 12380.72 | 12331.68 | **12325.99** | 12325.99 | 12325.99 |
| Simple | POST | 13932.40 | 13511.12 | 13420.27 | **13376.49** | 13378.13 | 13377.81 |
| FULL | PRE | 5028.875 | **4954.427** | 4967.318 | 4979.064 | 5000.829 | 5014.174 |
| FULL | POST | 9660.057 | 9371.813 | **9324.740** | 9350.235 | 9383.265 | 9416.592 |

Table 27. E37 - Mixture summaries (initial fit with $k$=3)

| Spec | Period | Component | prior | size | post>0 | ratio |
|---|---|---|---|---|---|---|
| Simple | PRE | Comp.1 | 0.695 | 904 | 1199 | 0.7540 |
| Simple | PRE | Comp.2 | 0.305 | 402 | 838 | 0.4800 |
| Simple | POST | Comp.1 | 0.211 | 308 | 902 | 0.3410 |
| Simple | POST | Comp.2 | 0.309 | 462 | 1264 | 0.3660 |
| Simple | POST | Comp.3 | 0.480 | 714 | 1187 | 0.6020 |
| FULL | PRE | Comp.1 | 0.207 | 45 | 492 | 0.0915 |
| FULL | PRE | Comp.2 | 0.371 | 164 | 503 | 0.3260 |
| FULL | PRE | Comp.3 | 0.423 | 308 | 469 | 0.6567 |
| FULL | POST | Comp.1 | 0.0869 | 51 | 1015 | 0.0502 |
| FULL | POST | Comp.2 | 0.5185 | 692 | 1015 | 0.6818 |
| FULL | POST | Comp.3 | 0.3946 | 284 | 987 | 0.2877 |

**Fit statistics**

| Spec | Period | LogLik | df | AIC | BIC |
|---|---|---|---|---|---|
| Simple | PRE | −6165.252 | 7 | 12 344.500 | 12 380.730 |
| Simple | POST | −6669.975 | 11 | 13 361.950 | 13 420.280 |
| FULL | PRE | −2390.376 | 32 | 4844.752 | 4980.690 |
| FULL | POST | −4573.521 | 32 | 9211.043 | 9368.944 |

Table 28. E38 - Best-by-BIC parameters — Simple specification

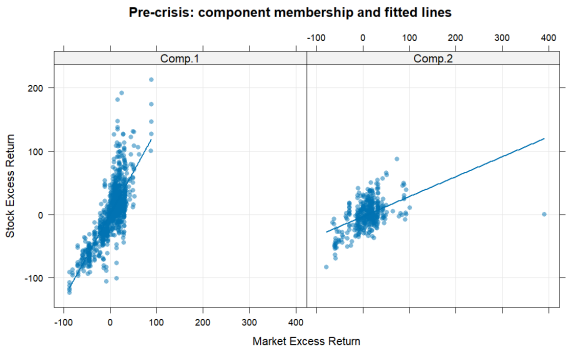
| | PRE ($k^*$=4) | | | | POST ($k^*$=4) | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | C1 | C2 | C3 | C4 | C1 | C2 | C3 | C4 |
| Intercept | -6.9053418 | 2.1385070 | 2.7261390 | 0.2849431 | 1.6904890 | 0.1691358 | -0.02276208 | -7.7984550 |
| `excessmarket` | 0.5615311 | 0.1045130 | 1.4751120 | 1.2960060 | 0.3253084 | 1.0582899 | 1.52774244 | 2.0338380 |
| $\sigma$ | 19.0629651 | 18.2934880 | 40.2378750 | 22.6148567 | 14.2485561 | 28.9073042 | 12.72614355 | 58.2882500 |

