Beyond the crisis: securitisation and mortgage risk in an evolving regulatory landscape

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"And now that you have reached your goal and are basking in your well deserved glory, shiny trophy in hand and showered with accolades and titles, will you be content to stop there?"

– Blue Prince

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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15 September 2025

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Abstract

This thesis examines how financial regulation influences credit risk in the European residential mortgage-backed securities (RMBS) market, with a focus on both post-crisis reforms and emerging environmental priorities. It brings together three empirical chapters that assess the effectiveness of institutional safeguards and risk indicators under macroeconomic stress. Chapters 2 and 3 analyse the impact of the 2018 European Securitisation Regulation using loan-level data from the European DataWarehouse. Chapter 2 shows that the regulation was associated with a significant decline in mortgage delinquency rates, suggesting that enhanced transparency and risk retention improved loan quality. Chapter 3 focuses on the STS framework, finding that STS-labelled deals outperformed non-STS counterparts and were more resilient during the COVID-19 shock. Chapter 4 shifts the focus on emerging regulatory initiatives and explores the role of environmental risk. It investigates whether energy performance certificates (EPCs) improve the predictive accuracy and discriminatory power of mortgage credit risk models. Using harmonised EPC data across several European countries, the chapter finds that incorporating energy efficiency significantly enhances model performance, particularly during periods of high energy inflation when vulnerabilities in household finances become more pronounced. Together, the chapters highlight how evolving regulatory frameworks, ranging from structural reforms to climate-related supervision, can shape the dynamics of credit risk in securitised markets, especially during times of macroe-

conomic stress.

Keywords: Securitisation regulation, residential mortgage-backed securities, mortgage delinquency, STS framework, energy performance certificates, credit risk modelling, macroeconomic shocks, COVID-19 pandemic, cost-of-living crisis, financial regulation.

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Chapter 1

Introduction

1.1 Background and regulatory landscape

1.1.1 Post-crisis securitisation reforms and the STS framework

The European residential mortgage-backed securities (RMBS) market underwent significant regulatory transformation following the global financial crisis. Before the crisis, securitisation practices often involved misaligned incentives and declining underwriting standards (Griffin & Maturana, 2016; Keys et al., 2010; Purnanandam, 2011; Titman & Tsyplakov, 2010). Evidence from the U.S. securitisation market demonstrates that insufficient screening and the absence of adequate risk retention (commonly referred to as lacking "skin in the game") resulted in poorer credit outcomes. Specifically, transactions structured without meaningful issuer risk exposure and with opaque documentation consistently faced higher losses and increased default rates (Begley & Purnanandam, 2017).

During this period, a strong investor demand for highly rated securities, coupled with banks' ability to shift loan risks onto external investors, encouraged increasingly lax lending standards. This practice led to the proliferation of substandard or "bad" loans across the financial system (Mian & Sufi, 2009). The burden of those non-performing loans was able to pass through the financial system, finally reaching the hands of unsuspecting investors, and this mainly happened because distorted incentives had developed at all stages of the securitisation process (Shin, 2009).

Recognising these fundamental flaws, European regulators initiated comprehensive post-crisis securitisation reforms. Central among these reforms is the European Securitisation Regulation (2017/2402), which, after its finalisation in 2017, came into force in January 2018. This regulation introduced the "Simple, Transparent and Standardised" (STS) securitisation framework alongside overarching requirements, such as enhanced investor due diligence, improved transparency and disclosure obligations, and a mandatory 5% risk retention by issuers. Collectively, these measures aim to reduce complexity, realign originator-investor incentives, and thereby restore investor confidence in the European RMBS market.

1.1.2 Emerging challenges: climate-related and environmental risks

The regulatory response to the financial crisis significantly improved the transparency, simplicity, and alignment of incentives within the European securitisation market. However, financial regulation continues to evolve, responding dynamically to emerging threats to financial stability. Among these, climate-related and environmental risks have become increasingly prominent. While earlier reforms primarily targeted the structural weaknesses exposed by the crisis, regulators now also recognise that climate change poses new systemic challenges for financial markets, including the mortgage and securitisation sectors.

In recent years, financial authorities and scholars have increasingly acknowledged that climate change represents a substantial threat to financial stability. Physical climate hazards (such as floods, heatwaves, and hurricanes) and the broader economic transition towards low-carbon solutions have the potential to trigger credit losses, market volatility, and correlated defaults across financial institutions. For instance, Battiston et al. (2021) offer a comprehensive analytical framework that connects climate risks directly to financial stability, illustrating how climate-related shocks can spread through complex bank-firm networks, thereby weakening the resilience of the banking sector.

Reflecting these concerns, European regulatory frameworks have begun explicitly addressing climate-related exposures as prudential risk factors. The European Central Bank's *Guide on climate-related and environmental risks* (European Central Bank, 2020) underscores this shift, setting clear supervisory expectations for banks to integrate climate considerations into all aspects of their risk management and internal modelling processes. To operationalise these requirements, European supervisors have also introduced climate stress tests designed to quantify potential financial losses stemming from severe climate scenarios, including both physical disasters and policy-driven economic transitions. Moreover, these evolving supervisory practices have prompted discussions around targeted regulatory measures for environmentally sustainable finance. Notably, the emergence of clearly defined "green securitisation" standards, along with proposals for differentiated capital treatment of climate-friendly assets, further illustrates how financial regulation is increasingly aligning prudential objectives with sustainability goals.

Academic research is starting to inform these policy moves. For example, theoretical work by Conlon et al. (2024) demonstrates that banks' credit risk can materially increase due to climate-related shocks, even when those risks are geographically or sectorally distant. Using syndicated loan data, the authors find that unexpected climate shocks significantly raise banks' default risk and systemic risk, prompting banks to curtail lending and build loan-loss reserves in response. These findings reinforce why prudential regulators are wary of climate risks: left unmanaged, environmental exposures in loan portfolios could impair asset quality and amplify systemic stress. In short, climate-related financial risk has rapidly moved from a niche concern to a mainstream regulatory priority, forming an important backdrop for the European mortgage-backed securities market's evolution.

A closely related development is the growing evidence that environmental characteristics of mortgaged properties can predict mortgage credit performance. Traditional credit risk models for mortgages emphasise borrower income, credit history, loan-to-value ratios, and macroeconomic factors (see, for instance, Cunningham and Capone Jr (1990), Jiang et al. (2014), and Vandell and Thibodeau (1985)). However, new research suggests that "green" properties (i.e., energy-efficient homes) tend to have lower default risk. This has opened a novel perspective on credit risk assessment in RMBS pools: could the energy performance of collateral properties be linked to borrowers' delinquency? Billio et al. (2022) provide one of the first large-sample evidence on this question, examining Dutch residential mortgages with energy efficiency ratings. They find that loans secured by energy-efficient homes (as defined using a provisional label assignment procedure) consistently show lower probabilities of default, even after controlling for borrower and loan characteristics. Interestingly, these risks are yet to be reflected in the industry practice. Bell et al. (2023) document this trend, showing that in the UK mortgage market, loans on energy-efficient homes do not carry lower interest spreads relative to otherwise similar loans on energy-inefficient homes. By recognising factors like energy efficiency in underwriting and securitisation, market participants and regulators can jointly foster a more climate-resilient RMBS market.

1.1.3 Regulatory effectiveness and macroeconomic shocks

The effectiveness of regulatory frameworks is often most clearly revealed during periods of severe economic stress. Recent macroeconomic shocks, notably the COVID-19 pandemic (2020–2021) and the subsequent European energy price crisis (2021–2022), serve as critical real-world stress tests of the resilience provided by the post-crisis regulatory reforms in the European RMBS market. These shocks presented unprecedented challenges, severely straining borrowers and lenders and providing an opportunity to empirically evaluate whether structural safeguards and enhanced regulatory standards functioned effectively.

Initial evidence from these episodes indicates notable resilience. Despite the sharp economic downturn, widespread furlough schemes, and business disruptions that followed the COVID-19 pandemic, the European mortgage market experienced only modest increases in defaults, with the RMBS sector remaining relatively stable overall. This stability can be partly attributed to extraordinary policy measures and fiscal support programs implemented by governments and central banks, including temporary payment moratoria and extensive liquidity provisions, which mitigated potential defaults and prevented cascading foreclosures (Narayan et al., 2021). Nevertheless, as emphasized by Colak and Öztekin (2021), pandemic-induced lockdown measures unintentionally heightened borrower vulnerabilities, leading to a global uptick in credit risk. Such unintended consequences underscore the complexity of macroeconomic shocks and their potential interactions with credit markets. In this context, assessing how regulatory improvements in securitisation markets performed during COVID-19 offers valuable insights into their effectiveness during severe economic disruptions.

Similarly, the cost-of-living crisis, characterised by surging energy prices and elevated inflation, has introduced another significant stress scenario. This crisis, coupled with a higher interest rate environment, has placed renewed pressure on household finances, particularly among borrowers whose homes have poor energy efficiency. Analysing these recent macroeconomic events thus provides a deeper understanding of how regulatory initiatives and emerging environmental factors interact in shaping the resilience of mortgage markets.

1.2 Context and motivation

This thesis sits at the intersection of securitisation regulation, credit risk analysis, and emerging trends in environmental finance. Its motivation is driven by two central observations. First, robust securitisation markets are critical for credit intermediation in Europe; their efficiency and sustainability depend fundamentally on investor confidence, asset quality, and transparent regulatory frameworks. Second, the risk dynamics within mortgage markets are evolving rapidly, with climate-related and environmental factors increasingly recognised by regulators as integral components of credit risk management and broader financial stability.

The introduction of the STS framework provides a concrete and timely opportunity to evaluate the broader effectiveness of post-crisis regulation in improving the quality and resilience of securitised mortgage portfolios. While these reforms were designed to restore investor confidence by curbing moral hazard and promoting greater transparency, empirical evidence on their impact remains limited. This thesis addresses that gap by analysing how key provisions of the European Securitisation Regulation have influenced credit performance and securitisation structure.

At the same time, the growing regulatory focus on environmental sustainability and the recent surge in inflation and interest rates have introduced new risk dimensions that warrant close attention. Climate-related vulnerabilities, such as poor energy efficiency and exposure to energy price volatility, can affect borrowers' ability to meet mortgage obligations, increasing the risk of delinquency. This have prompted regulators to explore how environmental considerations can be integrated into risk modelling, disclosure, and prudential frameworks. This evolving landscape calls for a parallel empirical effort to assess whether emerging environmental metrics, particularly energy efficiency, can meaningfully improve credit risk differentiation and loan quality.

The thesis is structured around these core themes. Specifically, chapters 2 and 3 empirically assess the effects of the 2018 European Securitisation Regulation, drawing from a shared dataset of residential mortgages from the European DataWarehouse. These chapters investigate whether the introduction of enhanced transparency requirements, risk retention rules, and the STS framework improved mortgage credit quality and securitisation structures, particularly during periods of economic disruption such as the COVID-19 pandemic. This analysis is based on a peer-reviewed article published in the *Journal of Banking and Finance* (Billio et al., 2023). Chapter 2 focuses on the general provisions of the regulation, while Chapter 3 isolates the specific contribution of the STS framework.

Chapter 4, by contrast, turns to the environmental dimension of credit risk. Building on a separate working paper (Billio et al., 2025),[1] it examines whether incorporating energy efficiency indicators, as measured by the Energy Performance Certificates (EPCs), can meaningfully improve risk differentiation and modelling performance in mortgage portfolios. This question becomes especially salient in the context of rising regulatory attention to climate-related risks and their implications for financial stability.

While each chapter can be read independently, a unifying thread across the thesis is the empirical assessment of credit performance under conditions of macroeconomic stress. The first two chapters evaluate the role of regulatory reforms in shaping credit outcomes

[1] Presented at the 2025 International Conference in Financial Science (ICFS), Naples, and the 2025 Social and Sustainable Finance (SSF) conference, Brunel University London. Accepted for presentation at the 2025 EFMA and FMA conferences.

during the COVID-19 pandemic, which triggered widespread economic disruption and offered a natural stress test of the securitisation framework. Chapter 4 shifts focus to the cost-of-living crisis, marked by high energy inflation and rising interest rates, to assess whether the informational value of EPC ratings becomes more pronounced under economic strain. Together, these chapters provide a cohesive analysis of how both post-crisis and forward-looking regulatory initiatives, particularly those addressing sustainability, interact with credit risk in periods of systemic pressure.

1.3 Literature review and contribution

1.3.1 Mortgage default in the subprime crisis and COVID periods

Periods of economic crisis offer a revealing lens through which to understand mortgage default. Defaults are not merely individual events; they have aggregate consequences. When households fall behind on mortgage payments, this financial stress can spill over into the broader economy through reduced consumption, forced property sales, and downward pressure on house prices. At the same time, crises highlight how defaults are not driven by income shocks alone, but are shaped by the institutional and financial architecture surrounding mortgage lending, such as loan features, securitisation structures, servicing arrangements, and policy responses.

This section reviews key academic contributions on mortgage default during the 2008–09 global financial crisis and the more recent COVID-19 pandemic. These two episodes differ starkly in origin and response, yet both illustrate how the design of mortgage markets affects household resilience. The global financial crisis revealed how unchecked credit expansion and securitisation weakened loan quality and amplified defaults. In contrast, COVID exposed the importance of policy design and intermediation capacity in shaping delinquency outcomes, despite deep but temporary income shocks.

A large body of research on the global financial crisis shows that the mortgage boom in the early 2000s was driven not just by borrower demand, but by aggressive credit supply into vulnerable segments. For instance, Mian and Sufi (2009) find that areas with high latent demand for credit, but weak fundamentals such as stagnant income growth, received the greatest expansion in mortgage lending during the boom, and experienced the sharpest rise in defaults after 2007. This points to the role of financial innovation and securitisation in enabling credit growth disconnected from repayment capacity. The link between securitisation and loan quality is further confirmed in loan-level studies. Keys et al. (2010) show that loans just above the FICO threshold for securitisation were more likely to be sold and were subject to laxer screening, resulting in higher delinquency rates. Piskorski et al. (2010) highlight that once loans became distressed, those that had been securitised were less likely to be renegotiated, likely due to contracting frictions and dispersed ownership. These findings suggest that the structure of the mortgage finance system itself contributed to the wave of defaults. Further evidence of deteriorating loan quality comes from Demyanyk and Van Hemert (2011), who document a progressive increase in risk layering during the pre-crisis years, and that securitisation originators were generally aware of it. Adelino et al. (2016) challenge the view that the crisis was confined to the subprime segment, showing that many defaults occurred among middle-income borrowers who had accessed aggressive credit products.

Mechanisms linking house prices and defaults are central to the crisis narrative. As prices fell, many households slipped into negative equity, which in turn reduced incentives to remain current on payments. Guiso et al. (2013) show that willingness to strategically default in the US market increases with the size of the equity shortfall, but also depends on social norms and perceptions of fairness. Campbell et al. (2011) find that foreclosures depress neighbouring property values, triggering localised feedback loops that deepen the crisis. In addition, structural models offer further insight into how cash-flow shocks interact with loan terms. Campbell and Cocco (2015) show that default risk rises when mortgage payments are high relative to income, when equity buffers are thin, and when refinancing is constrained.

In contrast, the COVID-19 recession triggered an unprecedented economic contraction but did not produce a comparable mortgage crisis. A key difference lies in the policy response. Large-scale forbearance programmes and foreclosure moratoria were introduced rapidly in many jurisdictions, breaking the usual link between income loss and repayment failure. Davis et al. (2023) note that COVID policies interrupted canonical foreclosure paths, with default risk reflecting policy design and servicer constraints more than pure borrower fundamentals in the short run. Yet access to these protections was not uniform. Kim et al. (2024) find that servicer frictions played a significant role: non-bank servicers with weaker liquidity positions were less able to deliver forbearance, leading to higher delinquency rates in affected areas. Meanwhile, private mechanisms such as refinancing were also limited. DeFusco and Mondragon (2020) show that during recessions, liquidity constraints restrict access to refinancing, even when interest rates fall. This underscores how credit frictions can prevent households from smoothing cash flows just when they need it most.

In summary, the great financial crisis highlighted how credit supply, loan quality, and securitisation shaped the default crisis, while COVID demonstrated the role of swift policy interventions and servicer capacity in cushioning household finances. Both episodes reveal that mortgage default is not solely a function of borrower characteristics, but reflects deeper structural features of the financial system. This insight is central to the analysis that follows in this thesis, which focuses on the interaction between mortgage contract characteristics, securitisation design, and collateral heterogeneity in shaping credit risk during times of stress.

1.3.2 Mortgage securitisations in Europe – a historical perspective

As the previous section highlighted, mortgage defaults during crises are influenced not only by borrower balance sheets, but also by how loans are originated, funded, and serviced. In the United States, securitisation played a central role in amplifying default risk during the subprime crisis. In Europe, however, the structure of mortgage funding has historically followed a different path, with important implications for how credit risk is transmitted in times of stress.

European mortgage markets have long operated under a dual funding model. Covered bonds provide a stable, on-balance-sheet instrument backed by regulated cover pools, while mortgage-backed securities (MBS) transfer credit risk off balance sheet to external vehicles. The coexistence of these two instruments, together with cross-country institutional differences, has created a more varied and flexible funding landscape than in the US. For instance, Boesel et al. (2018) show that European banks with covered bond programmes securitise a smaller share of their assets, all else equal. This difference is driven primarily by funding needs: under liquidity pressure, banks without access to covered bonds are more likely to increase securitisation activity, while those with covered bonds rely less on ABS issuance.

Understanding how securitisation developed in Europe before and after the global financial crisis is therefore essential for interpreting delinquency outcomes and evaluating the impact of regulatory reforms. Before the crisis, European banks did expand their use of securitisation, but the underlying motives and usage patterns diverged from those observed in the US. Using Italian bank-level data, Affinito and Tagliaferri (2010) show that banks more likely to securitise tended to be less capitalised, less liquid, less profitable, and more exposed to problem loans. This suggests that securitisation in Europe functioned primarily as a tool for managing funding and balance-sheet constraints, rather than as a means of regulatory arbitrage. It was used most actively by banks facing internal pressures, and served to free up space on their balance sheets by transferring risk externally.

A key question is whether securitisation in Europe contributed to weaker credit discipline prior to the crisis. On this point, the evidence is more nuanced. Kara et al. (2016) analyse syndicated loans and find that banks more active in securitisation did not systematically price loans more aggressively in the run-up to the crisis. Instead, spreads evolved largely in line with the credit cycle. This tempers the narrative, prominent in US studies, that securitisation inherently weakened lending standards. Still, a subsequent study revealed that incentives changed after securitisation: Kara et al. (2019) show that while loan pools selected for securitisation were not observably lower quality at origination, borrower credit quality deteriorated more over time compared to similar loans that remained on balance sheet. This suggests that reduced monitoring following securitisation may have undermined performance ex post.

Issuer reputation also played a role in shaping the quality of European securitisation markets. Deku et al. (2022) examine a large sample of securities issued between 1999 and 2007 and find that more reputable banks tended to securitise higher-quality loan pools, resulting in fewer downgrades and lower delinquency rates. However, this reputational advantage faded during the 2005–2007 boom, when rapid issuance was accompanied by a decline in screening standards.

Overall, the European experience differs from the US in two key aspects. First, the long-standing presence of covered bonds offers banks an alternative source of secured funding, reducing their reliance on securitisation. As a result, European banks have tended to use securitisation primarily as a funding instrument, particularly in response to liquidity needs, rather than as a tool for regulatory arbitrage. Second, while the US literature has documented clear evidence of adverse selection and lax origination linked to securitisation, the European evidence paints a more nuanced picture. Loan-level studies do not find strong signs of observable adverse selection at issuance; however, monitoring and screening incentives may deteriorate after loans are transferred off balance sheet, especially during periods of rapid issuance such as the pre-crisis boom. These institutional and structural differences help explain why mortgage delinquency in Europe may have evolved differently during crises, with risk transmission patterns that were more muted, delayed, or heterogeneous compared to the US.

1.3.3 Energy transition and the mortgage market

Building on the previous sections, which highlighted the role of funding structures and borrower characteristics in shaping mortgage performance during crises, the energy transition introduces an additional structural dimension. Specifically, the energy efficiency of a property can influence both its market valuation and the cash-flow resilience of the borrower, thereby affecting mortgage default risk and, potentially, loan pricing and product design.

An extensive European literature shows that energy efficiency is capitalised into property prices, suggesting that greener homes offer more valuable collateral. In the Netherlands, Brounen and Kok (2011) provide early evidence that the EU's Energy Performance Certificate (EPC) system conveys information that buyers are willing to pay for. In Ireland, Hyland et al. (2013) find significant sale and rental premia for energy-efficient homes, with larger effects in weaker market conditions. For England, Fuerst et al. (2015) use repeat-sales data to show that homes rated A or B command a clear premium over D-rated properties. Together, these studies suggest that energy-efficient homes are more valuable in the resale market, supporting the idea that, in the event of borrower default, higher expected recovery values could help absorb potential losses for lenders.

In parallel, growing evidence suggests that energy efficiency also improves mortgage performance through the borrower's cash-flow channel. Using Dutch loan-level data matched to EPC labels, Billio et al. (2022) find that loans secured on more efficient properties are significantly less likely to default, even after controlling for a wide range of borrower and loan characteristics. Similar findings emerge in the UK, where Guin et al. (2022) show that mortgages on energy-efficient homes are less likely to fall into arrears, and that this association is not fully explained by differences in borrower income. These results are consistent with an affordability mechanism: lower energy bills improve disposable income, increasing borrowers' ability to stay current on payments during economic shocks.

Despite the apparent credit risk advantages of energy-efficient housing, pre-regulatory evidence suggests that these characteristics were not systematically reflected in mortgage pricing. Analysing over 1.8 million UK mortgage contracts, Bell et al. (2023) find little evidence that banks priced EPC-related risks into interest rates prior to 2018. Any pricing differentials that did exist were small in magnitude once broader macroeconomic rate movements were taken into account. This suggests that market-based pricing lagged behind risk-based differentiation, with regulatory initiatives preceding widespread adjustment in lending practices.

Overall, the energy transition interacts with the same mechanisms identified in the crisis literature, such as collateral values, borrower cash flows, and intermediation, while introducing new dimensions of vulnerability and resilience. The evidence shows that energy-efficient properties command higher valuations and exhibit lower arrears and default rates, but that these characteristics have not yet been fully internalised by lenders in pricing decisions. Understanding how energy performance shapes both the value and performance of mortgage assets is therefore critical for assessing future vulnerabilities under conditions of climate and energy-price shocks.

1.3.4 Literature contribution

This thesis contributes to the academic literature on securitisation regulation, mortgage credit risk, and environmental finance, with a particular focus on how institutional safeguards and emerging risk factors influence loan performance in the European RMBS market. Each chapter offers an original empirical analysis that engages with and extends distinct strands of the literature.

Chapter 2 is the first study to empirically assess the impact of the 2018 European Securitisation Regulation on credit quality in the European residential mortgage-backed securities market. It shows that the regulatory overhaul was associated with a pre-pandemic decline in mortgage delinquencies of 34 basis points.[2] In doing so, the chapter contributes to the broader debate on the effectiveness of post-crisis regulatory reforms (Akseli, 2013; Benetton et al., 2020; Fender & Mitchell, 2009), and more specifically to the literature analysing the role of macroprudential policies in shaping mortgage market outcomes (Stanga et al., 2020).

[2]The increase in quality is substantial when we consider that our sample includes loans securitised into RMBSs that are eligible for repurchase agreements with the ECB and, as a consequence, have a generally high rating.

Chapter 3 extends this regulatory perspective by focusing on the specific role of the STS framework in shaping both securitisation structure and asset performance. Building on earlier work on structural complexity and default risk (Covitz et al., 2013), this is the first empirical analysis showing that STS-labelled deals achieve materially better credit outcomes, with a 0.39% lower annual delinquency rate compared to their non-STS counterparts. In addition, this chapter contributes to the literature on the credit market effects of the COVID-19 pandemic (Colak and Öztekin (2021), among others), by demonstrating that STS deals proved more resilient to systemic stress.

Chapter 4 shifts focus to the emerging regulatory emphasis on climate-related risks, contributing to a growing literature that links environmental performance to credit outcomes (Billio et al., 2022; Guin & Korhonen, 2020; Kaza et al., 2014). It provides the most comprehensive EU-wide study to date on the role of EPC ratings in predicting mortgage arrears and defaults. Unlike earlier studies, which typically focus on individual countries, this chapter harmonises EPC data across multiple European markets and demonstrates that energy efficiency enhances the predictive power of internal credit models. In doing so, it bridges two previously disconnected strands of literature, energy efficiency and credit risk modelling, and responds to recent calls for integrating climate-related information into financial risk frameworks (The European Central Bank's *Guide on climate-related and environmental risks* (European Central Bank, 2020)).

Taken together, these chapters offer new empirical evidence on how both established and emerging regulatory initiatives shape credit risk in securitised mortgage markets. They highlight the importance of regulatory design, structural simplicity, and climate-aligned data in enhancing financial resilience, particularly during periods of macroeconomic stress. The findings speak directly to ongoing policy debates about the future of sustainable securitisation and the integration of environmental risks into prudential supervision.

Chapter 2

The new European securitisation regulation: an empirical analysis of the general provisions

2.1 Introduction

The complexity of the securitisation market was one of the key factors behind the Great Recession of 2007–2009.[1] As Caballero and Simsek (2013) argue, financial complexity can foster uncertainty and confusion, discouraging investments in newly issued securities. In turn, this leads to increased volatility, reduced liquidity, and overall inefficiencies in trading, particularly in structured finance markets (Carlin et al., 2013).

In the aftermath of the global financial crisis, investor trust in securitised products deteriorated sharply. In Europe, for example, the proportion of asset-backed securities (ABS) placed with investors relative to the total amount issued fell from around 70% prior to the crisis to approximately 12% in 2008. More than a decade later, the European securitisation market has yet to return to its pre-crisis levels.[2]

[1] Antoniades (2016), Dungey et al. (2011), Fender and Mitchell (2009), Gorton (2009), Mian and Sufi (2009), and Shin (2009), among others.

[2] Source: AFME, Finance for Europe. Securitisation Data Report, European Structured Finance. Q4:2020.

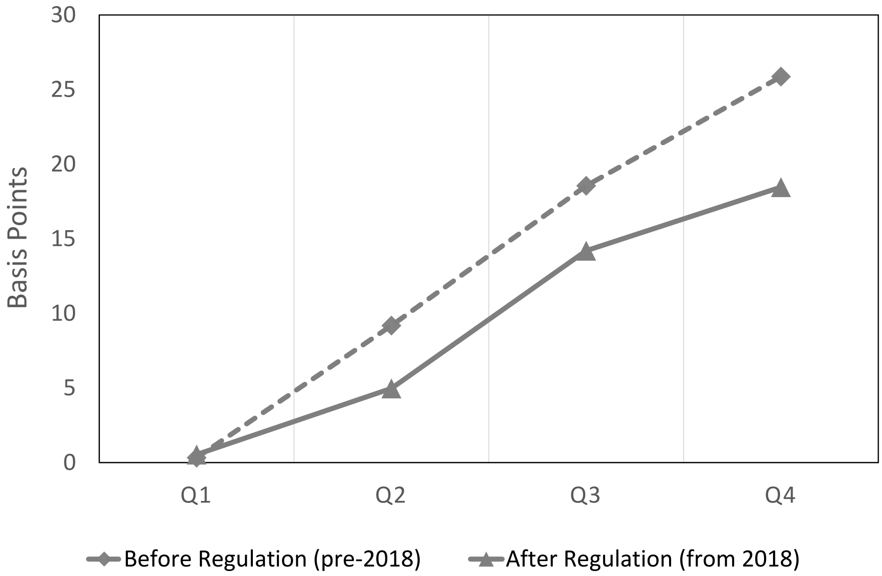
To address these issues, the European Union adopted a new regulatory framework aimed at reducing complexity, improving transparency, and restoring investor confidence in securitisation. The regulation, finalised in 2017 and introduced in January 2018, is characterised by two key components: (i) a set of general provisions applicable to all securitisations issued in the European Union, and (ii) a specific framework for Simple, Transparent and Standardised (STS) securitisations (The European Parliament and the Council, 2017).

This chapter focuses on the general provisions of the regulation, which apply universally to EU securitisations regardless of STS status. These include a ban on so-called "cherry-picking" practices, stricter transparency and disclosure requirements, and enhanced due diligence obligations for investors. These measures were intended to improve the overall quality and comparability of securitised instruments and ensure that all market participants, whether STS-compliant or not, adhere to fundamental standards of accountability and clarity. Assessing the effectiveness of these general provisions is crucial to understanding the broader impact of the regulation. By focusing on this part of the reform package, we aim to shed light on whether the regulation has succeeded in reducing information asymmetries and rebuilding trust in the securitisation market.

We contribute to the existing literature in several ways. To the best of our knowledge, this is the first study that empirically analyses the possible effects of the new ABS regulation on credit quality in the European residential mortgage-backed securities (RMBS) market. Residential mortgages are particularly relevant since they are the most popular ABS asset class in Europe, accounting for more than 41% of the European securitisation issuance volumes in 2020.[3] As can be seen in Figure 2.1, residential mortgages originated after 2018 show a significantly lower one-year delinquency probability than those pooled before the

[3] Source: AFME, Finance for Europe. Securitisation Data Report, European Structured Finance. Q4:2020.

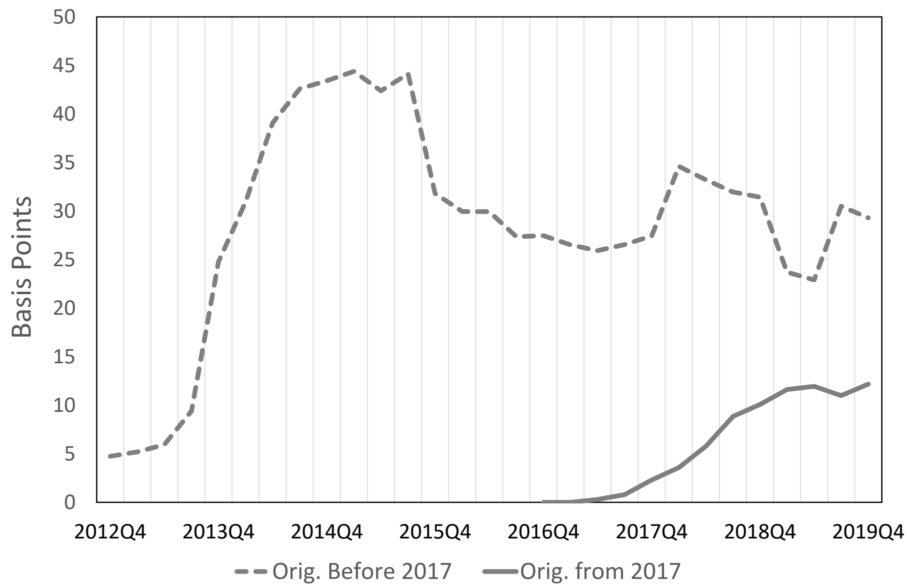
Figure 2.1. Cumulative delinquency of residential mortgages. The figure shows the average cumulative delinquency rates of mortgages originated before and after the introduction of the 2018 European ABS regulation, with quarterly data. A mortgage is considered delinquent if it has defaulted or is in arrears for at least two consecutive quarters.



regulation entered into force. The difference in annual delinquency rates is even stronger when we compare mortgages issued before and after the announcement of the new regulation in 2017, as shown in Figure 2.2.

We show that changes in the ABS regulatory framework are responsible for a pre-pandemic decline in annual residential mortgage delinquencies in Europe of 34 basis points (bp) after controlling for macro-economic conditions. This increase in mortgage quality is economically relevant as it represents 42% of the average delinquency rate (80 bp) over the entire observation period, 2013-2021. In addition, we find that the introduction of the regulation is linked to a lower number of RMBS tranches and a higher average tranche rating at origination. Our findings contribute to the broader debate on the effectiveness of regulatory reforms introduced in response to the 2008 financial crisis (see, for instance, Akseli (2013), Benetton et al. (2020), and Fender and Mitchell (2009)). More specifically,

Figure 2.2. Annual rolling average of quarterly delinquency rates of residential mortgages. The figure shows the annual average of quarterly delinquency rates of mortgages originated before and after the announcement of the European ABS regulation in 2017.



they relate to the literature examining the impact of macroprudential regulatory policies on mortgage market outcomes, including borrower default behaviour, as discussed by Stanga et al. (2020).

Beyond the overall decline in mortgage delinquencies, we investigate how the new ABS rules have affected different types of mortgages. Our results reveal that the impact of the regulatory changes is uneven across loan categories. In particular, mortgages classified as under-collateralised (those with a loan-to-value (LTV) ratio exceeding 1) exhibited higher delinquency rates in the period following the introduction of the new ABS rules, up to the onset of the COVID-19 pandemic. However, we show that the overall risk of RMBS was only marginally affected. This outcome is likely driven by the regulatory measures introduced to limit adverse selection, notably the prohibition of "cherry-picking" (Article 6) and the enhanced investor due diligence requirements (Article 5), which constrained the securitisation of riskier loans. These findings complement a broader literature investigating how changes in banking regulation affect the composition of credit supply and alter financial institutions' lending practices. For instance, Acharya et al. (2020) show that the introduction of loan-to-value and loan-to-income caps in Ireland prompted affected banks to reallocate mortgage credit toward high-income borrowers and regions less constrained by the regulatory thresholds. Similarly, Klein et al. (2020) document that the transparency regime introduced in Europe in 2013[4] encouraged the issuance of better-performing and more diversified ABS portfolios.

2.2 The new European ABS regulation

The 2008 financial crisis exposed significant vulnerabilities in the global securitisation market, including issues of opacity, misaligned incentives, and excessive complexity. In response, the European Union introduced a comprehensive regulatory framework aimed at restoring confidence in securitisation and ensuring the stability of financial markets. This initiative culminated in the adoption of Regulation (EU) 2017/2402, which came into force on 1 January 2018. The new ABS regulation overhauled the EU securitisation framework and introduced harmonised rules designed to improve transparency, simplify structures, and promote more consistent due diligence practices. It is structured into two main components: (i) a set of general provisions applicable to all securitisations, and (ii) a specific framework for Simple, Transparent, and Standardised (STS) securitisations.

The general provisions, outlined in Articles 1 to 17, apply universally to all securitisation transactions conducted within the EU. These include several notable regulatory innovations:

[4] Beginning in January 2013, banks using residential mortgage-backed securities in ECB repo operations were required to submit loan-level data in a detailed and standardised format. Non-compliance rendered the securities ineligible for ECB refinancing.

- *Enhanced investor due diligence.* Investors are required to undertake more comprehensive risk assessments of their securitisation positions, including analysis of the structure of the deal and the underlying exposures.
- *Ban on "cherry-picking."* Originators may no longer selectively transfer underperforming assets into securitisation vehicles while retaining better-performing exposures on their balance sheets. This rule (Article 6) aims to improve the quality of securitised asset pools and limit moral hazard.
- *Strengthened transparency requirements.* The regulation introduces detailed and standardised disclosure rules, mandating the use of securitisation repositories overseen by the European Securities and Markets Authority (ESMA).
- *Stricter credit-granting standards.* Article 9 of the regulation restricts the securitisation of loans originated after March 2016 unless the lender can demonstrate that the borrower's creditworthiness was assessed using verifiable information.
- *Prohibition of re-securitisation.* Re-securitisations, i.e., transactions where the underlying assets are themselves securitisation tranches, are banned under the new regime (Article 8), thereby limiting structural complexity.

These general provisions are the focus of this chapter. They represent a significant shift in the regulatory treatment of securitisation, particularly by increasing transparency and investor accountability, and are intended to improve the quality and stability of the market as a whole.

The second part of the regulation identifies the criteria that need to be met for a securitisation to be labelled as STS. Unlike other provisions of the new ABS regulation, which apply to all securitisations, the STS regime is optional. The criteria include requirements relating to the underlying assets (such as asset sale, asset homogeneity, origination standard), disclosure and verification (documentation content and clarity, external verification of underlying exposures) and transaction structure (risk retention compliance, interest rate and currency risk mitigation). The criteria do not necessarily imply that STS securitisations are less risky, but rather that the risk involved can be better assessed by a prudent and diligent investor.

While both sets of provisions aim to address structural weaknesses in the securitisation market, the remainder of this chapter focuses exclusively on the general rules applicable to all EU securitisations. The effects of the STS framework will be examined in detail in Chapter 3.

2.3 Data and methodology

We retrieve our data from the European DataWarehouse (EDW), the platform designated by the European Securities and Markets Authority (ESMA) in Europe for collecting and validating standardised loan-level data for asset-backed securities that are eligible for repurchase agreements with the ECB. Starting from January 2013, loan-by-loan information on residential mortgage-backed securities (those eligible to be accepted as collateral in Eurosystem credit operations) must be quarterly reported to this repository. For each loan, more than 150 variables can be reported by the originators of the securitisation, 55 of which are mandatory. These categories include borrowers' information, loan characteristics, information on the mortgaged property and performance indicators.

Our initial sample includes 40,295,781 quarterly observations, reported from 2012-Q3 to 2021-Q1. To estimate annual probabilities of default and construct a more balanced panel, we aggregate the data from quarterly to annual frequency. Results with quarterly data are reported in our robustness tests in Appendix 2.B, Table 2.B.1.

To isolate the effects of the general provisions introduced by the new EU ABS regulation, the analysis focuses on a subsample of loans securitised between January 2013 and December 2019. This time frame enables a clean comparison of the period before and after the introduction of the regulation in January 2018, while avoiding the confounding effects of the COVID-19 pandemic and the associated policy responses. Moreover, deals labelled as STS are excluded from this subsample to ensure that the results are not influenced by the additional criteria and requirements introduced under the STS framework.

The final number of deals, tranches, loans and observations by country of origination is shown in Table 2.1. As it can be noted in Panel A, the full annualised sample includes 8,961,130 observations, reported from 2013 to 2021, corresponding to 3,997,044 loans. The core subsample of securitised deals issued from 2013 to 2019 (Panel B) includes 233 deals, corresponding to 7,348,619 annual observations.

The majority of RMBS deals used in Eurosystem credit operations are issued in the Netherlands, France, Spain, and Italy. However, one should be cautious when using this data to characterise the Euro area residential mortgage market. For example, Germany is the country with the fewest number of deals in our sample despite having one of the most developed residential real estate markets. This underrepresentation arises because German loans are typically repackaged into covered bonds (referred to as "Pfandbriefe") which are seldom reported to the European DataWarehouse (Gaudêncio et al., 2019).

Despite the limited number of German deals, the dataset provides sufficiently broad coverage of the European RMBS market. In particular, it accounts for approximately 26.45% of the total European RMBS issuance in 2020.[5]

[5] Source: AFME, Finance for Europe. Securitisation Data Report, European Structured Finance. Q4:2020.

Table 2.1. Distribution of securitised mortgages by country of origination. The table reports country distributions of securitisation deals, tranches, mortgage loans, and annual observations at the loan level across the whole sample (Panel A), and the General provision subsample (Panel B). Only tranches with a non-missing rating at origination are reported in this table.

Panel (A): Full sample, from 2013 to 2020

Country of Origination	Deals	Tranches	Loans	Observations
Netherlands	98	320	1,026,506	2,282,395
France	27	48	1,230,701	2,349,192
Spain	41	64	439,218	1,344,009
Italy	42	104	442,117	1,029,704
Belgium	5	14	143,793	389,307
United Kingdom	37	140	207,073	503,021
Germany	3	0	314,464	572,654
Portugal	5	5	56,462	182,006
Ireland	23	87	136,710	308,842
Total	281	782	3,997,044	8,961,130

Panel (B): General provision subsample, from 2013 to 2019

Country of Origination	Deals	Tranches	Loans	Observations
Netherlands	80	208	721,117	1,622,397
France	22	38	991,249	1,952,896
Spain	36	61	411,770	1,310,758
Italy	39	95	318,607	756,700
Belgium	5	14	141,484	353,880
United Kingdom	30	103	141,426	387,579
Germany	3	0	314,464	572,654
Portugal	3	4	41,685	147,637
Ireland	15	44	96,271	244,118
Total	233	567	3,178,073	7,348,619

As complementary data, we collected tranche-level information from RMBS prospectuses to assess how the regulation may have influenced securitisation structuring practices. This dataset was enriched with tranche-specific characteristics, such as ratings at origination and tranche balances, sourced from Refinitiv Eikon (where available). It covers 567 tranches issued between 2013 and 2019, aligning with the general provisions subsample used in this chapter.

Table 2.2. Sample characteristics. The table reports loan level averages for the variables used in the main regressions for the full sample and the general provision subsample.

		Full sample	**General provision subsample**
	Sample Period	2013 - 2020	2013 - 2019
	No. of loans	3,997,044	3,178,073
	Variables	**Mean**	**Mean**
	Delinquent	0.008	0.009
	Securitised from 2018	0.314	0.138
	Originated from 2018	0.055	0.016
	Originated from 2017	0.108	0.030
Loan characteristics			
	Loan to Value	0.836	0.823
	Years to Maturity	17.9	15.7
	Interest Rate	2.639	2.683
Interest Type	Floating	0.278	0.256
	Fixed	0.345	0.383
	Hybrid	0.353	0.339
	Other	0.024	0.022
Payment Type	Annuity	0.617	0.599
	Linear	0.161	0.192
	Increasing	0.015	0.015
	Other	0.207	0.195
Purpose	Purchase	0.636	0.620
	Remortgage	0.120	0.123
	Renovation	0.074	0.073
	Construction	0.066	0.066
	Other	0.104	0.118
Borrower Characteristics			
	Second Time Borrower	0.245	0.242
Employment	Employed	0.828	0.827
	Unemployed	0.011	0.012
	Self Employed	0.103	0.101
	Legal Entity	0.002	0.002
	Student	0.002	0.001
	Pensioner	0.028	0.027
	Other	0.029	0.031
Macro-variables			
	ΔUnemployment	0.096	0.133
	ΔHouse Price Index	4.289	3.812

As shown in the summary statistics reported in Table 2.2, 0.9% of the loan-year observations in this sample are classified as delinquent. In terms of interest rate structure, the majority of loans (38.3%) feature a fixed rate, while 25.6% are issued at a fully floating rate. An additional 33.9% are categorised as hybrid-rate mortgages, either because the fixed rate is periodically adjusted or because a portion of the loan is financed at a variable rate.

Regarding the repayment structure, 59.9% of mortgages follow an annuity repayment plan, characterised by fixed monthly instalments with varying interest and principal components. The majority of loans (62.0%) were originated for home purchase purposes, followed by re-mortgages (12.3%), renovations (7.3%), and construction loans (6.6%). The model also includes controls for loan's first available interest rate reported in the ED database, which averages 2.68% across the sample, as well as the number of years to maturity and the loan-to-value (LTV) ratio at reporting date.

Borrower characteristics include the borrower's employment status,widely used in the credit risk literature (e.g., Quercia et al., 2012; Vandell & Thibodeau, 1985), and an indicator for whether the borrower has received multiple loans within the sample (*Second Time Borrower*). The majority of borrowers (82.7%) are employed, with self-employed borrowers accounting for 10.1% of the sample. Only 1.2% of loans are linked to unemployed individuals, while a small fraction (0.2%) is associated with legal entities such as limited liability companies (LLCs).