TABLE 29. E39 - Best-by-BIC parameters — FULL specification

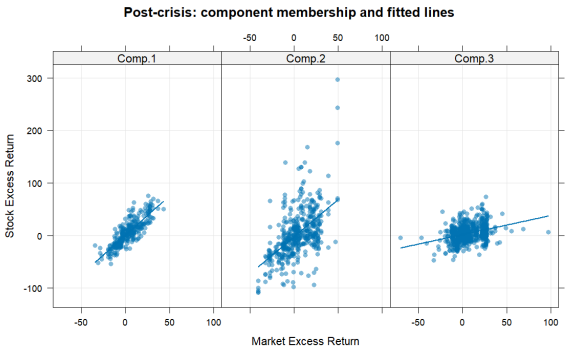
| | PRE ($k^*$=2) | | POST ($k^*$=3) | | |
|---|---|---|---|---|---|
| Variable | C1 | C2 | C1 | C2 | C3 |
| Intercept | 0.3962824 | -9.5660050 | 5.076694e+00 | 1.055289e+02 | 0.18869840 |
| excessmarket | 0.6148215 | 1.4395000 | 1.462228e+00 | 1.100301e+00 | 0.53203791 |
| Loan_Loss_to_Equity | -141.8599993 | -8.0336790 | 1.195162e+01 | 1.393656e+02 | -101.32849900 |
| Capital_Adequacy_Total_Capital | -16.9108927 | 111.3401070 | 2.395440e+02 | 7.838903e+02 | -209.57845446 |
| Capital_Adequacy_Tier1_Capital | -67.3198114 | 65.7899250 | -2.740017e+02 | -1.115566e+03 | 179.26705568 |
| NPL_to_Net_Loans | 5.4635124 | 111.4864130 | -3.132179e+01 | 3.308464e+02 | -80.91399679 |
| RWA_to_Assets | 14.3120840 | -8.9120780 | -6.042528e-01 | -6.200375e+01 | 12.03837128 |
| Debt_to_Equity | -1.1404460 | -1.0939210 | -7.787488e-01 | -6.910676e+00 | 1.06126502 |
| FCF_to_Income | -0.6042260 | 1.8305350 | -8.040471e-03 | -2.377215e-02 | -0.01126789 |
| $\sigma$ | 16.9032557 | 25.4756270 | 1.345723e+01 | 2.285288e+01 | 16.81462612 |

TABLE 30. E40 - Component-wise diagnostics (MAP assignment) — combined

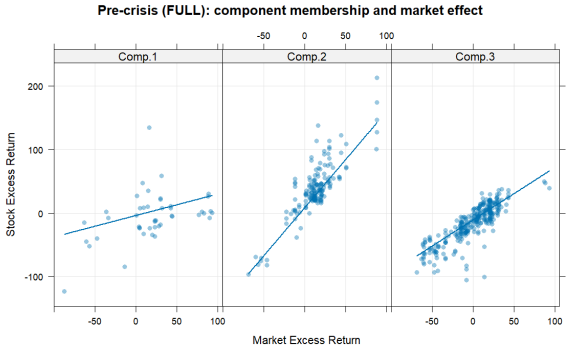
| Spec | Period | Component | $n$ | $R^2$ | RMSE | MAE |
|---|---|---|---|---|---|---|
| Simple | PRE | Comp.1 | 904 | 0.6152527 | 28.86370 | 20.60093 |
| Simple | PRE | Comp.2 | 402 | 0.2186369 | 19.69434 | 15.05328 |
| Simple | POST | Comp.1 | 308 | 0.7062054 | 13.38909 | 10.23746 |
| Simple | POST | Comp.2 | 462 | 0.2909970 | 38.74685 | 26.85788 |
| Simple | POST | Comp.3 | 714 | 0.1041931 | 15.21835 | 11.60682 |
| FULL | PRE | Comp.1 | 45 | 0.8231697 | 15.92396 | 12.494851 |
| FULL | PRE | Comp.2 | 164 | 0.7546229 | 21.57759 | 15.881981 |
| FULL | PRE | Comp.3 | 308 | 0.8537743 | 11.13742 | 9.369932 |
| FULL | POST | Comp.1 | 51 | 0.6412002 | 42.04028 | 33.290109 |
| FULL | POST | Comp.2 | 692 | 0.7492345 | 13.21982 | 10.130324 |
| FULL | POST | Comp.3 | 284 | 0.4620414 | 12.88406 | 9.798951 |



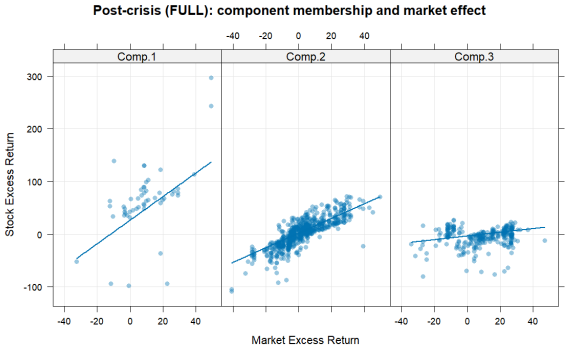

(A) Pre-crisis (simple specification). Scatter of stock excess return vs. market excess return.




(B) Post-crisis (simple specification). Three-component mixture of linear regressions.