The regression framework also includes macroeconomic controls. Specifically, it incorporates country-specific unemployment rates and house price indices (HPI), lagged by one year. These indicators are widely recognised as key drivers of credit performance. Several studies show that during periods of economic expansion, marked by rising GDP and housing prices, non-performing loan ratios tend to decline (e.g., Ozili, 2015; Škarica, 2014).

Conversely, higher unemployment is consistently found to impair borrowers' repayment capacity, increasing the likelihood of default (e.g., Gyourko & Tracy, 2014; Nkusu, 2011).

2.4 Model specification

To measure the impact of the new ABS regulation on the quality of securitised loans, we use a panel-probit model. This approach, and its alternative logistic methodology, is generally used in the literature that analyses loan delinquencies (see, for instance, Cunningham and Capone Jr (1990), Jiang et al. (2014), and Vandell and Thibodeau (1985)). Our baseline model, implemented on the general provision sample, is specified as follows:

$$\begin{aligned} \textit{Loan delinquency}_{i,t} = \alpha &+ \beta_1 \textit{Origination from 2018}_i \\ &+ \beta_2 \textit{Int. Rate at reporting}_i + \beta_3 \textit{Years to maturity}_{i,t} \\ &+ \gamma \textit{Loan characteristics}_i + \delta \textit{Borrower's characteristics}_i \\ &+ \theta \textit{Macro-variables}_{i,t-1} + \textit{ABS deal FE} + \textit{Year FE} + \varepsilon_{i,t} \end{aligned} \tag{2.1}$$

where *Loan delinquency*$_{i,t}$ is a binary variable that takes value 1 if loan i defaults or is in arrears for at least two consecutive quarters in year t. *Origination from 2018* is a dummy variable indicating whether loan i has been originated before or after the new regulation was introduced. Loan and borrower's characteristics are a set of dummy variables that we describe in Appendix 2.A. Macro-variables include country-specific changes in unemployment rates and house price indexes (HPI). These are lagged by one-year, as their effect on the defaults rate are not likely to be immediate (Gerardi et al., 2018).

Including these variables is particularly important as it allows us to distinguish between changes in default probabilities driven by the overall market and those driven by specific securitisation features. Since all loans in a deal are usually originated by the same bank, deal fixed effects allow us to control for RMBS deal-specific structural features and bank credit practices, while year fixed effects will capture changes related to the reporting period.

Finally, to examine the impact of the new regulation on RMBS ratings and their securitisation structure, we utilise our tranche-level dataset and employ an ordinal logistic model. This approach is commonly used in the literature to analyse credit ratings (e.g., Nickell et al. (2000); De Moor et al. (2018)), and allows us to estimate the tranche likelihood of being rated AAA – A3, BAA1 – BAA3 or BA1 – C (i.e., speculative). The model is specified as follows:

$$Rating\ band_i = \alpha + \beta_1 Origination\ from\ 2018_i + \varepsilon_i \tag{2.2}$$

where *Origination from 2018*$_i$ is a binary variables that take value 1 if tranche *i* belongs to an RMBS deal originated from 2018. To account for the differences in the balance at origination of each tranche, we incorporate weighting in our analysis. This approach ensures that each tranche receives proportionate importance based on its relative value.

2.5 Results

2.5.1 The effects of general provision on loan delinquency

First, having excluded from our analysis all deals that meet the STS requirements, we analyse the default risk impact of the general provision regulation. The results are reported in Table 2.3. In line with our expectations, mortgages issued from 2018, when the general provision rules entered into force, tend to have, on average, a 34 bp lower annual probability of being delinquent than those issued before the new regulation.

This improvement is particularly notable given that our sample includes only RMBS deals eligible for repo borrowing with the European Central Bank. Importantly, repo borrowing often takes place long after a securitisation is issued, sometimes years later, depending on the bank's funding needs. As a result, banks have a strong incentive to ensure, from the moment of issuance, that their securitisations will remain eligible throughout their life. This helps preserve access to central bank funding, which is especially valuable in times of market stress. Such forward-looking behaviour likely explains the marked improvement in loan quality observed immediately after the introduction of the regulation in 2018. Even before the provisions became fully binding, banks began to adapt their securitisation practices to align with the anticipated regulatory requirements, effectively front-loading compliance to ensure continued eligibility and funding flexibility under the ECB's collateral framework.

The scale of the improvement is economically meaningful. The 34 basis point decline in delinquency rates far exceeds the average default rate of 5 basis points for an Aa3–A1 rated bond, which corresponds to the average rating of tranches in our sample.[6]

[6] The average for the general provision sample is 23.5 (rating equivalent), which corresponds to a rating between AA3 (24 rating equivalent) and A1 (23 rating equivalent). Default rates are taken from Moody's Investor Service (2021), Exhibit 43 "Average cumulative issuer-weighted global default rates 1983-2020".

Table 2.3. The effect of the new European ABS regulation on mortgage delinquency rates. Panel A, specification 1, reports panel probit regression results for the baseline model in Equation 2.1, which includes *Origination from 2018*, a dummy that identifies securitised mortgages originated after the introduction of the new European ABS regulation. In specification 2, *Origination from 2018* is replaced by *Securitisation from 2018*, a dummy that identifies mortgages securitised after the introduction of the new European ABS regulation. Panel B reports regression results when explanatory variables are gradually added to the model. The sample includes non-STS deals only. The definition of the remaining variables can be found in Appendix 2.A. Sample period: 2013 to 2019. Robust standard errors are clustered at deal level. The symbols ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Baseline Model		
Dep. Var.: Mortgage delinquency indicator	**Marginal Effect (bp)**	
	(1)	**(2)**
Origination from 2018	**-33.59****	
	(15.88)	
Securitisation from 2018		**11.65**
		(9.51)
Years to Maturity	11.93***	11.7***
	(2.82)	(2.82)
Interest Rate	0.03	0.03
	(0.02)	(0.02)
Loan-to-value		
0.6 ≤ LTV <0.7	4.25**	4.23**
	(1.73)	(1.71)
0.7 ≤ LTV <0.8	10.94***	10.93***
	(2.64)	(2.65)
0.8 ≤ LTV <0.9	17.19***	17.14***
	(3.44)	(3.44)
0.9 ≤ LTV <1	29.80***	29.73***
	(5.36)	(5.33)
LTV ≥ 1	39.78***	39.96***
	(6.50)	(6.39)
Interest Rate Type		
Floating Int. Type	23.13***	23.37***
	(4.08)	(4.13)
Hybrid Int. Type	3.82	3.52
	(5.37)	(5.30)
Other Int. Type	14.51**	15.03***
	(7.14)	(7.36)
Payment Type		
Linear Payment Type	-28.45***	-27.01***
	(7.88)	(8.14)
Increasing Payment Type	42.10***	42.19***
	(13.09)	(13.24)
Other Payment Type	2.86	3.41
	(3.53)	(3.55)
Purpose		
Remortgage Purpose	22.82*	22.39*
	(12.57)	(12.44)
Renovation Purpose	14.38***	14.33***
	(4.67)	(4.65)
Construction Purpose	-6.85*	-7.04**
	(3.58)	(3.45)
Other Purpose	42.27***	41.99***
	(9.84)	(9.82)
Borrower characteristics		
Second Time Borrower	2.12	1.78
	(3.39)	(3.38)

Table 2.3 continued from previous page

Dep. Var.: Mortgage delinquency indicator	**Marginal Effect (bp)**	
	(1)	**(2)**
Unemployed	57.68***	57.52***
	(7.21)	(7.26)
Self-employed	48.30***	48.22***
	(4.78)	(4.77)
Legal Entity	112.23***	110.68***
	(40.11)	(39.96)
Student	-14.61	-14.96
	(9.33)	(9.27)
Pensioner	16.82**	16.85**
	(7.20)	(7.20)
Other employment	22.25***	22.24***
	(4.92)	(5.00)
Macro-variables		
ΔHouse Price Index	-2.51	-2.47
	(2.28)	(2.27)
ΔUnemployment	104.22	112.92
	(305.24)	(302.76)
Deal Fixed Effects	*Yes*	*Yes*
Time Fixed Effects	*Yes*	*Yes*
Observations	7,114,158	7,114,158
Pseudo R-squared	0.153	0.153

Panel B: Robusteness

Dep. Var.: Mortgage delinquency indicator	**Marginal Effect (basis points)**			
	(1)	**(2)**	**(3)**	**(4)**
Origination from 2018	-32.01	-32.78**	-33.17**	-33.59**
	(16.96)	(15.71)	(15.90)	(15.88)
Loan Characteristics		Yes	Yes	Yes
Borrower Characteristics			Yes	Yes
Macro-Variables				Yes
Deal FE	Yes	Yes	Yes	Yes
Annual FE	Yes	Yes	Yes	Yes
Obs.	7,114,158	7,114,158	7,114,158	7,114,158
Pseudo-R^2	0.145	0.149	0.153	0.153

Interestingly, while the improvement in loan quality is clear for mortgages originated from 2018 onwards, specification 2 shows no significant change in delinquency rates for loans securitised from 2018, regardless of their time of origination. This suggests that, although banks responded promptly to the introduction of the new ABS regulation by tightening lending standards, they continued to include older, riskier loans in post-2018 securitisations.

Such behaviour is consistent with a transitional strategy, whereby banks gradually align new lending with regulatory expectations while still relying on existing loan stock to fill securitisations. This may reflect operational or economic incentives to avoid leaving pre-2018 loans on balance sheet, especially if they remain eligible for ECB operations. Consequently, while origination behaviour appears forward-looking, securitisation decisions may reflect a more pragmatic balancing of regulatory compliance and portfolio management.

The remaining coefficients of the model provide insight into the factors driving delinquencies and generally confirm what has been found in the literature. As expected, mortgages characterised by higher loan-to-value ratios at origination, as well as those with higher interest rates, show, on average, larger delinquency rates. Specifically, as the loan-to-value ratio increases, the delinquency rates significantly increase in a monotonic way.

As far as the interest rate type is concerned, our results highlight that when interest rate uncertainty is higher, borrowers tend to default more. This is the reason that, on average, loans with a floating interest rate show higher default probabilities than those with a fixed interest rate (baseline for this variable). The amortisation schedule of principal and interest rates also plays a role in explaining mortgage defaults. Mortgages with increasing payment amounts (i.e. negative amortisation mortgages in which the borrower pays less than the interest due each month, resulting in a higher loan balance over time) are more likely to enter delinquency. On the contrary, delinquency rates are lower when instalments are decreasing over time (linear payment type).

Finally, when borrowers' employment status is considered, the results show that loans given to self-employed workers and to the unemployed tend to default more than those granted to regular employed borrowers (which are the baseline), with 48.3 bp and 57.7 bp higher annual default rate. Interestingly, legal entities (LLC) show the highest delinquency risk. Although it is true that the limited liability structure of these borrowers may inherently result in higher default probabilities, it is important to consider that this category represents only 0.2% of our mortgage population. As a result, their credit behaviour becomes more challenging to generalise.

It is crucial to emphasize that, apart from LLC borrowers, European mortgage holders have no incentive to default in case of negative equity due to the full recourse nature of their mortgage contracts. This helps alleviate concerns regarding potential endogeneity in our model. As noted in the literature (e.g., Gupta and Hansman (2022)), borrowers with a higher likelihood of default may intentionally choose riskier contract types, such as high loan-to-value (LTV), flexible rate, and interest-only mortgages. The selection of these contracts can serve as an indicator of the borrower's risk tolerance, potentially influencing their future decision to engage in strategic default (Byrne et al., 2017). However, the prevalence of full recourse mortgages in Europe significantly mitigates this potential source of endogeneity.[7]

Recourse mortgage holders lack the motivation to engage in strategic default as they remain personally liable for any negative equity in their mortgages. Consequently, they tend to prioritize mortgage payments over other expenses to avoid default (Gross et al. (2022); Hatchondo et al. (2013)). This characteristic of recourse mortgages greatly reduces the relevance of endogeneity concerns associated with contract type selection within our European mortgage sample. This is because the propensity to default for a borrower with a recourse mortgage becomes inconsequential. Default is generally considered a last resort compelled by the borrower's inability to repay the mortgage, rather than a strategic decision made while the borrower is still capable of honouring the mortgage repayments.

[7] See for further reference: https://www.stlouisfed.org/publications/regional-economist/july-2013/europe-may-provide-lessons-on-preventing-mortgage-defaults.

The presence of recourse loans also mitigates the possibility that interest rate uncertainty could drive strategic defaults in our sample. To provide assurance that this is the case, we proxy for interest rate uncertainty by computing the volatility of the monthly Euribor, measured by the standard deviation of the previous 12 months with respect to the observation date (Sarkar & Ariff, 2002). This methodology, although backward looking, simulates the decisions an agent can make based on the historical information they possess. The results obtained when the volatility of the interest rate is used in place of the time fixed effects are consistent with our main findings (see Appendix 2.B – Table 2.B.3).

We further expand our results by analysing the quality of mortgages issued from 2017. This allows us to investigate whether banks started to change their behaviour from the announcement of the new regulation in 2017, rather than from January 2018 when the new rules were officially introduced. The results are reported in Table 2.4.

Table 2.4. The effect of the European ABS regulation announcement on mortgage delinquency rates. The table reports panel probit regression results for the baseline model in Equation 2.1, with dummies identifying alternative origination periods. The first specification distinguishes between mortgages originated from 1 January 2018 and those originated in 2017; the second specification identifies mortgages originated from 1 January 2017, the year in which the final draft of the new regulation was announced. Sample period: 2013 to 2019. The sample includes non-STS deals only. Robust standard errors are clustered at deal level. The symbols ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Dep. Var: Mortgage delinquency indicator	**Marginal Effect (basis points)**	
	(1)	**(2)**
Origination from 2018	-41.18**	
	(16.48)	
Origination in 2017	-37.33***	
	(8.64)	
Origination from 2017		-38.13***
		(9.58)
Loan Characteristics	Yes	Yes
Borrower Characteristics	Yes	Yes
Macro-Variables	Yes	Yes
Deal and Time FE	Yes	Yes
Obs.	7,114,158	7,114,158
Pseudo-R^2	0.153	0.153

Specification 1 in the Table shows that loans issued in 2017 exhibit a 37 bp reduction in annual delinquency probability compared to those issued prior to 1 January 2017. Likewise, loans issued from 1 January 2018, display a lower annual delinquency rate of 41 bp. More generally, as can be seen in specification 2, banks seem to have improved their credit practices since 2017, when the final draft of the regulation was announced, with loans originated from 2017 showing a 38 bp lower annual delinquency probability than those issued before 1 January 2017.[8]

Regarding this matter, a potential concern arises regarding the possibility that the improvement in loan quality may be driven by factors unrelated to the new ABS regulation. To address this concern, we conduct a series of robustness checks, which we present in Appendix 2.B. In Table 2.B.1, specifically for specifications 3 and 4 with quarterly data[9], we demonstrate that our main findings remain consistent when we limit the analysis to the first two years of data available after a loan has been originated. This approach helps alleviate concerns that older loans might be overrepresented in the sample, and that more recently issued loans might exhibit lower delinquency rates simply due to a shorter reporting period. However, we acknowledge that the impact of loan securitisation timing may introduce additional complexities. As loans could potentially be securitised long after their origination, we recognise the potential for selection effects to arise. To address this concern, in Table 2.B.2, specification 4, we only include in the sample the first two annual observations after loan securitisation, rather than limiting the analysis to the first two years after origination. This approach mitigates any biases introduced by varying securitisation timelines and offers a nuanced perspective that complements our analysis in Table 2.B.1.

[8] As a robustness check, we show in Appendix 2.B, Table 2.B.1, that results hold when using quarterly data.

[9] To prevent identification issues arising from fewer available observations, the analyses in Table 2.B.1 are run with quarterly data.

Additionally, we address concerns regarding the representativeness of the loan and borrower information at origination used in our model. We provide evidence in Table 2.B.1, specification 5, that by excluding the regulation period from the analysis (specifically, loans securitised from 2017), there is no significant decrease in delinquency rates observed for more recently issued loans (i.e., loans issued from 2015-Q1).

Furthermore, we show in Table 2.B.2, that results hold when we apply additional loan exclusions to the sample. In specification 1, we exclude loans originated before 2010, that is, loans possibly originated over the credit bubble. In specification 2, we eliminate loans issued before 2013 to account for the possible effect of the increasing transparency introduced at the beginning of that year.[10] In specification 3, we exclude loans reported in 2013 and 2014 to account for possible confounding effects relative to the European sovereign debt crisis. Although the main effects of the sovereign debt crisis were experienced between 2010 and 2012, government bond spreads in Europe's periphery remained elevated in 2013 and 2014, which represent the first two years of our sample period, compared to pre-Great Recession levels.

Finally, in Table 2.B.3, specifications 1, we have added the lagged country-specific GDP to the model to control for the possible effect of the business cycle on delinquencies. Our main results remain unchanged, as the general provision demonstrates a statistically significant reduction in default rates. We also run our main model by replacing the time FE with the time-varying change in the Euribor index (3-months), specification 2. This allows us to capture the impact of short-term interest rate fluctuations on the probability of default. The results are consistent with our main findings.

[10] Starting January 2013, banks that use residential mortgage-backed securities in repo borrowing are required to report loan-level data in a detailed and standardised format set by the ECB.

Next, we explore the potential impact of the ban on cherry-picking and the increased investor due diligence, both of which are components of the general provision regulation, on banks' issuance of loans with "risky" characteristics. The restriction on transferring loans with higher expected losses than those retained on the balance sheet to external entities may lead banks to shift the composition of their portfolios towards safer assets. At the same time, heightened investor awareness regarding the riskiness of underlying assets could incentivise banks to enhance the quality of securitised loans. To further explore this, we examine loan characteristics associated with higher delinquency probabilities across the entire sample. To do so, we employ our model and introduce interactions between the loan origination period and variables such as employment status and loan-to-value ratio, both of which are significant drivers of default based on our previous findings. The outcomes of this analysis are presented in Table 2.5. In specification 1, the coefficients of the interactions between risky employment statuses (unemployed, legal entity, pensioner, and other borrowers) with "Origination from 2017" are not statistically significant. This implies that loans originated from 2017 for these borrowers exhibit a risk reduction that is not statistically significantly different from other loans originated from 2017, i.e. -31.5 bp. However, the self-employed borrowers stand out as their interaction with "Origination from 2017" shows a positive and statistically significant increase in default probability by 21.9 bp. Nevertheless, this increase is not substantial enough to offset the baseline reduction in default probability of loans originated from 2017. In summary, it can be concluded that the default risk for risky borrowers, following the introduction of the general provision regulation, has either decreased or remained unchanged. Moving to specification 2, we examine the interaction between different loan-to-value (LTV) ratios and "Origination from 2017". Again, all LTV ratios up to 100% demonstrate a risk reduction that is not statistically significantly different from other loans originated from 2017. However, loans with an LTV above 100% appear to exhibit a slight increase in risk. It is important to note that this subset of mortgages is relatively small, comprising only 14,142 loans, representing a mere 0.46% of our sample.

Table 2.5. Borrower risk, loan-to-value and mortgage delinquency. The table reports panel probit regression results for the baseline model in Equation 2.1, in which employment status (model 1) and loan-to-value ratios (model 2) are interacted with the post-reform origination dummy. The sample includes non-STS deals only. Variable definitions are reported in Appendix 2.A. Sample period: 2013 to 2019. Robust standard errors are clustered at a deal level. The symbols ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: Mortgage delinquency indicator	**Marginal Effect (bp)**	
	(1)	**(2)**
Origination from 2017	**-31.50***** **(6.95)**	**-31.38***** **(6.43)**
Unemployed	58.37*** (7.30)	57.87*** (7.24)
Self_Employed	49.07*** (4.87)	48.75*** (4.81)
Legal Entity	119.89*** (44.06)	114.30*** (39.87)
Pensioner	16.98** (7.43)	17.09** (7.30)
Other borrower	22.58*** (4.84)	22.57*** (4.90)
Unemployed * Orig. 2017	**11.36** **(12.07)**	
Self_Employed * Orig. 2017	**21.89**** **(8.80)**	
Legal Entity * Orig. 2017	**50.4** **(32.03)**	
Pensioner * Orig. 2017	**15.14** **(10.74)**	
Other borrower * Orig. 2017	**14.83** **(28.48)**	
0.6 ≤ LTV <0.7	4.28** (1.75)	4.48*** (1.75)
0.7 ≤ LTV <0.8	10.92*** (2.64)	11.08*** (2.71)
0.8 ≤ LTV <0.9	17.32*** (3.48)	17.45*** (3.50)
0.9 ≤ LTV <1	30.10*** (5.42)	30.32*** (5.47)
LTV ≥ 1	39.95*** (6.45)	39.76*** (6.46)
0.6 ≤ LTV <0.7 * Orig. 2017		**-4.94** **(6.11)**
0.7 ≤ LTV <0.8 * Orig. 2017		**4.36** **(4.46)**
0.8 ≤ LTV <0.9 * Orig. 2017		**9.26**

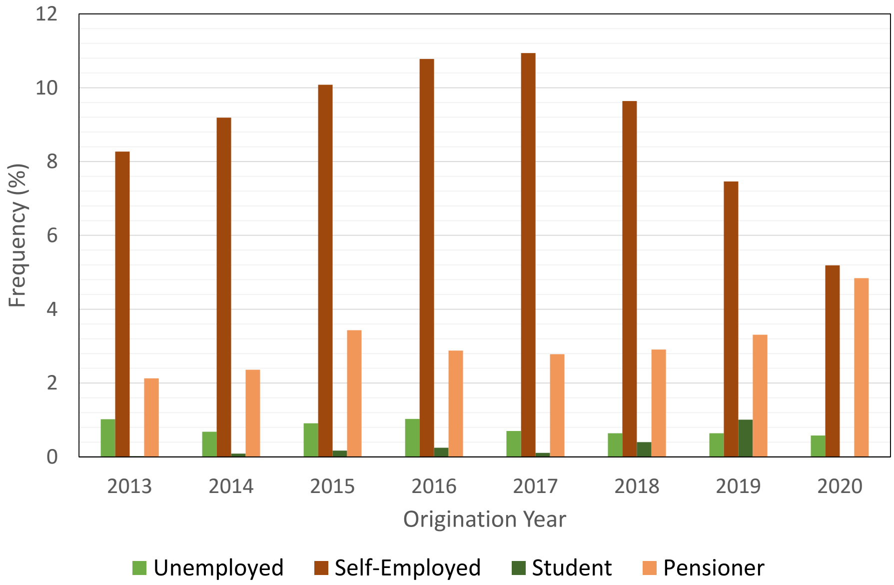
Table 2.5 continued from previous page

Dep. Var.: Mortgage delinquency indicator	**Marginal Effect (bp)**	
	(1)	**(2)**
		(9.28)
0.9 $\leq$ LTV <1 * Orig. 2017		**13.12**
		(13.30)
LTV $\geq$ 1 * Orig. 2017		**35.45*** **
		(10.45)
Loan Characteristics	Yes	Yes
Borrower Characteristics	Yes	Yes
Macro-Variables	Yes	Yes
Deal and Time FE	Yes	Yes
Obs.	7,114,158	7,114,158
Pseudo-R^2	0.153	0.153

The interpretation of these findings may be improved by an analysis of the distribution of our mortgage population by employment status and year of origination (Figure 2.3), and by loan-to-value bucket and year of origination (Figure 2.4).

The fraction of loans granted to self-employed applicants (represented in brown) consistently decreases following the introduction of the new ABS regulation. In contrast, there is a corresponding increase in the proportion of loans given to pensioners, who are relatively less risky (see Table 2.3). Similarly, when examining loan-to-value (LTV) ratios based on the year of origination, it is notable that the percentage of mortgages with an LTV ratio above 0.8 experiences a significant decline from 2017 to 2019. Although there is a partial rebound in 2020, its level remains below those seen prior to 2017. This reversal in trend can potentially be attributed to government initiatives enacted in response to the COVID-19 pandemic, such as mortgage forbearance programs and temporary relaxation of lending standards. Overall, these findings support the conclusion that the prohibition on cherry-picking may have motivated banks to reduce the proportion of loans with riskier characteristics.

Figure 2.3. Distribution of residential mortgages by employment status and year of origination. The top figure shows the distribution of unemployed, self-employed, student, and pensioner borrowers by year of origination. The bottom figure shows the distribution of employed borrowers by year of origination.



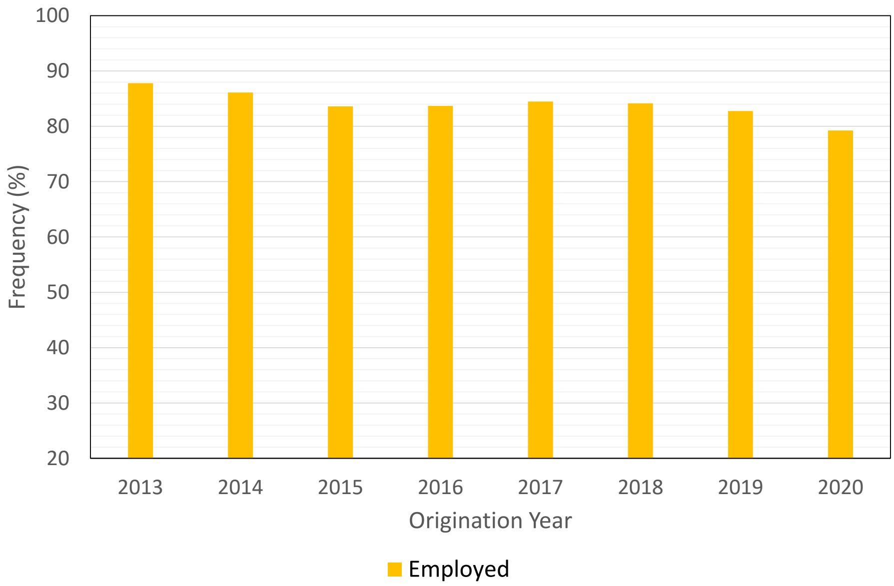
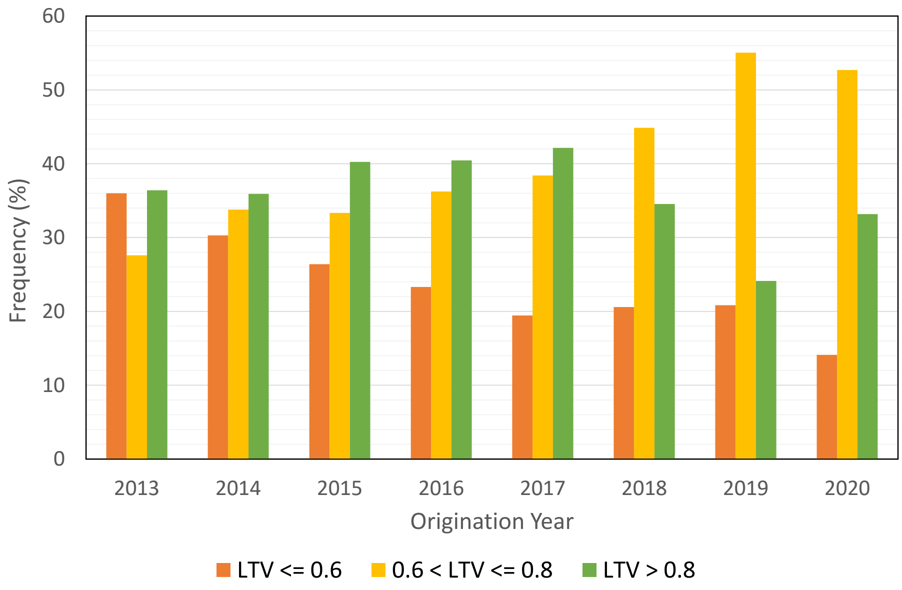


Figure 2.4. Distribution of residential mortgages by loan-to-value bucket and year of origination.



2.5.2 The effects of general provision on the securitisation structure

Our analysis thus far has demonstrated an improvement in the quality of securitised loans due to the implementation of the new securitisation regulation. However, we have yet to examine whether this regulatory regime has also influenced the securitisation structure. It is crucial to address this question because while the enhancement in loan quality is positive, there may be a potential increase in overall securitisation risk, possibly stemming from changes in tranche composition and quality (Peña-Cerezo et al., 2019). To investigate this concern, our study specifically focuses on examining the impact of the general provisions of the new securitisation regulation on the securitisation structure. We accomplish this by comparing the structure of RMBS deals originated before and after the introduction of the regulation, with the exclusion of STS deals. The results are presented in Table 2.6.

Table 2.6. Effect of regulatory changes on the tranche composition of residential mortgage securitisations. The table displays illustrates the difference between RMBS deals issued before and after the regulation, with a sample period from 2013 to 2019 and includes only non-STS deals. The symbols ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

	pre-regulation	**post-regulation**		
Variable description	**Mean (1)**	**Mean (2)**	**Difference (2) - (1)**	**p-value**
number of tranches	3.23	4.25	1.02	0.000***
senior tranches (%)	85.6	89.1	3.5	0.294
mezzanine tranches (%)	1.6	0.8	-0.8	0.594
subordinated tranches (%)	13	10	-3	0.3462
- of which retained tranches (%)	6.1	6.2	0.1	0.96
average tranche rating per securitisation (value weighted)	24.5	25.8	1.3	0.059*

Table 2.6 presents the average number of tranches, the average relative size of senior, mezzanine, and subordinated tranches, the average relative size of retained tranches, and the (value weighted) average deal rating. To test the statistical difference between the analyzed groups, a two-tailed t-test is employed, with the null hypothesis assuming that the difference equals zero. The findings suggest that RMBS deals issued after the regulation exhibit a higher average number of tranches (+1.0), which is highly statistically significant, and a higher average deal rating (+1.3), significant at the 10% level.

Overall, the findings suggest that the securitisation regulation has had a measurable, albeit limited, impact on the structure of RMBS deals under the general provisions.[11] The observed increase in the average deal rating is consistent with the regulatory objective of promoting higher-quality securitisations. Additionally, the post-regulation period is characterised by an increase in the average number of tranches per deal. This shift suggests a more refined structuring approach, which may enhance credit protection for senior tranche holders. A larger number of tranches allows for a more granular distribution of risk and creates additional layers of subordination. This increased structural depth can improve the absorption of credit losses, as intermediate tranches act as a buffer between the junior and

[11]The impact of the STS provisions on securitisation structures will be analysed in detail in Chapter 3.

senior tranches, thereby reducing the likelihood that losses reach the most senior claims, particularly under stressed conditions.

To further investigate this aspect, we perform a stress-testing exercise to evaluate the expected losses for RMBS originators and tranche holders under various scenarios. The default rate for each scenario is derived from the distribution of loan default rates within our sample of securitisations. By employing this methodology, we are able to analyse and assess the impact of different securitisation structures on the risk borne by investors and originators, particularly in relation to the risk levels associated with the underlying assets. The results of this analysis are presented in Table 2.7.

The table presented provides a comparison of the expected losses for securitisations issued both before and after the implementation of the regulation. Panel A of the table examines a scenario in which a loss given default (LGD) of 100% is assumed, meaning that no recovery from defaulted loans is anticipated, resulting in the complete loss of the invested capital. This serves to depict the worst-case scenario. In Panel B, a more realistic LGD of 68.5% is considered, with a corresponding recovery rate of 31.5%. The 68.5% LGD is calculated as a weighted average of the 25th percentile recovery rates across the countries included in our sample, thereby providing a more representative estimate.[12]

The findings from the stress-testing exercise confirm that the new general provisions have had a very limited impact on the risk borne by investors in affected securitisations. Specifically, even under an extreme stress scenario (assuming a loss given default (LGD) of 100% and a default rate corresponding to the 99% quantile of the observed distribution) the majority of losses are absorbed by the originators, with only a small fraction passed on to junior tranche holders. These results suggest that, while the general provisions have

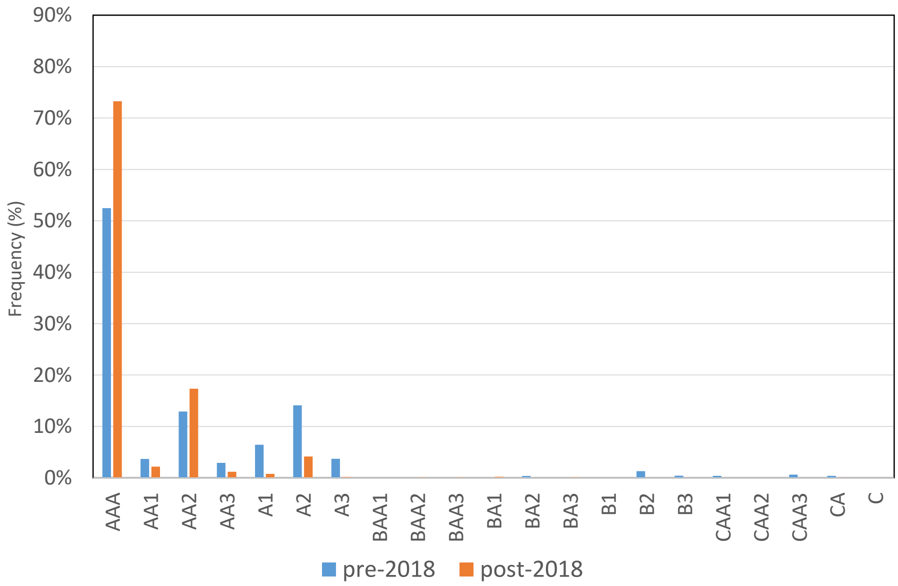
[12] Source: European Banking Authority (2020) Report on the Benchmarking of National Loan Enforcement Frameworks. https://www.eba.europa.eu/sites/default/documents/files/document_library. UK is not included as data on recoveries could not be obtained.

Table 2.7. Estimated expected loss for originators and tranche holders: stress testing exercise. The table presents the expected loss for RMBS originators and investors (senior, mezzanine and subordinated tranche holders) under different scenarios. The default rates for each scenario are derived from the distribution of loan default rates within our sample of securitisations (average, 90%, 95% and 99% quantiles). Expected losses to the subordinated tranches are expressed as a percentage of the tranche value net of the retained tranche ("Sub. minus retained"), which is considered separately. In Panel A, a 0% recovery rate (LGD=100%) is assumed, while in Panel B, a 31.5% recovery rate (LGD=68.5%) is applied. The recovery rate in Panel B is calculated as the weighted average of the 25th percentile recovery rates across the countries included in our sample, with the exception of the UK, where data on recoveries could not be obtained (Source: European Banking Authority, 2020). The sample period is from 2013 to 2019 and includes only non-STS deals.

Panel A: LGD=100%			**Expected loss to investors**			**Expected loss to originator**
				Tranches		
Sub-sample	**Parameter**	**Default rate %**	**Senior**	**Mezzanine**	**Sub. minus retained**	**Retained**
Pre-reg.	Average	0.98%	0.0%	0.0%	0.0%	16.1%
Post-reg.		0.52%	0.0%	0.0%	0.0%	8.4%
Pre-reg.	90% qnt	2.71%	0.0%	0.0%	0.0%	44.5%
Post-reg.		1.23%	0.0%	0.0%	0.0%	19.8%
Pre-reg.	95% qnt	3.96%	0.0%	0.0%	0.0%	65.0%
Post-reg.		1.92%	0.0%	0.0%	0.0%	31.0%
Pre-reg.	99% qnt	7.65%	0.0%	0.0%	22.5%	100.0%
Post-reg.		7.21%	0.0%	0.0%	26.5%	100.0%

Panel B: LGD=68.5%			**Expected loss to investors**			**Expected loss to originator**
				Tranches		
Sub-sample	**Parameter**	**Default rate %**	**Senior**	**Mezzanine**	**Sub. minus retained**	**Retained**
Pre-reg.	Average	0.98%	0.0%	0.0%	0.0%	11.1%
Post-reg.		0.52%	0.0%	0.0%	0.0%	5.7%
Pre-reg.	90% qnt	2.71%	0.0%	0.0%	0.0%	30.5%
Post-reg.		1.23%	0.0%	0.0%	0.0%	13.6%
Pre-reg.	95% qnt	3.96%	0.0%	0.0%	0.0%	44.5%
Post-reg.		1.92%	0.0%	0.0%	0.0%	21.3%
Pre-reg.	99% qnt	7.65%	0.0%	0.0%	0.0%	85.9%
Post-reg.		7.21%	0.0%	0.0%	0.0%	79.6%

Figure 2.5. Rating distribution of MBS tranches.



contributed to a reduction in underlying asset risk, they have had little to no effect on the protection available to senior investors within the securitisation structure.

To supplement our findings, we conduct an additional analysis of tranche ratings at the origination stage within the RMBS sample. This step is crucial to assess the combined effect of the observed improvement in underlying loan quality and the limited changes in securitisation structure. If these developments did not translate into higher tranche ratings at origination, it would suggest that the overall impact of the new regulation on securitisation quality was minimal. Figure 2.5 presents the value-weighted distribution of tranche ratings at origination, comparing deals issued before and after the introduction of the general provisions. The figure confirms that the regulatory measures have had a positive influence on tranche ratings. For instance, 73% of RMBS tranches originated after the introduction of the new regulation hold a AAA rating, compared to 52% of tranches issued prior to the regulation.

To further validate the impact of the regulation on rating improvements, we utilise a simple ordinal logistic model to estimate the likelihood of tranches being rated AAA – A3, BAA1 – BAA3, or BA1 – C (i.e., speculative). To consider variations in the balance at origination for each tranche, we incorporate weighting in our analysis, giving proportional importance to each observation based on its relative size. The results of this analysis are presented in Table 2.8. The results indicate that RMBS tranches issued after the introduction of the new regulation exhibit a significantly higher probability of receiving a rating of AAA – A3, while demonstrating a reduced likelihood of being assigned a BAA1 or lower rating.

Table 2.8. Effect of regulatory changes on tranche ratings. The table presents the estimation of an ordered logit regression using value-weighted observations, with the thresholds of the dependent variable identifying different rating bands. The variable of interest utilised in the specification is the dummy variable "Origination from 2018". This specification focuses on the tranche-level sample spanning from 2013 to 2019. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Marginal Effect	
	Orignation from 2018
Rating band	(1)
AAA - A3	0.029**
	(0.013)
BAA1 - BAA3	-0.002**
	(0.001)
BA1 - C (speculative)	-0.027**
	(0.012)
Obs.	425
Pseudo-R^2	0.043

2.6 Conclusions

In this chapter, we investigate the impact of the general provisions introduced by the 2018 securitisation regulation on securitised residential mortgages. Using loan-level data from the European DataWarehouse, the designated platform in Europe for collecting information related to asset-backed securities eligible for repurchase agreements, we assess how the regulation has influenced loan quality and securitisation structures in the RMBS market.

Our findings indicate that loans securitised in RMBS deals issued after the introduction of the general provisions exhibit an annual probability of delinquency that is, on average, 34 basis points lower than loans originated before the regulation. This improvement in loan quality is particularly notable given the already high credit quality of the sample, which consists predominantly of RMBS deals eligible for ECB operations. Because of this eligibility, banks have an incentive to align with regulatory expectations from the moment new provisions are introduced. In this case, the 2018 introduction of the general provisions may have prompted banks to originate higher-quality loans in anticipation of continued eligibility for central bank funding. This forward-looking behaviour likely contributes to the observed improvement in loan quality following the introduction of the new rules

However, the effect of the new regulatory framework is not uniform across all mortgage types. In particular, under-collateralised loans, those with a loan-to-value (LTV) ratio above 1, exhibited higher delinquency rates in the period following the introduction of the general provisions. Nevertheless, we observe a decline in the proportion of loans with riskier characteristics, such as loans granted to self-employed borrowers or associated with very high LTV ratios. This shift in the composition of securitised pools is consistent with the intended effects of the ban on cherry-picking introduced by the general provisions, which appears to have incentivised banks to reduce the securitisation of riskier loans.

In addition to examining loan quality, we analyse the extent to which the general provisions have affected securitisation structures. Our results suggest that the regulation has had only a limited impact in this regard. While RMBS deals issued after the implementation of the general provisions exhibit a slightly higher average number of tranches and a modest improvement in average deal ratings, the overall structure remains largely unchanged. Stress-testing exercises confirm that, even under extreme default scenarios, losses are almost fully absorbed by originators, with only a negligible share reaching junior tranche holders. Finally, by analysing the distribution of tranche ratings at origination, we show that the regulatory changes have contributed to an improvement in securitisation quality at the tranche level. Specifically, the proportion of tranches rated AAA increased significantly following the regulation, and ordinal logistic regression results corroborate that post-regulation tranches are more likely to attain higher credit ratings.

Taken together, these findings suggest that the general provisions have been effective in promoting higher-quality securitisation practices, primarily through improvements in the underlying loan pool, without materially increasing structural risks for investors. One limitation of our analysis is that it is restricted to securitised loans; we are unable to assess the broader impact of the regulation on loans originated and retained by lenders in their portfolios. Future research should seek to incorporate additional loan-level data to capture a more comprehensive view of the regulation's effects across the wider mortgage market.

Moreover, further analysis is required to fully understand the overall impact of the securitisation regulation, which also introduced a specific framework for Simple, Transparent and Standardised (STS) securitisations. This will be examined in detail in Chapter 3.

Appendices to Chapter 2

2.A Variable list

Table 2.A.1. Variable definitions

Variable	**Definition**
Loan Performance	
Delinquent	An indicator variable equal to one if the loan has defaulted or entered delinquency for at least two consecutive quarters, and zero otherwise.
Regulation indicators	
Originated from 2018 (2017)	An indicator variable equal to one if the loan has been originated from 1 January 2018 (1 January 2017), and zero otherwise.
Originated in 2017	An indicator variable equal to one if the loan has been originated from 1 January 2017 to 31 December 2017, and zero otherwise.
Loan's characteristics	
Loan to Value	A categorical variable indicating whether the loan-to-value ratio at origination belongs to the following ranges: (0–0.6] baseline, (0.6–0.7], (0.7–0.8], (0.8–0.9], (0.9–1], above 1.
Years to Maturity	The natural logarithm of the number of years remaining until maturity.
Interest Rate	Loan's first available interest rate reported in the ED database in percentage points.
Interest Rate Type	A categorical variable indicating whether the loan has a fixed interest type (baseline), floating, hybrid, or other less frequent interest rate type specifications.
Payment Type	A categorical variable indicating whether the loan is an annuity with fixed instalments (baseline), or whether its amortisation schedule is linear (with decreasing instalments), increasing (with first payments including only a portion of the interest that will later be charged), or other less frequent payment type specifications.
Purpose	A categorical variable indicating whether the loan has been issued for purchase purposes (baseline), remortgage, renovation, construction, or other less frequent purpose specifications.
Borrower's characteristics	
Second Time Borrower	An indicator variable equal to one if the loan is not the first loan a borrower gets from a given bank, and zero otherwise.