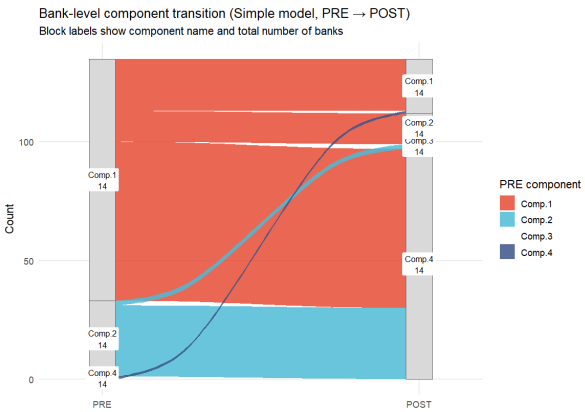



(C) Pre-crisis (FULL specification). Mixture with bank fundamentals in the mean and bank as concomitant.

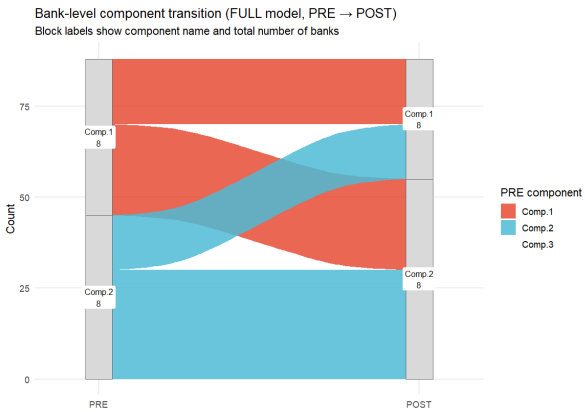



(D) Post-crisis (FULL specification). Three-component mixture with covariates.

FIGURE 36. E41 - Mixture regression diagnostics: same scatter fitted under different models. Panels (a–d): simple pre-crisis, simple post-crisis, FULL pre-crisis, FULL post-crisis.




(A) Bank-level transitions between mixture components from PRE to POST under the *simple* model.




(B) Bank-level transitions between mixture components from PRE to POST under the *FULL* model.

FIGURE 37. E42 - PRE→POST component transitions by model

TABLE 31. E43 - LASSO/Elastic-Net — Main metrics with `lambda.1se`

| Model | $\alpha^*$ | $\lambda^*$ | Train | | | Test | | |
|---|---|---|---|---|---|---|---|---|
| | | | $R^2$ | RMSE | MAE | $R^2$ | RMSE | MAE |
| PRE — SIMPLE | 1.00 | 205.958 | 0.4894 | 32.29 | 23.51 | 0.005652 | 35.36 | 25.87 |
| POST — SIMPLE | 0.75 | 111.267 | 0.2474 | 28.92 | 19.11 | 0.2124 | 24.38 | 16.21 |
| PRE — FULL | 0.50 | 19.4186 | 0.5663 | 31.69 | 22.93 | 0.06791 | 36.78 | 27.46 |
| POST — FULL | 1.00 | 14.0216 | 0.2854 | 30.18 | 20.43 | 0.2478 | 27.75 | 18.09 |

TABLE 32. E44 - Non-zero coefficients with `lambda.1se`

| Model | Intercept | $\beta_{\text{mkt}}$ (`excessmarket`) |
|---|---|---|
| PRE — SIMPLE | — | 0.4978751 |
| POST — SIMPLE | — | 0.3405643 |
| PRE — FULL | -3.8988611 | 0.5800264 |
| POST — FULL | 0.7233562 | 0.1876562 |

TABLE 33. E45 - Comparison of $\lambda$ selection (`lambda.1se` vs `lambda.min`)

| Scenario | Selection | $\alpha^*$ | $\lambda^*$ | Test | | | # Non-zero |
|---|---|---|---|---|---|---|---|
| | | | | $R^2$ | RMSE | MAE | coeffs |
| PRE — SIMPLE | `1se` | 1.00 | 205.958 | 0.005652 | 35.36 | 25.87 | 1 |
| PRE — SIMPLE | `min` | 0.00 | 586.576 | 0.005652 | 34.77 | 26.49 | 1 |
| POST — SIMPLE | `1se` | 0.75 | 111.267 | 0.2124 | 24.38 | 16.21 | 1 |
| POST — SIMPLE | `min` | 0.00 | 30.6962 | 0.2124 | 22.23 | 14.94 | 1 |
| PRE — FULL | `1se` | 0.50 | 19.4186 | 0.06791 | 36.78 | 27.46 | 2 |
| PRE — FULL | `min` | 1.00 | 1.37627 | 0.06685 | 35.73 | 27.52 | 4 |
| POST — FULL | `1se` | 1.00 | 14.0216 | 0.2478 | 27.75 | 18.09 | 2 |
| POST — FULL | `min` | 1.00 | 6.06961 | 0.2478 | 25.49 | 16.80 | 2 |