Table 2.A.1 continued from previous page

Variable	Definition
Employment	A categorical variable indicating whether the borrower is employed (baseline), unemployed, self-employed, is a legal entity (limited liability company), a student, a pensioner, or other less frequent employment specifications.
Macro variables	
Δ*Unemployment*	One-year lagged country-specific change of the unemployment rate.
Δ*House Price Index*	One-year lagged country-specific change of the house price index.
Tranche-level characteristics	
Rating band	A categorical variable indicating whether a tranche is rated AAA - A3, Baa1 - Baa3 or Ba1 - C (i.e., speculative grade). Ratings from different rating agencies are slotted into each band according to the variable *Rating equivalent* from Eikon (the variable ranges from 1 to 27, with 27 corresponding to AAA). In our analysis, we use the first rating available in Eikon (LSEG) for any given tranche following its issuance as a proxy for the rating at origination.
Originated from 2018	An indicator variable equal to one if the tranche belongs to a deal that has been issued on or after 1 January 2018, and zero otherwise.
Tranche balance	Tranche balance at origination

2.B Robustness analyses

Table 2.B.1. The effects of the ABS regulation on loan delinquencies with quarterly data. This table reports panel probit regression results for the baseline models in Equation 2.1, with quarterly data. The sample is restricted to the first two years after loan origination in specifications 3 and 4. In specification 5 we further exclude loans securitised from 2017-Q1. The sample includes non-STS deals only. Sample period: 2013 to 2019. Variable definitions are reported in Appendix 2.A. Robust standard errors are clustered at deal level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Loan delinquency indicator	**Marginal Effects (basis points)**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Origination from 2018	-15.24**	-18.37***	-6.27***	-5.65***	
	(3.30)	(6.63)	(1.07)	(1.12)	
Origination in 2017		-9.91***		-9.95***	
		(2.65)		(2.70)	
Securitised from 2015					-1.04
					(0.95)
Loan characteristics	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes	Yes
Macro-variables	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No
Observations	31,710,814	31,710,814	5,899,735	5,899,735	3,819,223
Pseudo-R^2	0.137	0.137	0.189	0.191	0.188

Table 2.B.2. The effect of the new regulation on loan delinquency rates: alternative sample periods. This table reports panel probit regression results for the baseline models in Equation 2.1. In specification 1, we exclude loans originated before 2010. In specification 2, we exclude loans originated before 2013. In specification 3, we exclude deals originated in 2013 and 2014. In specification 4, we only include the first two observations per loan. The general provision sample, 2013 to 2019, is used in specifications 1-4 and includes non-STS deals only. Variable definitions are reported in Appendix 2.A. Robust standard errors are clustered at deal level. Robust standard errors are clustered at deal level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Loan Delinquency indicator	**Marginal Effects (basis points)**			
	(1)	(2)	(3)	(4)
Origination from 2017	-18.10***	-10.10**	-37.20***	-47.58***
	(6.21)	(4.44)	(9.41)	(13.48)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Macro-variables	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Country FE	No	No	No	No
Observations	4,104,857	2,454,218	6,702,056	4,942,727
Pseudo R-squared	0.186	0.237	0.150	0.179

Table 2.B.3. The effect of the new regulation on loan delinquency rates with controls for business cycle, market interest rates, and interest rate uncertainty. This table reports panel probit regression results for the baseline models in Equation 2.1. Additional controls include country-specific lagged GDP (DeltaGDP - Specification 1), lagged 3-month Euribor index (DeltaEuribor 3m - Specification 2), and the lagged standard deviation of the 3-month Euribor index (DeltaEuribor 3m stdev - Specification 3). The sample spans from 2013 to 2019, and include non-STS deals only. Robust standard errors are clustered at deal level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Loan delinquency indicator	**Marginal Effects (basis points)**		
	(1)	**(2)**	**(3)**
Origination from 2018	-33.60**	-39.23**	-39.06**
	(15.88)	(15.64)	(15.70)
DeltaGDP	Yes	No	No
DeltaEuribor_3m	No	Yes	No
DeltaEuribor_3m_stdev	No	No	Yes
Other characteristics	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Time FE	Yes	No	No
Country FE	No	No	No
Observations	7,114,158	7,114,158	7,114,158
Pseudo-R^2	0.153	0.151	0.153

Chapter 3

STS securitisations and market resilience: evidence from the COVID-19 period

3.1 Introduction

As discussed in Chapter 2, the complexity of the securitisation market was widely identified as one of the key factors contributing to the Great Financial Crisis of 2007–2009. Several studies highlight how securitisation opacity and structural complexity fuelled systemic risk and undermined investor confidence (Antoniades, 2016; Dungey et al., 2011; Fender & Mitchell, 2009; Gorton, 2009; Mian & Sufi, 2009; Shin, 2009). In response, the European Union introduced a new regulatory framework aimed at improving the functioning and resilience of securitisation markets.[1] While the previous chapter focused on the effects of the general provisions, which apply to all securitisations, this chapter shifts attention to the *Simple, Transparent and Standardised (STS)* regime introduced as part of the same reform. We examine the effectiveness of the STS framework in promoting safer securitisation practices, both in normal times and under systemic stress conditions.

[1] A detailed description of the new European regulatory framework is provided in Section 2.2 of Chapter 2.

The STS framework was introduced to promote higher-quality securitisation practices through a clearly defined set of criteria aimed at reducing structural complexity, enhancing transparency, and improving comparability across deals (The European Parliament and the Council (2017)). Unlike the general provisions of the new ABS regulation, which apply to all securitisations, the STS regime is optional. To qualify for the STS label, transactions must meet specific requirements related to the underlying assets (including asset homogeneity and origination standards), disclosure and verification (such as clear documentation and external verification of underlying exposures), and transaction structure (including risk retention compliance). By granting regulatory recognition to securitisations that meet these standards, the STS label is intended to help restore investor confidence and support the long-term viability of securitisation as a funding channel.

It is important to underline that the STS criteria do not necessarily imply that STS securitisations are less risky, but rather that the risk involved can be better assessed by a prudent and diligent investor. Caballero and Simsek (2013) argue that financial complexity can generate confusion and uncertainty, discouraging investment and undermining market functioning. Similarly, Carlin et al. (2013) show that complex markets tend to be more volatile, less liquid, and less efficient than simpler ones, highlighting the need for standardised frameworks such as STS. From this perspective, a reduction in complexity is expected to positively affect asset performance. For instance, Ertan et al. (2017) show that greater market comparability and transparency are associated with lower default rates of securitised loans.

However, the benefits of the STS label may not be guaranteed. Similarly to what happened to highly rated ABS tranches during the sub-prime crisis (Benmelech & Dlugosz, 2009), STS labels could be exploited to pass credit risk to third parties without adequate compensation, eventually incentivising the issuance of riskier loans.

This chapter provides empirical evidence on the performance and structural characteristics of STS securitisations, with a particular focus on the period surrounding the COVID-19 pandemic. The first part of the analysis investigates the relationship between the STS label and realised mortgage delinquencies, including during the pandemic period when the resilience of securitised loan pools was tested by unprecedented macroeconomic and policy shocks. The second part turns to the structure of STS-labelled RMBS, assessing whether and how their composition and credit enhancement mechanisms differ from non-STS deals.

This chapter makes two main contributions to the literature. First, we examine the relationship between underlying asset quality and securitisation structure. We show that less complex securitisations meeting the new criteria of simplicity, transparency, and standardisation (STS) perform significantly better than their non-STS counterparts, exhibiting a 0.39 percentage point lower annual delinquency rate.

However, it is important to consider the potential behavioural distortions introduced by the STS framework. For instance, McGowan and Nguyen (2023) warn that the STS label may create a false sense of security, leading investors to underprice risk and accept riskier loans without adequate compensation. Similarly, (Coval et al., 2009) argue that the ability to transfer credit risk through securitisation can erode lending standards. Despite these concerns, other studies point to potential benefits. For example, Covitz et al. (2013) find that securitisation programmes with stronger observable characteristics are more resilient to market disruptions.

Our structural analysis shows that STS deals tend to have fewer tranches and lower subordination levels, which could, in principle, increase the risk exposure of senior investors.

However, we also find that STS tranches are more likely to receive higher ratings. This suggests that the observed structural differences are not the result of opportunistic behaviour, but instead reflect genuine improvements in asset quality and deal design

Second, we contribute to the literature that analyses the impacts of the COVID-19 pandemic on the credit market. Recent studies tend to focus on the effects of the pandemic on credit supply (Colak & Öztekin, 2021; Horvath et al., 2023) and the effectiveness of policy interventions (Moulton et al., 2022; Sarker, 2020). We show that the COVID-19 pandemic led to an increase in residential mortgage delinquencies in Europe that started in the first quarter of 2020 and peaked in the third quarter of the same year. The rise in delinquencies is heterogeneous across countries and borrower characteristics. Specifically, our model shows that the default probability in our sample goes from an annualised 36 bp in Q4-2019 to 88 bp in Q1-2020, peaking at 109 bp in Q3-2020.

However, the newly introduced STS securitisations prove to be effective in tackling the negative effects of the pandemic. Loans securitised in STS deals generally perform better than their non-STS counterparts, showing a 77 bp lower annual delinquency probability when the COVID-19 period is considered. Indeed, the negative effects of the pandemic are much more contained for this new type of less-complex securitisation after controlling for loan and borrower characteristics. For instance, when considering loans issued in 2018, while the average quarterly delinquency rate of non-STS loans peaks at an annualised 141 bp in Q3-2020, the delinquency rate of STS loans is only around 15 bp in the same period. This is particularly relevant if we consider that the new STS criteria do not have implications for the quality of the securitised assets, as they only require that common standards of simplicity, transparency, and standardisation are met.

3.2 Data and methodology

As in Chapter 2, our analysis draws on loan-level data from the European DataWarehouse (EDW), the platform designated by the European Securities and Markets Authority (ESMA) for collecting and validating standardised information on asset-backed securities eligible for repurchase agreements with the European Central Bank (ECB). Since January 2013, originators of eligible residential mortgage-backed securities (RMBS) have been required to report detailed loan-level data to this repository on a quarterly basis. For each securitised loan, more than 150 variables may be reported, of which 55 are mandatory. These variables cover a broad range of categories, including borrower demographics, loan and product features, property details, and performance indicators.

Our full initial sample consists of 40,295,781 loan-quarter observations spanning from 2012-Q3 to 2020-Q4. To mitigate issues related to missing or inconsistent quarterly reporting, we aggregate the data to an annual frequency for our baseline regressions, which results in a more balanced panel.[2] The distribution of loans, tranches, deals, and observations by country of origination is reported in Table 3.1. As shown in Panel A, the full annual sample comprises 8,961,130 observations, corresponding to 3,997,044 unique loans over the period 2013–2021.

To isolate the effects of the STS provisions, which apply only to securitisations that voluntarily comply with the new criteria, from the broader general provisions, we restrict our main sample to RMBS deals issued from 2018 onwards, when the new regulatory framework was introduced. As shown in Panel B of Table 3.1, this subsample includes 1,256,011 loans and 2,191,967 annual observations, corresponding to 112 RMBS deals and 215 tranches. Of these deals, 43 (39%) have been granted STS status under the new regime.

[2]Results based on the full quarterly panel are presented as robustness checks in Appendix 3.B, Table 3.B.1.

Table 3.1. Distribution of securitised mortgages by country of origination. The table reports country distributions of securitisation deals, tranches, mortgage loans, and annual observations at the loan level across the whole sample (Panel A), and the STS subsample (Panel B). Only tranches with a non-missing rating at origination are reported in this table.

Panel (A): Full sample, from 2013 to 2020				
Country of Origination	**Deals**	**Tranches**	**Loans**	**Observations**
Netherlands	98	320	1,026,506	2,282,395
France	27	48	1,230,701	2,349,192
Spain	41	64	439,218	1,344,009
Italy	42	104	442,117	1,029,704
Belgium	5	14	143,793	389,307
United Kingdom	37	140	207,073	503,021
Germany	3	0	314,464	572,654
Portugal	5	5	56,462	182,006
Ireland	23	87	136,710	308,842
Total	281	782	3,997,044	8,961,130
Panel (B): STS subsample, from 2018 to 2020				
Netherlands	43	112	484,375	891,414
France	11	10	293,424	464,617
Spain	9	3	30,246	36,070
Italy	12	9	204,032	364,651
Belgium	1	0	39,719	74,715
United Kingdom	17	37	87,666	142,479
Portugal	3	1	34,708	95,983
Ireland	16	43	81,841	122,038
Total	112	215	1,256,011	2,191,967

Summary statistics are reported in Table 3.2. As can be noted, the more recent STS sample is broadly aligned with the characteristics of the full initial sample. Key loan- and borrower-level variables, such as loan-to-value ratios, interest rates, borrower employment status, and delinquency rates, all exhibit similar distributions.

Table 3.2. Sample characteristics. The table reports loan-level averages for the variables used in the main regressions for the full sample and the STS sub-sample.

		Full sample	**STS subsample**
	Sample Period	2013 - 2020	2018 - 2020
	No. of loans	3,997,044	1,256,011
	Variables	**Mean**	**Mean**
	Delinquent	0.008	0.007
	Securitised from 2018	0.314	1.000
	STS securitisation	0.150	0.477
Loan characteristics			
	Loan to Value	0.836	0.876
	Years to Maturity	17.9	25.7
	Interest Rate	2.639	2.385
Interest Type	Floating	0.278	0.329
	Fixed	0.345	0.209
	Hybrid	0.353	0.437
	Other	0.024	0.026
Payment Type	Annuity	0.617	0.680
	Linear	0.161	0.048
	Increasing	0.015	0.011
	Other	0.207	0.261
Purpose	Purchase	0.636	0.681
	Remortgage	0.120	0.120
	Renovation	0.074	0.074
	Construction	0.066	0.063
	Other	0.104	0.063
Borrower Characteristics			
	Second Time Borrower	0.245	0.256
Employment	Employed	0.828	0.830
	Unemployed	0.011	0.006
	Self Employed	0.103	0.109
	Legal Entity	0.002	0.002
	Student	0.002	0.002
	Pensioner	0.028	0.032
	Other	0.029	0.020
Macro-variables			
	ΔUnemployment	0.096	-0.007
	ΔHouse Price Index	4.289	5.800

To explore whether securitisations granted STS status differ systematically from non-STS deals, Table 3.3 presents a comparison of borrower and loan characteristics across the two groups within the post-2018 sample.

Table 3.3. Mortgage distribution by loan characteristics. The table shows the distribution of residential mortgages for STS and non-STS securitisations across loan and borrower characteristics. Variable definitions are reported in Appendix 3.A. Sample period: 2018 to 2020.

General		**No. of Loans**	**Observations (%)**			
	non-STS	751,336	59.82			
	STS	504,675	40.18			
Employment		**Employed (%)**	**Unemployed (%)**	**Self_Employed (%)**	**Legal (%)**	**Other (%)**
	non-STS	79.59	0.63	11.00	0.21	8.47
	STS	87.80	0.46	8.95	0.00	2.78
Interest Rate Type		**Floating (%)**	**Fixed (%)**	**Hybrid (%)**	**Other (%)**	
	non-STS	31.58	10.40	56.50	1.52	
	STS	8.63	54.46	35.93	0.97	
Payment Type		**Annuity (%)**	**Linear (%)**	**Increasing Inst. (%)**	**Other (%)**	
	non-STS	56,61	9.06	0.01	34.32	
	STS	77.49	1.69	2.42	18.4	
Purpose		**Purchase (%)**	**Re-mortgage (%)**	**Renovation (%)**	**Construction (%)**	**Other (%)**
	non-STS	70.57	13.61	3.31	2.66	9.84
	STS	71.23	7.90	10.70	9.10	1.08
Loan-to-value		**LTV $<$ 0.7 (%)**	**0.7 $\leq$ LTV <0.8 (%)**	**0.8 $\leq$ LTV <0.9 (%)**	**0.9 $\leq$ LTV <1 (%)**	**LTV $>$ 1 (%)**
	non-STS	29.43	14.43	18.09	13.76	24.28
	STS	22.23	10.86	13.47	18.66	34.78

The results show that the distribution of mortgages by borrower employment status is nearly identical between the two groups. However, notable distinctions emerge in other dimensions. For instance, while 31.6% of non-STS loans carry a floating interest rate, this figure falls to just 8.6% among STS loans. Conversely, the share of loans with a fixed interest rate is substantially higher in STS deals (54.5%) compared to non-STS transactions (10.4%).

Differences are also evident in terms of loan-to-value (LTV) ratios. STS loans are more likely to be under-collateralised, with 34.8% exhibiting an LTV ratio above one, compared to 24.3% in the non-STS group. In addition, STS deals display markedly lower shares of atypical loan characteristics, such as non-standard amortisation types or interest rate structures. These patterns are consistent with the simplicity and standardisation objectives of the STS framework.

Beyond structural differences, STS deals also appear to be backed by better-performing loan pools. Within our sample, only 0.20% of STS loans are recorded as delinquent, compared to 1.62% of loans in non-STS deals over the same period. This initial evidence suggests that STS securitisations may be associated with both improved design features and stronger underlying asset quality.

3.3 Model specification

To assess the impact of securitisation complexity on mortgage default rates during the STS sample period, we estimate a panel-probit model consistent with the baseline specification used in Chapter 2. Our main model is defined as follows:

$$\begin{aligned} \textit{Loan delinquency}_{i,t} = \alpha &+ \beta_1 \textit{STS Securitisation}_i \\ &+ \beta_2 \textit{Int. Rate at origination}_i + \beta_3 \textit{Years to maturity}_{i,t} \\ &+ \gamma \textit{Loan characteristics}_i + \delta \textit{Borrower's characteristics}_i \\ &+ \theta \textit{Macro-variables}_{i,t-1} + \textit{Country FE} + \textit{Year FE} + \varepsilon_{i,t} \end{aligned} \tag{3.1}$$

where the dependent variable, *Loan delinquency*, is a binary indicator equal to one if the loan is in arrears during year t, and zero otherwise. The key explanatory variable, *STS Securitisation*, is a dummy that equals one if the loan is securitised in a deal labelled as Simple, Transparent and Standardised (STS), and zero otherwise.

To examine the performance of STS securitisations during the COVID-19 crisis, we extend our specification by interacting the *STS Securitisation* dummy with a *Pandemic Period* indicator, which equals one for loans reported from 2020-Q1 onwards. This interaction allows us to assess the differential impact of the pandemic on loans in STS deals relative to non-STS deals. To avoid collinearity issues between country and deal-level fixed effects, we include country fixed effects in our baseline model. Standard errors are clustered at the deal level to account for within-deal correlation.

In the second part of the analysis, we examine whether STS securitisations are associated with better credit ratings at the tranche level. We estimate an ordinal logistic model to assess the probability that a tranche is rated within one of three categories: AAA–A3, Baa1–Baa3, or Ba1–C (i.e., speculative-grade). This approach is commonly used in the literature to analyse credit ratings (see, for example, Nickell et al. (2000) and De Moor et al. (2018)). The model is specified as follows:

$$Rating\ band_i = \alpha + \beta_1 STS\ Securitisation_i + \varepsilon_i \tag{3.2}$$

where *STS Securitisation* is a binary variable equal to one if tranche *i* belongs to a deal classified as STS. To account for the relative importance of each tranche, we weight the regressions by tranche balance at origination.

3.4 Results

This section presents the empirical results and is structured into three parts. We begin in Section 3.4.1 by examining the overall impact of the COVID-19 pandemic on mortgage delinquencies across Europe. This analysis provides a benchmark for understanding the extent of credit deterioration during the crisis period.

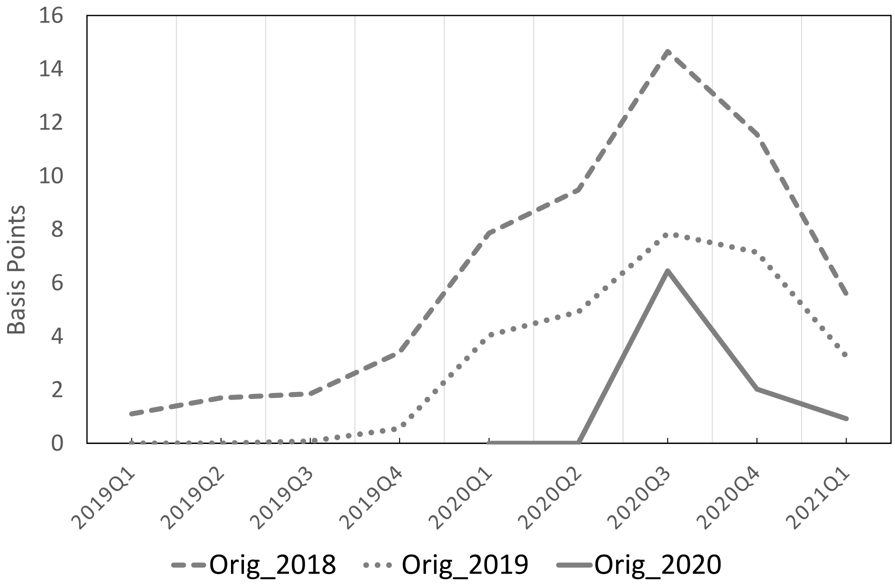
In Section 3.4.2, we turn our attention to STS securitisations. We investigate whether the quality of loans securitised in STS deals differs from that of non-STS transactions, and assess the relative resilience of STS securitisations to the pandemic shock.

Finally, Section 3.4.3 focuses on the structure of RMBS deals. We compare structural features and credit ratings across STS and non-STS transactions, evaluating whether the introduction of the STS framework has led to observable changes in tranche composition and overall deal architecture.

3.4.1 Covid-19 and loan delinquencies

Despite the enhanced credit quality of securitised residential mortgages following the introduction of the new ABS regulation (as shown in Chapter 2), the credit risk landscape was significantly impacted by the COVID-19 pandemic. Banks faced heightened pressure on their credit portfolios, which in turn affected their stability. Governments worldwide implemented measures such as country-wide lockdowns and stimulus packages to mitigate the adverse effects of the pandemic. While these government policies appeared to have a generally positive effect on stocks (Narayan et al., 2021), the same cannot be said for credit instruments. As highlighted by Colak and Öztekin (2021), lockdown measures inadvertently strained borrowers, leading to a global increase in credit risk. This observation aligns with our mortgage population, which exhibits a substantial surge in delinquency rates even among loans originated after the implementation of the new regulation. This trend is illustrated in Figure 3.1, with the quarterly delinquency rate of loans issued in 2018 doubling from 3 bp in 2019-Q4 to 8 bp in 2020-Q1, peaking at 15 bp in 2020-Q3. Similar patterns emerge for loans originated in 2019 and 2020.

Figure 3.1. Quarterly delinquency rates by year of origination during the COVID-19 pandemic

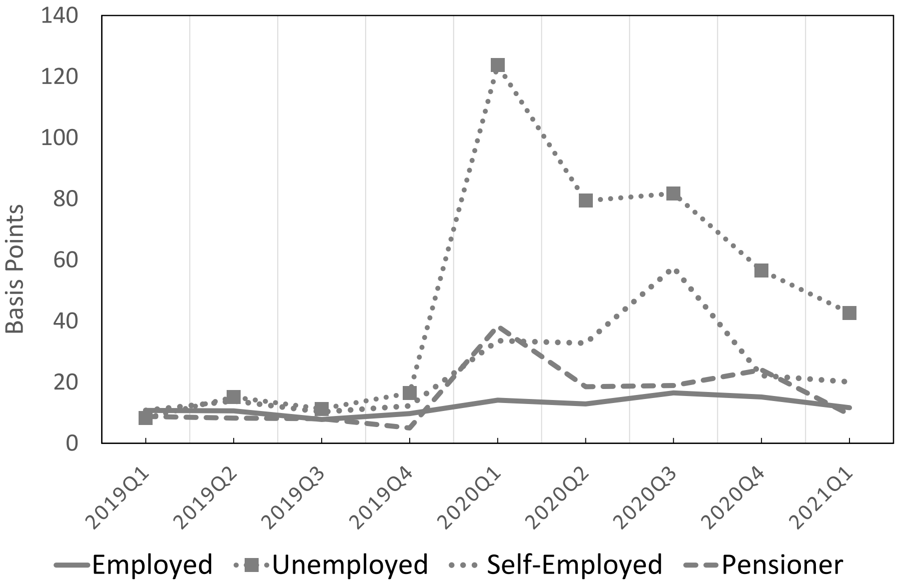


Borrowers have not all been equally affected by the pandemic, as illustrated in Figure 3.1. Unemployed and self-employed borrowers experienced the most significant increases in delinquency rates. For example, the delinquency rate for unemployed borrowers surged from 16 bp in 2019-Q4 to 123 bp in 2020-Q1. Similarly, self-employed borrowers experienced a rise from 12 bp at the end of 2019 to 58 bp in 2020-Q3. In contrast, employed borrowers only saw a modest increase of 6 bp in delinquency rates in the same period. This can be attributed to employed borrowers being the primary beneficiaries of furlough schemes, which were widely implemented across Europe during the COVID-19 pandemic to address rising unemployment rates.[3]

Furthermore, the severity of the pandemic's impact on loan delinquencies appears to have been influenced by country-specific factors (Colak & Öztekin, 2021). As depicted in Figure 3.3, mortgage delinquency ratios varied significantly among the countries in our

[3] See "Pandemic takes toll on self-employed, parents and less well off", Financial Times. May 25, 2021.

Figure 3.2. Quarterly delinquency rates by employment status during the COVID-19 pandemic.

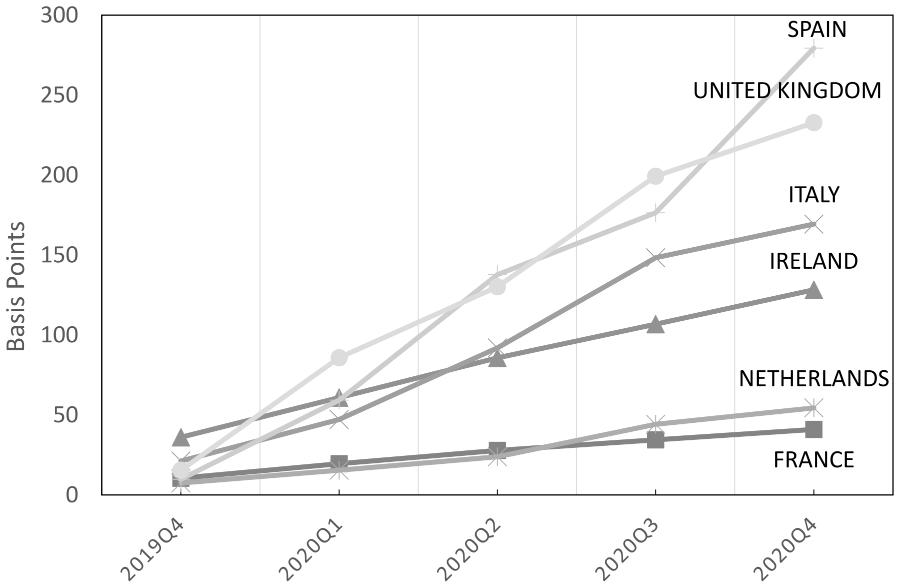


sample during the pandemic. For instance, in France, only 0.30% of active loans originated in 2019 became delinquent by the end of 2020. However, countries like Spain and the United Kingdom experienced delinquency ratios above 2.1% during the same period. Interestingly, there appears to be a strong association between the severity of the pandemic in a country and loan delinquencies. Countries with changes in excess mortality rates below the European average (+11.7%), such as Ireland, France, and the Netherlands, exhibited lower delinquency rates. On the other hand, countries with significantly higher changes in excess mortality rates, such as Spain and Italy, displayed higher loan delinquency ratios during the pandemic.[4]

It is important to note that loan delinquencies do not automatically result in defaults, particularly given the extraordinary circumstances surrounding the pandemic. Payment holiday schemes have been widely implemented to alleviate the financial distress caused by

[4]Source: Eurostat, excess mortality - monthly data. Available at: https://ec.europa.eu/eurostat/databrowser/view/demo_mexrt/default/table?lang=en.

Figure 3.3. Cumulative delinquency rates by country of issuance. This figure shows the cumulative delinquency rates by the country of issuance during the COVID-19 pandemic relative to the total number of active loans in Q4-2019.

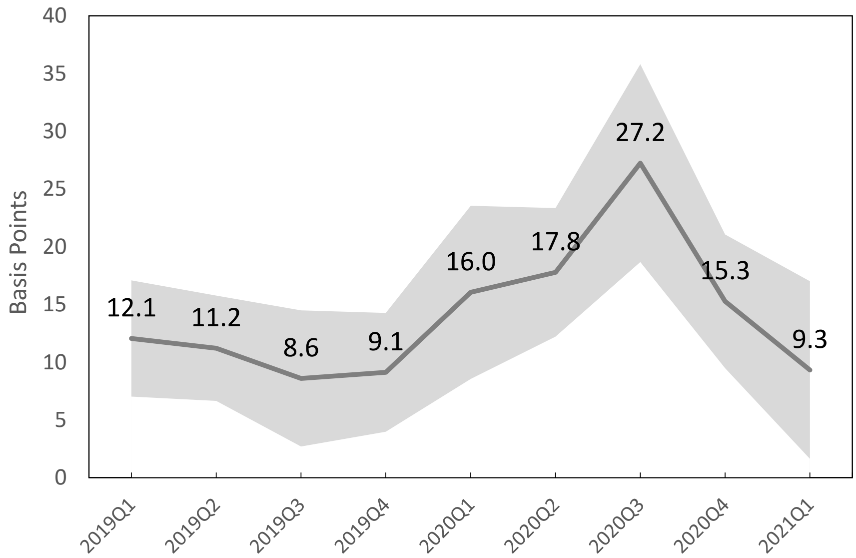


the crisis. However, prolonged payment holidays could pose potential challenges for banks as debts accumulate over time.[5] Therefore, it is crucial to assess the extent of the COVID-19 pandemic's impact on loan delinquencies while controlling for loan characteristics, borrower information, and country-specific factors. To accomplish this, we estimate Equation (3.1) on the STS sample using quarterly data and quarterly fixed effects. The marginal effects of the quarter fixed effects are presented in Figure 3.4.

Our model confirms that the likelihood of delinquency began to rise in 2020-Q1 and reached its peak in 2020-Q3, with all coefficients for the year 2020 being statistically significant at a confidence level of 5% or higher. Specifically, the delinquency probability increased by 18 basis points from 2019-Q4 to 2020-Q3. However, it rapidly returned to pre-pandemic levels in the first quarter of 2021.

[5] See "Analysis: Pandemic payment holidays mask wave of European problem debt", Reuters. November 11, 2020.

Figure 3.4. Quarter fixed effects of loan delinquencies and COVID-19. The figure displays the marginal coefficients, along with their corresponding 95% confidence intervals computed using the delta method, of the quarter fixed effect in the probit regression model for loan delinquencies as defined in Equation 2.1. These coefficients were estimated using quarterly data.



3.4.2 Simple, Transparent and Standardised securitisation

We then examine the impact of the newly introduced STS securitisation standards on mortgage quality. STS labels are used to identify ABSs that are deemed "simple" in terms of their underlying assets, "transparent" in the information available to investors, and "standardised" for easy comparison with other securitised structures. However, it's important to note that STS labels do not inherently indicate the quality of the underlying assets. This raises the concern that STS deals, despite their lower complexity, may include loans of subpar quality. The adherence to regulatory standards might mistakenly be interpreted by investors as a signal of higher credit quality, potentially making these deals more readily tradable. As already noted in Section 3.2, STS deals appear to be characterised by better-performing underlying assets. Within our STS subsample, only 0.20% of STS loans experience delinquency, while the delinquency rate for their non-STS counterparts reaches 1.62% during the same period. To complement these preliminary findings, we employ Equation (3.1) on the STS subsample, thereby controlling for loan characteristics, borrower information, and macroeconomic conditions. The outcomes are presented in Table 3.4, where we exclude the pandemic period in specification 1 and analyze the full sample in specification 2.

Table 3.4. The effect of the STS regulation on mortgage delinquency rates. Panel A reports panel probit regression results for the baseline model in Equation 3.1. Our main variable of interest, *STS Securitisation*, is an indicator variable that takes the value of one if the mortgage belongs to an STS deal, and zero otherwise. The sample period spans from 2018 to 2020. In specification 1 we exclude the pandemic period. Specification 3 includes only originators that issued both STS and non-STS deals. Variable definitions are reported in Appendix 3.A. Panel B reports results from Equation 3.1 for the full sample period when explanatory variables are gradually added to the model. Robust standard errors are clustered at a deal level and reported in round brackets. The symbols ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel A: Baseline Model	**Marginal effect (basis points)**		
Dep. Var.: Delinquency Indicator	**(1)** **2018 to 2019**	**(2)** **2018 to 2020**	**(3)** **2018 to 2020**
STS Securitisation	**-39.32*****	**-77.42*****	**-15.95*****
	(9.10)	**(20.65)**	**(2.77)**
Years to Maturity	7.53	17.40***	4.20
	(6.87)	(5.93)	(3.49)
Interest Rate	9.56***	17.63***	10.67***
	(2.71)	(5.03)	(3.68)
Loan-to-value			
0.6 ≤ LTV <0.7	0.08	-10.30	1.58
	(3.06)	(8.39)	(2.34)
0.7 ≤ LTV <0.8	1.90	-10.72	-2.61
	(3.23)	(10.05)	(1.87)
0.8 ≤ LTV <0.9	6.80	-0.11	3.63
	(4.75)	(11.18)	(3.22)
0.9 ≤ LTV <1	13.35**	11.90	5.67*
	(5.96)	(11.32)	(3.19)
LTV ≥ 1	35.30***	40.90***	14.50***
	(8.43)	(12.80)	(4.66)
Interest Rate Type			
Floating Int. Type	19.69***	49.89***	38.89
	(6.42)	(18.14)	(36.37)
Hybrid Int. Type	-6.58	-9.22	4.30
	(10.35)	(10.17)	(19.27)
Other Int. Type	7.08	29.31*	14.65
	(12.24)	(16.60)	(25.42)
Payment Type			
Linear Payment Type	-17.85***	-17.15**	-.259
	(6.42)	(7.98)	(11.03)
Increasing Payment Type	30.51**	7.88	24.17
	(12.66)	(9.44)	(41.41)

Table 3.4 continued from previous page

Dep. Var.:	**Marginal effect (basis points)**		
Delinquency Indicator	**2018 to 2019**	**2018 to 2020**	**2018 to 2020**
Other Payment Type	-1.48	-1.68	-12.36***
	(4.37)	(7.39)	(4.24)
Purpose			
Remortgage Purpose	6.04	-3.26	1.60
	(4.90)	(7.65)	(5.36)
Renovation Purpose	-1.74	3.95	1.19
	(4.22)	(6.70)	(3.08)
Construction Purpose	9.60	15.80	-3.73
	(12.55)	(15.38)	(4.53)
Other Purpose	5.91	3.75	-18.24***
	(4.28)	(7.61)	(3.58)
Borrower characteristics			
Second Time Borrower	-3.47	11.71	-1.21
	(2.58)	(9.27)	(0.91)
Unemployed	34.06	100.81***	35.04
	(26.69)	(29.02)	(31.30)
Self-employed	5.56	33.72***	7.10***
	(5.87)	(8.59)	(2.23)
Legal Entity	41.66	183.97***	-
	(53.60)	(6786)	
Student	33.09	-8.66	-
	(42.92)	(16.51)	
Pensioner	0.75	14.01	-6.60
	(13.30)	(18.54)	(8.88)
Other employment	36.89**	65.48***	5.31
	(14.21)	(13.54)	(20.45)
Country			
France	27.95***	68.29***	-
	(8.92)	(21.77)	
Ireland	61.57**	74.68***	-
	(28.11)	(26.12)	
Italy	41.8	167.37**	-
	(29.83)	(75.29)	
Netherlands	42.97***	26.75***	-
	(16.15)	(5.30)	
Portugal	8.31	1.06	-
	(6.98)	(3.67)	
Spain	21.16	187.05***	-
	(25.7)	(45.24)	
United Kingdom	25.86**	97.59**	-
	(11.16)	(38.01)	
Macro-variables	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Originator Fixed Effects	No	No	Yes

Table 3.4 continued from previous page

Dep. Var.:	**Marginal effect (basis points)**		
Delinquency Indicator	**2018 to 2019**	**2018 to 2020**	**2018 to 2020**
Observations	1,024,924	2,147,141	623,675
Pseudo R-squared	0.064	0.107	0.044

Panel B: Robusteness, 2018 to 2020

Dep. Var: Mortgage delinquency indicator	**Marginal Effect (basis points)**			
	(1)	**(2)**	**(3)**	**(4)**
STS Securitisation	-91.08***	-82.27***	-76.16***	-77.42***
	(30.18)	(22.81)	(20.02)	(20.65)
Loan Characteristics		Yes	Yes	Yes
Borrower Characteristics			Yes	Yes
Macro-Variables				Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs.	2,147,141	2,147,141	2,147,141	2,147,141
Pseudo-R^2	0.0767	0.0975	0.104	0.107

Upon analysis, it becomes evident that loans securitised in STS deals in 2018 and 2019, prior to the pandemic, exhibit an annual delinquency probability that is 39 basis points lower than their non-STS counterparts. Interestingly, when considering the entire 2018-2020 period (Specification 2), including the pandemic, the disparity in delinquency rates becomes even more pronounced, with the STS delinquency rate decreasing by -77 basis points. These findings contradict the notion that STS securitisation may encourage banks to issue and securitise lower-quality loans. Instead, it appears that banks opt to securitise higher-quality loans when the ABS structure facilitates a more accurate and straightforward assessment of associated risks.

Furthermore, the full output in specification 2 sheds light on the factors linked to an increase in delinquency probabilities during the 2018-2020 period. Notably, delinquencies in the period that includes the crisis predominantly stem from borrower characteristics and the loans' country of origination. For example, unemployed borrowers experience a 101 bp higher annual delinquency probability compared to employed borrowers, a significant deviation from the 34 basis point higher delinquency probability observed prior to the pandemic. Consistent with our earlier findings, delinquency rates are also found to be elevated for loans issued in Spain, Italy, and the United Kingdom.

To address potential concerns regarding different risk propensities between financial institutions issuing STS deals and those issuing non-STS deals, we conducted a separate analysis focusing on a sample comprising only banks that have issued both STS and non-STS deals. This restricted sample consists of 623,713 loan-level observations relative to 45 financial institutions. By running our main model (Equation (3.1)) on this restricted sample, we aim to determine whether banks specifically select safer loans for their STS deals. We report our results in specification 3, showing that loans securitised in STS deals show a 16 bp lower annual probability of delinquency than loans securitised in non-STS deals issued by the same group of financial institutions, in line with our main results.

Additionally, we conduct a series of robustness checks, which are reported in Appendix 3.5. The most important of these is presented in Table 3.B.2, Specification 3, where we control for government support during the COVID-19 period using the Economic Support Index (ESI) from the Oxford COVID-19 Government Response Tracker (OxCGRT).[6] The ESI captures whether governments provided income support, such as salary coverage, direct cash payments, or universal basic income, and whether they imposed freezes on financial obligations (e.g., loan repayments) (Hale et al., 2022). By accounting for this index, we mitigate concerns that the observed resilience of STS deals might simply reflect more generous government interventions rather than structural differences in deal quality.

[6]More information on the Oxford COVID-19 Government Response Tracker (OxCGRT) is available at: https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker.

Table 3.B.2 also reports additional robustness checks aligned with those in Chapter 2. Specifically, Specification 1 additionally controls for the business cycle; Specification 2 incorporates time-varying changes in the Euribor index; and Specification 4 includes a measure of interest rate uncertainty. Finally, in Table 3.B.1, Specification 2, we show that our results remain robust when restricting the sample to only the first two annual observations following securitisation. This helps ensure that our findings are not driven by longer-term selection dynamics.

In the following figures we provide a closer examination of default rates in both STS and non-STS deals during the pandemic. When focusing on loans originated in 2018 (Figure 3.5), we observe that while the quarterly delinquency rate for non-STS loans reaches a peak of 35 basis points in 2020-Q3, the delinquency rate for STS loans only reaches 4 basis points during the same period. Similar results are obtained for loans originated in 2019 (Figure 3.6) and 2020 (Figure 3.7). Generally, the delinquency rate for non-STS loans increases by an average of 24 basis points from 2019-Q3 to 2020-Q3. In contrast, the delinquency rate for STS loans increases by only 3 basis points during the same period.

We substantiate these findings by incorporating an interaction term between the variable "STS Securitisation" and the variable "Pandemic Period" into our model. The results of this analysis are presented in Table 3.5. As observed in specification 1, loans are more likely to be delinquent by approximately 46 basis points during the pandemic period. Notably, STS loans exhibit significantly lower delinquency rates compared to their non-STS counterparts. In specification 2, when we introduce the interaction between the variables "STS Securitisation" and "Pandemic Period", we observe that the positive impact of lower complexity in STS deals on delinquency rates is even more pronounced during the adverse shocks of the COVID pandemic.

Figure 3.5. STS vs non-STS securitisations during the COVID pandemic: origination in 2018. The Figure show quarterly delinquency rates of STS and non-STS securitisations for mortgages originated in 2018.

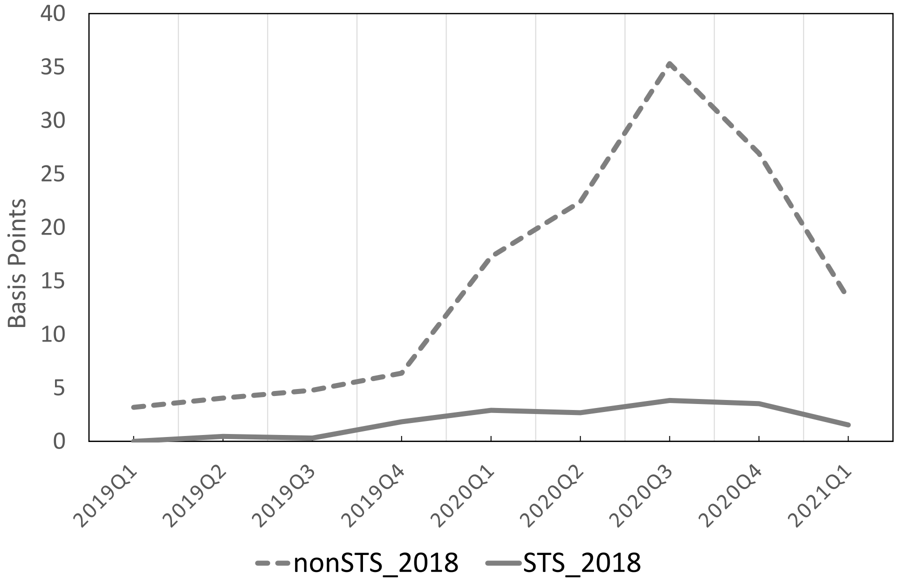


Figure 3.6. STS vs non-STS securitisations during the COVID pandemic: origination in 2019. The Figure show quarterly delinquency rates of STS and non-STS securitisations for mortgages originated in 2019.

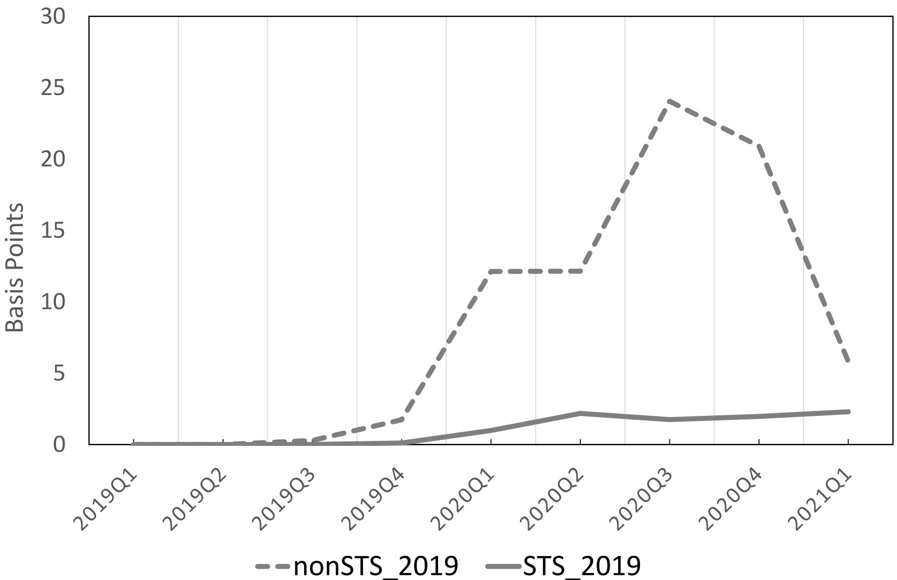


Figure 3.7. STS vs non-STS securitisations during the COVID pandemic: origination in 2019. The Figure show quarterly delinquency rates of STS and non-STS securitisations for mortgages originated in 2020.