TABLE 34. E46 - Rolling-origin (`lambda.1se`) — Mean test metrics across train proportions

| Scenario | $\overline{R^2}_{\text{test}}$ | $\overline{\text{RMSE}}_{\text{test}}$ | $\overline{\text{MAE}}_{\text{test}}$ |
|---|---|---|---|
| PRE — SIMPLE | 0.1260696 | 35.7429861 | 26.5383169 |
| POST — SIMPLE | 0.1962778 | 25.9908190 | 17.2646672 |
| PRE — FULL | 0.1373570 | 35.0817490 | 26.2961520 |
| POST — FULL | 0.2257591 | 28.2698749 | 18.7331209 |

TABLE 35. E47 - Models with lags — Metrics with `lambda.1se`

| Model | $\alpha^*$ | $\lambda^*$ | Train | | | Test | | |
|---|---|---|---|---|---|---|---|---|
| | | | $R^2$ | RMSE | MAE | $R^2$ | RMSE | MAE |
| PRE — SIMPLE+LAGS | 0.25 | 23.8692 | 0.5294 | 30.47 | 21.93 | 0.00475 | 35.39 | 25.88 |
| POST — SIMPLE+LAGS | 1.00 | 9.74233 | 0.2463 | 28.83 | 19.09 | 0.2124 | 24.03 | 15.99 |
| PRE — FULL+LAGS | 0.75 | 15.5932 | 0.5767 | 31.24 | 22.49 | 0.06013 | 36.77 | 27.41 |
| POST — FULL+LAGS | 1.00 | 14.0216 | 0.2854 | 30.18 | 20.43 | 0.2478 | 27.75 | 18.09 |

TABLE 36. E50 - Models with lags — Non-zero coefficients with `lambda.1se`

| Model | Intercept | $\beta_{\text{mkt}}$ | $\beta_{\text{L1(mkt)}}$ | $\beta_{\text{L1(stock)}}$ |
|---|---|---|---|---|
| PRE — SIMPLE+LAGS | -1.77091017 | 0.35255407 | 0.18307306 | 0.09920385 |
| POST — SIMPLE+LAGS | 0.89410370 | 0.35417280 | — | — |
| PRE — FULL+LAGS | -4.05603361 | 0.56221434 | 0.04459676 | 0.00380399 |
| POST — FULL+LAGS | 0.72335620 | 0.18765620 | — | — |

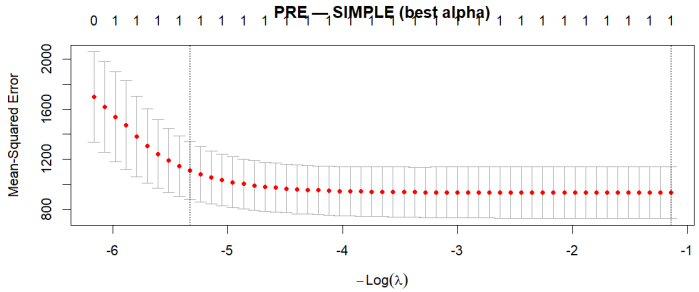



FIGURE 38. E51 - POST — SIMPLE (best $\alpha = 0.75$). Time-blocked 10-fold cross-validation curve of MSE along the regularisation path.

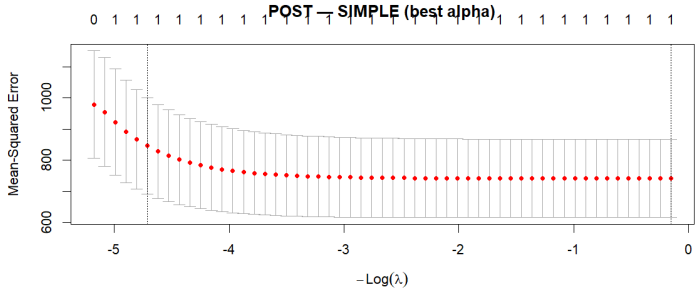



FIGURE 39. E52 - PRE — SIMPLE (best $\alpha = 1$). Time-blocked 10-fold cross-validation curve of MSE along the regularisation path.