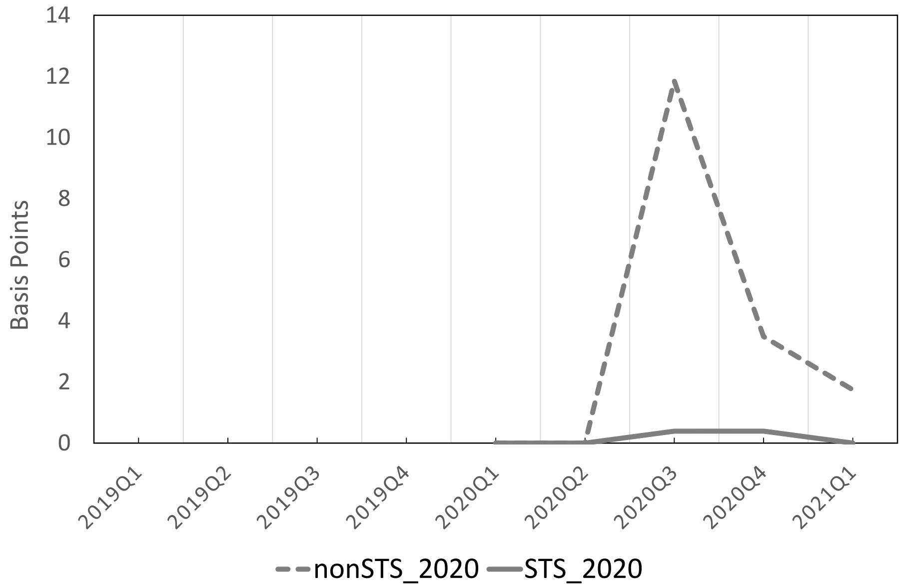


Table 3.5. Effect of the STS regulation on mortgage delinquency during the pandemic. The table reports panel probit regressions results for the baseline model in Equation 3.1 with the addition of a pandemic period dummy and its interaction with STS securitisation. The variable *STS securitisation* equals one if the mortgage belongs to an STS deal, and zero otherwise. The variable *Pandemic Period* is equal to one for mortgages reported from 2020, and zero otherwise. The definitions of the other variables are reported in Appendix 3.A. Sample period: 2018 to 2020. Robust standard errors are clustered at a deal level. The symbols ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Dep. Var: Loan delinquency indicator	**Marginal Effect (basis points)**	
	(1)	**(2)**
STS Securitisation	-74.35***	-25.37***
	(20.92)	(8.37)
Pandemic Period	46.00***	44.99***
	(13.20)	(12.74)
STS Securitisation Pandemic Period*		**-84.60*****
		(22.64)
Loan Characteristics	*Yes*	*Yes*
Borrower Characteristics	*Yes*	*Yes*
Macro-variables	*Yes*	*Yes*
Country FE	*Yes*	*Yes*
Obs.	2,147,141	2,147,141
Pseudo-R^2	0.099	0.102

Overall, due to the higher quality of their underlying assets, STS deals appear to be more resilient in managing the negative effects of the pandemic, resulting in improved performance as financial instruments. These findings are significant, especially considering that the improved performance has been achieved by enhancing the simplicity, transparency, and standardisation of asset-backed securities, without imposing restrictions on the quality of the securitised loans.

3.4.3 The effects on the securitisation structure

Our analysis thus far has demonstrated an improvement in the quality of securitised loans due to the implementation of the new securitisation regulation. However, we have yet to examine whether this regulatory regime has also influenced the securitisation structure. It is crucial to address this question because while the enhancement in loan quality is positive, there may be a potential increase in overall securitisation risk, possibly stemming from changes in tranche composition and quality (Peña-Cerezo et al., 2019). To investigate this concern, our study specifically focuses on examining the impact of the new securitisation regulation on the securitisation structure. We accomplish this by comparing the structure of STS and non-STS deals. The results are presented in Table 3.6.

Table 3.6. Effect of regulatory changes on the tranche composition of residential mortgage securitisations. The table illustrates the changing composition of tranches in European residential mortgage-backed securitisations, comparing STS to non-STS deals. Sample period: from 2018 to 2020. The symbols ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

	Non-STS	**STS**		
Variable description	**Mean (1)**	**Mean (2)**	**Difference (2) – (1)**	**p-value**
number of tranches	5.07	3.82	-1.25	0.011**
senior tranches (%)	86.7	90.4	3.7	0.021**
mezzanine tranches (%)	1.1	1.5	0.4	0.461
subordinated tranches (%)	12	8.1	-3.9	0.027**
- of which retained tranches (%)	5.3	4.7	-0.6	0.595
average tranche rating per securitisation (value weighted)	25.6	26.5	0.84	0.002***

Table 3.6 presents the average number of tranches, the average relative size of senior, mezzanine, and subordinated tranches, the average relative size of retained tranches, and the (value weighted) average deal rating for each subsample. To test the statistical difference between the analysed groups, a two-tailed t-test is employed, with the null hypothesis assuming that the difference equals zero. The results indicate that STS deals have a statistically significantly lower number of tranches (-1.25), higher relative size of senior tranches (+3.7%), lower relative size of subordinated tranches (-3.9%), and a significantly higher average deal rating (+0.84) compared to non-STS deals. Interestingly, there are no statistically significant differences in the percentage of retained tranches between the two groups.

The overall findings strongly indicate that the securitisation regulation has had a significant impact on the composition of RMBS deals, particularly within the STS deals group. The observed increase in the average deal rating aligns with the regulatory objective of promoting high-quality securitisations. However, the decrease in the number of tranches and the smaller subordinated tranches of STS securitisations could potentially pose risks for investors. This is because the default risk can more easily affect senior tranche holders, given the thinner subordinated tranches and fewer tranches available to absorb losses. To address this concern, we perform a stress-testing exercise to evaluate the expected losses for RMBS originators and tranche holders under various scenarios. The default rate for each scenario is derived from the distribution of loan default rates within our sample of securitisations. By employing this methodology, we are able to analyse and assess the impact of different securitisation structures on the risk borne by investors and originators, particularly in relation to the risk levels associated with the underlying assets. The results of this analysis are presented in Table 3.7.

Table 3.7. Estimated expected loss for originators and tranche holders: stress testing exercise. The table presents the expected loss for RMBS originators and investors (senior, mezzanine and subordinated tranche holders) under different scenarios. The default rates for each scenario are derived from the distribution of loan default rates within our sample of securitisations (average, 90%, 95%, and 99% quantiles).

Panel A: LGD=100%			**Expected loss to investors**			**Expected loss to originator**
			Tranches			
Sub-sample	**Parameter**	**Default rate %**	**Senior**	**Mezzanine**	**Sub. minus retained**	**Retained**
Non-STS	Average	1.49%	0.0%	0.0%	0.0%	28.1%
STS		0.29%	0.0%	0.0%	0.0%	6.2%
Non-STS	90% qnt	3.94%	0.0%	0.0%	0.0%	74.2%
STS		0.65%	0.0%	0.0%	0.0%	13.8%
Non-STS	95% qnt	5.42%	0.0%	0.0%	1.7%	100.0%
STS		0.79%	0.0%	0.0%	0.0%	16.9%
Non-STS	99% qnt	17.45%	5.0%	100.0%	100.0%	100.0%
STS		1.14%	0.0%	0.0%	0.0%	24.2%
Panel B: LGD=68.5%			**Expected loss to investors**			**Expected loss to originator**
			Tranches			
Sub-sample	**Parameter**	**Default rate %**	**Senior**	**Mezzanine**	**Sub. minus retained**	**Retained**
Non-STS	Average	1.49%	0.0%	0.0%	0.0%	19.3%
STS		0.29%	0.0%	0.0%	0.0%	4.2%
Non-STS	90% qnt	3.94%	0.0%	0.0%	0.0%	50.9%
STS		0.65%	0.0%	0.0%	0.0%	9.5%
Non-STS	95% qnt	5.42%	0.0%	0.0%	0.0%	70.0%
STS		0.79%	0.0%	0.0%	0.0%	11.5%
Non-STS	99% qnt	17.45%	0.0%	0.0%	99.3%	100.0%
STS		1.14%	0.0%	0.0%	0.0%	16.6%

The table presented provides a comparison of the expected losses for STS and non-STS securitisations. Panel A of the table examines a scenario in which a loss given default (LGD) of 100% is assumed, meaning that no recovery from defaulted loans is anticipated, resulting in the complete loss of the invested capital. This serves to depict the worst-case scenario. In Panel B, a more realistic LGD of 68.5% is considered, with a corresponding recovery rate of 31.5%. The 68.5% LGD is calculated as a weighted average of the 25th percentile recovery rates across the countries included in our sample, thereby providing a more representative estimate.[7]

[7]Source: European Banking Authority (2020) Report on the Benchmarking of National Loan Enforcement Frameworks. https://www.eba.europa.eu/sites/default/documents/files/document_library. UK is not included as data on recoveries could not be obtained.

Our findings indicate that non-STS securitisations can lead to significant losses for the originator and, in extreme scenarios based on our in-sample observations, for mezzanine and senior investors as well. For instance, when we consider default rates associated with securitisations in the 99th percentile of our sample and assume an LGD of 100%, we observe that non-STS senior, mezzanine, and subordinated tranche holders suffer losses of 5%, 100%, and 100% respectively. In contrast, investors holding STS tranches do not experience any losses in the same scenario. Similarly, when we consider a less extreme LGD of 68.5%, we find that non-STS subordinated tranche holders still face a substantial loss of 99.3%. Additionally, our tests demonstrate that, in all cases considered, the STS originator's retained tranche serves as effective default protection for all tranches issued to investors, regardless of their seniority. Overall, our evidence suggests that despite the thinner subordinated tranches in STS securitisations, the significantly lower default rates of the underlying assets result in reduced losses for both tranche holders and originators. Based on these results, we conclude that the new STS regulation effectively incentivises issuers to develop and promote securitisations with contained credit risk.

To supplement our findings, we conduct a further analysis of the tranche ratings at the origination stage within the RMBS sample. If the observed changes in the securitisation structure did not lead to higher ratings at origination, it would indicate a minimal impact of the new regulation on the overall quality of the securitisation. Figure 3.8 illustrates the value-weighted distribution of tranche ratings at origination, categorized by subsample.

It is evident that the regulatory measures have had a positive influence on tranche ratings. For instance, 79% of STS tranches possess a AAA rating, contrasting with the 61% of non-STS tranches. To further validate the impact of the regulation on rating improvements, we utilise a simple ordinal logistic model to estimate the likelihood of tranches being rated AAA

Figure 3.8. Rating distribution of MBS tranches.

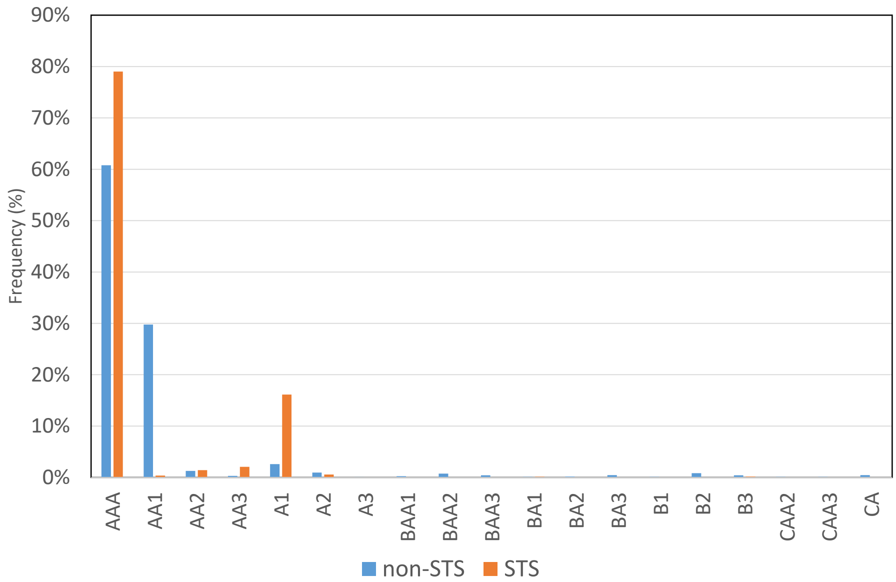


Table 3.8. Effect of regulatory changes on tranche ratings. The table presents the estimation of an ordered logit regression using value-weighted observations, with the thresholds of the dependent variable identifying different rating bands. The variable of interest, employed in this specification, is the dummy variable “STS securitisation”. Sample period: from 2018 to 2020. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Marginal Effect	
	STS Securitisation
Rating band	(1)
AAA - A3	0.038**
	(0.016)
BAA1 - BAA3	-0.012**
	(0.006)
BA1 - C (speculative)	-0.026**
	(0.013)
Obs.	163
Pseudo-R^2	0.075

– A3, BAA1 – BAA3, or BA1 – C (i.e., speculative). To consider variations in the balance at origination for each tranche, we incorporate weighting in our analysis, giving proportional importance to each observation based on its relative size. The results of this analysis are presented in Table 3.8. The results indicate that STS RMBS tranches exhibit a significantly higher probability of receiving a rating of AAA – A3, while demonstrating a reduced likelihood of being assigned a BAA1 or lower rating than their non-STS counterparts.

3.5 Conclusions

This chapter investigates the role of the Simple, Transparent and Standardised (STS) framework, introduced as part of the 2018 European securitisation regulation, in shaping the performance and structure of residential mortgage-backed securities (RMBS). Using loan-level data from the European DataWarehouse, we analyse whether RMBS deals meeting the STS criteria demonstrate superior credit performance and structural characteristics relative to their non-STS counterparts.

Our findings indicate that the introduction of the STS label is associated with a significant improvement in the credit quality of securitised mortgage loans. Although the STS criteria do not directly mandate higher asset quality, STS-labelled deals include loans with lower default rates and greater resilience to macroeconomic shocks. This is particularly evident during the COVID-19 pandemic, when loans securitised in STS deals recorded an annual delinquency probability 77 basis points lower than those in non-STS deals. These results should be understood in the broader context of the pandemic's disruptive effects, which led to a notable increase in residential mortgage delinquencies across Europe. The impact was heterogeneous, with self-employed and unemployed borrowers particularly affected, and countries experiencing varying degrees of credit deterioration depending on the severity of the crisis and the strength of policy responses. Taken together, our findings help to mitigate concerns that the STS label may create a false sense of security and encourage the securitisation of riskier loans without appropriate safeguards.

In addition to superior credit performance, STS deals also display distinct structural features. Compared to non-STS transactions, they tend to have fewer tranches and a lower share of subordinated tranches, which could raise concerns about the potential transfer of credit risk to senior noteholders. However, our tranche-level analysis shows that these structural changes are accompanied by significantly higher tranche ratings at origination. This suggests that the improvements in the overall quality of the securitised pool outweigh any potential increases in risks linked to the securitisation structure.

Overall, our findings support the view that greater standardisation and transparency can enhance the resilience of securitisation markets, particularly during periods of macroeconomic stress. Taken together with the results of Chapter 2, this underscores the beneficial effects of the new European securitisation regulation in improving both loan quality and structural robustness.

Appendices to Chapter 3

This Appendix is organised as follows.

3.A Variable list

Table 3.A.1. Variable definitions

Variable	Definition
Loan Performance	
Delinquent	An indicator variable equal to one if the loan has defaulted or entered delinquency for at least two consecutive quarters, and zero otherwise.
Regulation indicators	
STS Securitisation	An indicator variable equal to one if the loan is securitised in deals defined as STS according to the ESMA STS register, and zero otherwise.
Covid-19 indicators	
Pandemic Period	An indicator variable equal to one for loans reported from 2020-Q1, and zero otherwise.
Loan's characteristics	
Loan to Value	A categorical variable indicating whether the loan-to-value ratio at origination belongs to the following ranges: (0–0.6] baseline, (0.6–0.7], (0.7–0.8], (0.8–0.9], (0.9–1], above 1.
Years to Maturity	The natural logarithm of the number of years remaining until maturity.
Interest Rate	Loan's first available interest rate reported in the ED database in percentage points.
Interest Rate Type	A categorical variable indicating whether the loan has a fixed interest type (baseline), floating, hybrid, or other less frequent interest rate type specifications.
Payment Type	A categorical variable indicating whether the loan is an annuity with fixed instalments (baseline), or whether its amortisation schedule is linear (with decreasing instalments), increasing (with first payments including only a portion of the interest that will later be charged), or other less frequent payment type specifications.
Purpose	A categorical variable indicating whether the loan has been issued for purchase purposes (baseline), remortgage, renovation, construction, or other less frequent purpose specifications.
Borrower's characteristics	
Second Time Borrower	An indicator variable equal to one if the loan is not the first loan a borrower gets from a given bank, and zero otherwise.

Table 3.A.1 continued from previous page

Variable	Definition
Employment	A categorical variable indicating whether the borrower is employed (baseline), unemployed, self-employed, is a legal entity (limited liability company), a student, a pensioner, or other less frequent employment specifications.
Macro variables	
Δ*Unemployment*	One-year lagged country-specific change of the unemployment rate.
Δ*House Price Index*	One-year lagged country-specific change of the house price index.
Tranche-level characteristics	
Rating band	A categorical variable indicating whether a tranche is rated AAA - A3, Baa1 - Baa3 or Ba1 - C (i.e., speculative grade). Ratings from different rating agencies are slotted into each band according to the variable *Rating equivalent* from Eikon (the variable ranges from 1 to 27, with 27 corresponding to AAA). In our analysis, we use the first rating available in Eikon (LSEG) for any given tranche following its issuance as a proxy for the rating at origination.
STS Securitisation	An indicator variable equal to one if the tranche belongs to a deal defined as STS according to the ESMA STS register, and zero otherwise.
Tranche balance	Tranche balance at origination.

3.B Robustness analyses

Table 3.B.1. Baseline model with quarterly data and alternative sample restriction. This table reports panel probit regression results for the baseline model. Specification (1) utilises quarterly data. Specification (2) utilises annual data, but includes only the first two observations per loan. Sample period: 2018 to 2020. Robust standard errors are clustered at the deal level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Loan Delinquency Indicator	**Marginal Effects (basis points)**	
	(1)	**(2)**
STS	-21.56***	-77.51***
	(4.70)	(20.73)
Loan characteristics	Yes	Yes
Borrower characteristics	Yes	Yes
Macro-variables	Yes	Yes
Deal FE	No	No
Time FE	Yes	Yes
Country FE	Yes	Yes
Observations	10,910,110	2,147,141
Pseudo-R^2	0.089	0.104

Table 3.B.2. The effect of the new regulation on loan delinquency rates with controls for business cycle, market interest rates, COVID-related government interventions, and interest rate uncertainty. This table reports panel probit regression results for the baseline models in Equation 2.1. Additional controls include country-specific lagged GDP (DeltaGDP - Specification 1), lagged 3-month Euribor index (DeltaEuribor 3m - Specification 2), a measure of country-specific government intervention during the COVID pandemic (ESI Index - Specification 3), and the lagged standard deviation of the 3-month Euribor index (DeltaEuribor 3m stdev - Specification 4). Sample period: 2018 to 2020. Robust standard errors are clustered at the deal level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Loan delinquency indicator	**Marginal Effects (basis points)**			
	(1)	**(2)**	**(3)**	**(4)**
STS	-72.26***	-63.66***	-79.41***	-72.35***
	(20.10)	(21.56)	(20.48)	(20.86)
DeltaGDP	Yes	No	No	No
DeltaEuribor_3m	No	Yes	No	No
ESI Index	No	No	Yes	No
DeltaEuribor_3m_stdev	No	No	No	Yes
Other characteristics	Yes	Yes	Yes	Yes
Deal FE	No	No	No	No
Time FE	Yes	No	Yes	No
Country FE	Yes	Yes	Yes	Yes
Observations	2,147,158	2,147,158	2,147,158	2,147,158
Pseudo-R^2	0.101	0.083	0.107	0.098

Chapter 4

Integrating energy performance into rating models: a European perspective

4.1 Introduction

Climate change and growing concerns over energy import dependency have emerged as central policy challenges for the European Union (EU). Within this context, the residential housing sector, which is responsible for a large share of both energy use and greenhouse gas emissions,[1] has attracted particular regulatory attention. As part of its broader climate and energy strategy, the EU has placed strong emphasis on improving energy efficiency in buildings. This emphasis is reflected in recent legislative initiatives, such as Directive (EU) 2023/1791, which identifies energy efficiency as a key lever not only for reducing carbon emissions but also for strengthening the Union's energy autonomy by curbing reliance on imported fuels. By lowering aggregate energy demand, energy-efficient solutions also contribute to mitigating volatility in energy prices and shielding households and economies from price shocks.

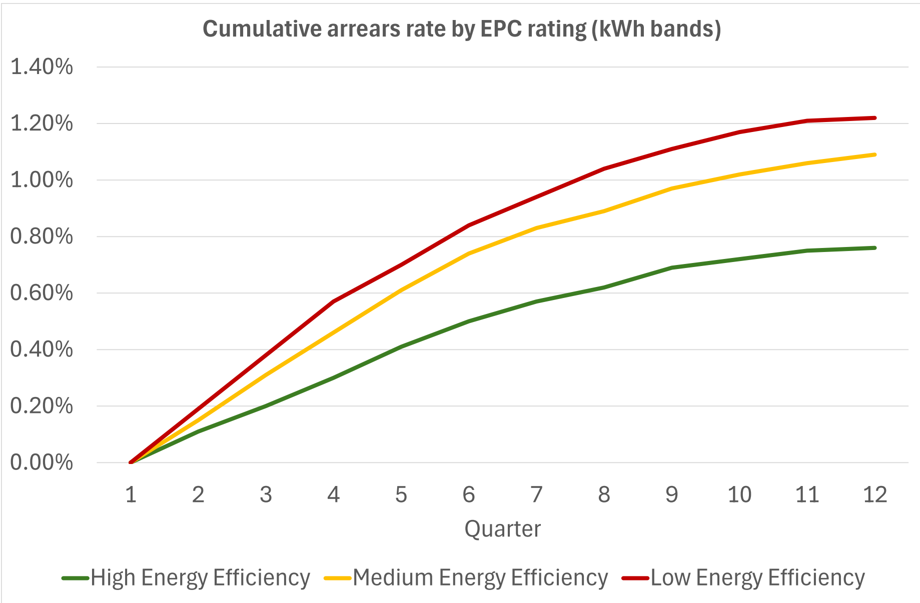
[1]For example, in the UK, the residential sector is considered the third most polluting sector, after transport and energy supply. See Nathalie Thomas, "UK's 'inefficient' homes exacerbate zero-carbon challenge," *Financial Times*, 24 August 2020. Available at: https://www.ft.com/content/cf668430-fee8-45d4-982c-4b2996186879.

The urgency of implementing such measures has grown in light of recent geopolitical developments, notably the war in Ukraine and coordinated production limits by OPEC, which have severely disrupted global energy markets. Against this backdrop, accelerating the uptake of energy efficiency in residential properties is seen not only as an environmental imperative but also as a way to enhance economic and energy resilience.

In the financial domain, the European Central Bank (ECB) has recognised the materiality of climate-related and environmental (C&E) risks to the stability of the banking sector. The ECB's *Guide on climate-related and environmental risks* (European Central Bank, 2020) articulates supervisory expectations for banks, highlighting the need for a strategic, forward-looking, and comprehensive approach to managing these emerging risk drivers. Specifically, Expectation 8.1 of the guide states that "climate-related and environmental risks are expected to be included in all relevant stages of the credit-granting process and credit processing," emphasising the integration of material C&E risk factors across credit risk management frameworks. Furthermore, institutions are encouraged to incorporate these risks into their internal credit and market risk models, ensuring that the treatment of C&E risks is consistent with the management of other significant risk factors. This evolving regulatory landscape underscores the importance of assessing whether energy efficiency indicators, such as the Energy Performance Certificate (EPC) rating, can enhance credit risk models. The present chapter aims to empirically investigate this question, evaluating both the statistical contribution of EPC ratings and their implications for mortgage risk assessment.

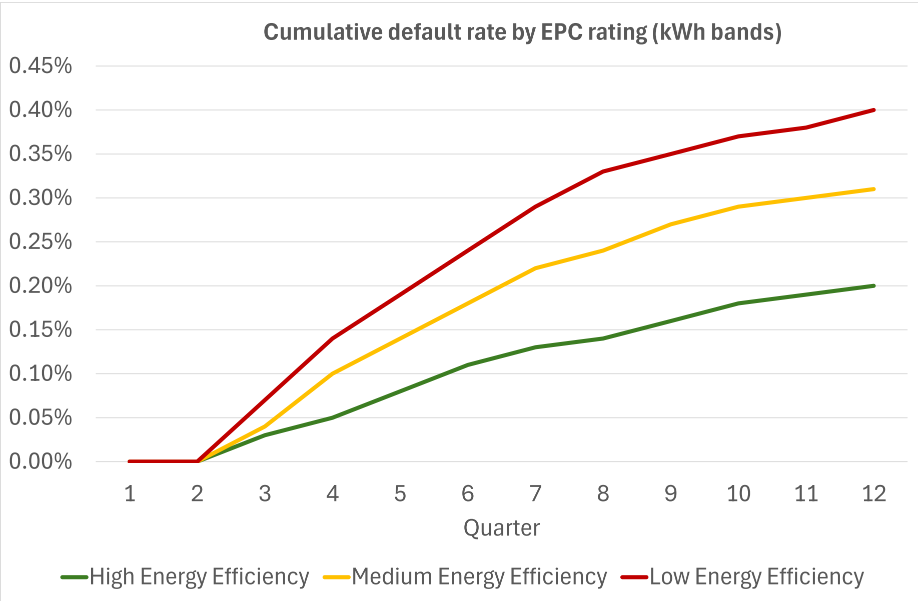
As it is shown in figures 4.1 and 4.2, lower collateral energy efficiency is associated with higher arrears and default rates. From a theoretical perspective, energy efficiency can enhance the value and resilience of real estate collateral by reducing exposure to energy-

Figure 4.1: Cumulative arrears rate by EPC rating. This figure shows the cumulative arrears rate (arrears as a percentage of loan balance) over 12 quarters, split by EPC rating (high, medium, and low energy efficiency). The sample includes loans with EPC ratings populated at the reporting date, based on RMBS data.



related cost increases and the risk of regulatory obsolescence linked to the green transition. As climate policy frameworks continue to evolve, properties with low energy performance are more likely to face elevated operating costs and may require substantial retrofitting to comply with stricter environmental regulations, raising concerns about potential "stranding" risk (Ferentinos et al., 2023). In contrast, energy-efficient buildings offer dual advantages: they reduce households' ongoing energy expenditure and provide a buffer against future regulatory costs. This makes them more stable and attractive from a collateral standpoint. Yet, there is limited evidence that banks and other financial institutions are systematically integrating these transition risks into their credit risk assessment practices. For instance, Bell et al. (2023) show that lenders generally do not adjust mortgage interest rates to reflect a property's energy performance, suggesting that the theoretical relevance of energy efficiency

Figure 4.2: Cumulative default rate by EPC rating. This figure shows the cumulative default rate (defined as two consecutive quarters in arrears) over 12 quarters, split by EPC rating (high, medium, and low energy efficiency). The sample includes loans with EPC ratings populated at the reporting date, based on RMBS data.



is not fully embedded in current pricing and underwriting standards. This disconnect highlights an important gap between environmental risk considerations and lending practices, which may have implications for both market stability and the effectiveness of climate policy.

This chapter makes a novel contribution to the literature by providing the most comprehensive EU-wide analysis to date on the predictive role of EPC ratings in explaining mortgage arrears and defaults. Unlike prior studies (Billio et al., 2022; Guin & Korhonen, 2020; Kaza et al., 2014), which typically focus on individual countries, our research expands the geographical scope to encompass multiple European markets. In doing so, we respond to calls in the literature for broader, cross-country investigations into the link between energy efficiency and credit risk. A key innovation of our approach lies in the harmonisation of EPC information across countries. By converting all energy labels into a unified measure (annual energy consumption per square metre (kWh/m²/year)) we enable consistent and comparable analysis across different regulatory contexts and EPC frameworks.

Another key contribution of this chapter lies in bridging the fields of energy efficiency and credit risk modelling by examining whether EPC ratings enhance the predictive performance of rating models. While a substantial body of research has explored statistical and machine learning methods to improve mortgage risk prediction (see, for instance, the surveys by Thomas (2000) and Hand and Henley (1997), as well as more recent applications in mortgage default modelling by Fitzpatrick and Mues (2016) and Sirignano et al. (2021)) none of these studies has considered the role of energy performance as a predictive input. To the best of our knowledge, this chapter is the first to systematically investigate whether the inclusion of EPC ratings improves the discriminatory power of credit risk models, as measured by standard performance metrics such as the Gini coefficient and the Kolmogorov–Smirnov statistic. By doing so, it adds a novel dimension to the existing literature and responds to growing regulatory and market interest in embedding environmental risk considerations into traditional credit risk assessment frameworks. More broadly, identifying a reliable link between energy performance and credit risk can inform lending practices and help align financial incentives with environmental objectives. This alignment may, in turn, support the development of targeted policy tools (such as subsidies or guarantees for green properties) that accelerate the transition to greener housing. These measures can reduce financial strain on households (e.g., through lower energy bills) while improving the resilience and overall quality of mortgage portfolios.

4.2 Data and Methodology

The dataset used in this study is sourced from the European DataWarehouse (EDW), the repository designated by the European Securities and Markets Authority (ESMA) for the collection and validation of standardised loan-level data on securitised assets across Europe. The dataset adheres to the updated ESMA reporting templates, which replaced the former European Central Bank (ECB) templates in 2021. These revised templates are used for the quarterly submission of loan-level data for asset-backed securities eligible for repurchase agreements with the ECB. The reporting framework encompasses both mandatory and optional fields, capturing detailed information on loan characteristics, borrower profiles, and collateral attributes, as well as performance indicators. In total, securitisation originators can report over 150 variables per loan, though only a subset is compulsory. Notably, at the time of data extraction for this analysis, the Energy Performance Certificate (EPC) rating was classified as an optional field, meaning its availability depended on the discretion of the reporting institutions.

4.2.1 Sample Overview

The EDW source dataset comprises 28,060,021 quarterly loan-level observations covering the period from Q1 2021 to Q1 2024. The dataset begins in Q1 2021, coinciding with the introduction of the updated ESMA reporting template, which replaced the former ECB framework. This new template introduced the Energy Performance Certificate (EPC) rating as an optional field, making Q1 2021 a natural starting point for this analysis.

As summarised in Table 4.1, the initial dataset includes 139 RMBS deals, 3,208,747 unique loans, and 3,529,410 associated collaterals across multiple European countries. The majority of securitised deals originate from France, United Kingdom, and the Netherlands, reflecting prevailing issuance trends in the European RMBS market during the sample period.

Table 4.1. Source data overview by country. This table summarises the number of deals, loans, collaterals, and observations across various countries in the source RMBS dataset. Sample period: 2021Q1—2024Q1.

Country	N. of deals	N. of loans	N. of collaterals	N. of observations
Belgium	3	371,954	461,847	2,946,420
France	20	1,129,983	1,129,990	10,695,857
Germany	5	562,297	593,236	4,117,751
Ireland	15	145,917	146,537	1,090,709
Italy	12	211,631	241,167	2,140,501
Netherlands	49	274,444	293,420	2,255,173
Portugal	3	20,047	20,541	167,056
Spain	15	419,968	565,555	4,046,088
United Kingdom	17	72,506	77,117	600,466
Total	139	3,208,747	3,529,410	28,060,021

To refine the dataset in line with the research objectives, specific exclusions and data adjustments are implemented. Loans are monitored throughout the sample period unless they encounter a terminal event, such as default, write-off, or full redemption. If a loan defaults, it is removed from the analysis from that point onward. Furthermore, loans issued for *release equity* purposes are excluded, as these transactions, often linked to cash-out refinancing, differ substantially from conventional mortgage loans in terms of borrower incentives and risk characteristics (Billio et al., 2022).

As the primary objective of this study is to evaluate the impact of EPC rating information on the performance of a mortgage rating model, another key exclusion criterion is the retention of only those loan observations for which the EPC rating is populated. The key explanatory variable in this analysis is the Energy Efficiency Tier (EE Tier), derived from the EPC kWh/m²/year measure, which quantifies the energy efficiency of the collateral. To assess its impact on mortgage performance, we construct a continuous variable representing the average energy consumption of the collaterals securing each loan, measured in kWh/m²/year. This measure is based on the EPC ratings provided in the EDW database[2].

Since EPC rating systems vary across countries, we standardise these ratings by converting them into numerical values corresponding to the midpoint of the energy consumption range (in kWh/m²/year) associated with each EPC band in each country.[3] This transformation, detailed in Table 4.H.1, enables comparability across different jurisdictions by aligning the diverse EPC rating scales within a unified framework. For instance, in France, an EPC rating of A corresponds to an energy consumption range of 1–50 kWh/m²/year, while an EPC B rating falls within 51–95 kWh/m²/year.

To obtain a representative measure of a loan's energy efficiency, we compute a weighted average of the EPC values across all associated collaterals. The weighting is based on the original value of each collateral, ensuring that properties with higher valuations contribute more significantly to the loan's overall energy efficiency score. Specifically, for loan l in quarter q, the weighted average is calculated as:

$$\text{EPC}_{lq} = \frac{\sum_{i=1}^{n_l} w_{iq} \cdot \text{EPC}_{iq}}{\sum_{i=1}^{n_l} w_{iq}} \tag{4.1}$$

where n_l represents the number of collaterals linked to loan l in quarter q, w_{iq} denotes the original value of collateral i, and EPC_{iq} is the numerical EPC value assigned to collateral i. For ease of interpretation, we further classify loans into three energy efficiency tiers. Loans in the lowest third of the distribution (i.e., those with the lowest energy consumption) are categorised as *high efficiency*, those in the middle third as *medium efficiency*, and those in the highest third (i.e., those with the highest energy consumption) as *low efficiency*.

[2]The EPC rating is reported at the collateral level under the variable "RREC10" in the ESMA template.

[3]See "The Babel Tower of Energy Performance Certificate Ratings and Databases in Europe," European DataWarehouse, 7 July 2022. Available at: https://eurodw.eu/the-babel-tower-of-energy-performance-certificate-ratings-and-databases-in-europe/.

Our analysis centres on delinquency indicators as the dependent variables, each assessed over a 12-month horizon. The target variables are structured as follows:

- **Arrears:** A dummy variable set to 1 if the loan is at least one quarter in arrears within the next 12 months.
- **Material Arrears:** A dummy variable set to 1 if the loan is at least one quarter in arrears within the next 12 months, and the arrears balance exceeds 1% of the current loan balance.
- **Default:** A dummy variable set to 1 if the loan is at least two consecutive quarters in arrears within the next 12 months.
- **Material Default:** A dummy variable set to 1 if the loan is at least two consecutive quarters in arrears within the next 12 months, and the arrears balance exceeds 1% of the current loan balance.

We include arrears indicators in addition to default measures, as they capture earlier signs of borrower distress. One of the primary channels through which energy efficiency may influence mortgage performance is its impact on household utility costs. Properties with lower energy efficiency tend to generate higher energy expenses, potentially reducing borrowers' disposable income and increasing the likelihood of delayed mortgage payments, which is reflected in the arrears measures.

Additionally, for each loan we collect a comprehensive set of control variables to account for borrower, loan, and collateral factors that could influence mortgage delinquency. Additionally, macroeconomic indicators, such as unemployment rates and house price indices, are obtained from the OECD database. Other key variables, including inflation rates and energy price indices, are sourced from Eurostat.[4] Macroeconomic indicators, while not typically required in the development of a credit rating model, since such models primarily rely on borrower and loan characteristics to assess credit risk, are incorporated in this study for two key purposes. First, they allow us to identify periods of elevated energy inflation, which is relevant for understanding the potential impact of energy costs on mortgage performance. Second, they are included in the analysis examining the relationship between EPC ratings and the probability of default, ensuring that observed effects are not merely driven by broader macroeconomic conditions.

After applying the exclusions outlined above, the final dataset consists of 4,503,026 observations. Summary statistics for the key variables in this sample, including borrower, loan, and collateral characteristics, as well as macroeconomic indicators, are presented in Table 4.2.

Table 4.2. Summary statistics for categorical and continuous variables.

Variable	Min	Mean	Max
Delinquency			
Arrears (bps)	0	49.571	1
Material Arrears (bps)	0	12.576	1
Default (bps)	0	16.766	1
Material Default (bps)	0	4.404	1
Energy Efficiency			
EPC kWh/m²/year: High Efficiency	0	32.318%	1
EPC kWh/m²/year: Medium Efficiency	0	50.942%	1
EPC kWh/m²/year: Low Efficiency	0	16.740%	1
Loan Characteristics			
Loan Purpose: Purchase	0	78.499%	1

[4] It is important to note that certain Eurostat data series for the United Kingdom were discontinued following Brexit. To ensure consistency in the dataset, we supplement these missing series with equivalent data from the UK's Office for National Statistics (ONS). Specifically, overall inflation is derived from Eurostat's online data code `prc_hicp_manr - CP00` and supplemented with the ONS Series ID `D7G7 (00)` for the UK. Similarly, energy inflation is primarily sourced from Eurostat under the data code `prc_hicp_manr - 045`, with the ONS Series ID `D7GT (04.5)` used for UK-specific data.

Table 4.2 continued from previous page

Variable	Min	Mean	Max
Loan Purpose: Construction	0	8.611%	1
Loan Purpose: Remortgage	0	9.958%	1
Loan Purpose: Renovation	0	2.762%	1
Loan Purpose: Other	0	0.169%	1
Int. Type: Fixed	0	59.989%	1
Int. Type: Floating	0	3.328%	1
Int. Type: Other	0	36.683%	1
LTV at first reporting date	0.04	0.68	1.10
Time to maturity (quarters)	2.00	72.41	148.00
Interest rate (%)	0.00	2.10	5.70
Quarters since reporting	1.00	5.50	13.00
Borrower Characteristics			
Employment: Employed - private sector	0	38.494%	1
Employment: Employed - public sector	0	13.876%	1
Employment: Employed - unknown	0	33.349%	1
Employment: Pensioner	0	4.299%	1
Employment: Self-employed	0	8.037%	1
Employment: Unemployed	0	0.912%	1
Employment: Other	0	1.033%	1
Customer type: Existing	0	27.150%	1
Customer type: New	0	40.600%	1
Customer type: Other	0	32.250%	1
Income (€)	0.00	48,668.29	235,741.00
Collateral Characteristics			
Occupancy Type: Owner Occupied	0	90.052%	1
Occupancy Type: Buy to Let	0	8.125%	1
Occupancy Type: Holiday	0	1.805%	1
Occupancy Type: Other	0	0.018%	1
Property Type: Residential Flat	0	27.950%	1
Property Type: Residential House	0	69.231%	1
Property Type: Residential Terrace	0	0.376%	1
Property Type: Other	0	2.443%	1
Property value (€)	11,716.88	159,370.00	876,000.00
Macro-economic Factors			
House price index change (%)	-4.10	6.14	19.00

Table 4.2 continued from previous page

Variable	Min	Mean	Max
Unemployment rate change (%)	3.40	6.22	15.40
Inflation change (%)	-0.07	5.97	14.13
Energy inflation change (%)	-47.67	30.66	152.97

The summary statistics presented in Table 4.2 provide key insights into the dataset, particularly regarding delinquency and energy efficiency characteristics. The delinquency indicators suggest that instances of arrears and default are relatively infrequent but still significant within the sample. On average, 0.496% of loan observations experience arrears within a 12-month horizon, while more severe delinquency classifications, such as default and material arrears, occur at lower frequencies of 0.168% and 0.126%, respectively. Material default, the strictest measure of delinquency, is observed in only 0.044% of loan observations. These figures are in line with expectations, given that the dataset consists of loans securitised into RMBSs that are eligible for repurchase agreements with the ECB. As a result, these securitisations typically have high credit ratings, reflecting stringent underwriting standards and low-risk loan pools. Additionally, the large sample size ensures that delinquency events remain statistically significant. For instance, an arrears incidence of 49.6 bps translates to approximately 22,322 observations, providing ample data to assess mortgage performance under varying conditions. Regarding energy efficiency, the EPC kWh/m²/year classification shows a substantial spread in the energy performance of mortgaged properties. Among the loans with available EPC data, approximately 32.3% of the sample falls into the high energy efficiency category, 50.9% into the medium efficiency tier, and 16.7% into the low efficiency category. This distribution suggests that a significant proportion of securitised mortgages are associated with properties of moderate energy efficiency, while a smaller share is linked to homes with high energy consumption. Given the hypothesised link between energy efficiency and mortgage performance, this variation provides a strong basis for evaluating the impact of EPC ratings on credit risk. The remaining variables align with expectations. In particular, the average loan-to-value (LTV) ratio at reporting is 68%, reflecting a typical balance between borrower equity and loan financing in securitised mortgage pools. The average interest rate stands at 2.1%, consistent with the interest rate environment during the sample period. Regarding borrower characteristics, the majority are employed in the private sector (38.49%), with an average reported income of €48,668. In terms of collateral, most properties are owner-occupied (90.05%), while only 8.12% are classified as buy-to-let. The average property valuation at the reporting date is €159,370.

4.2.2 Methodology

In this chapter, we develop and evaluate a series of rating models to assess whether the inclusion of the Energy Performance Certificate (EPC) rating improves the prediction of residential mortgage arrears and defaults.

To address this research question, we employ a logistic regression-based rating model that incorporates a *Weight of Evidence (WoE)* approach to transform categorical and continuous risk factors. As discussed in more detail later in the chapter, this approach is commonly used in the literature and aligns with credit risk industry standards. The methodology follows a structured framework to systematically evaluate the predictive power of different variables, with a specific focus on comparing model performance with and without the inclusion of EPC ratings. This allows us to quantify the impact of energy efficiency information on mortgage risk assessment.

The methodology consists of several key steps, summarised below and discussed in detail in the following subsections:

1 **Initial variable selection and ranking:** Candidate risk drivers are identified and ranked based on their predictive power. Gini coefficients and Information Value (IV) metrics are used to determine their contribution to the likelihood of arrears and default and select the variables with the highest predictive power.

2 **WoE transformation:** Selected variables undergo a Weight of Evidence (WoE) transformation to ensure a monotonic relationship with the target variable. This step enhances interpretability and provides a structured framework for logistic regression modelling.

3 **Stepwise variable integration:** WoE-transformed variables are incrementally added to the logistic regression model through a stepwise process, retaining only those that improve model performance, maintain statistical significance, and align with expected risk relationships.

4 **Scaling and rating transformation:** The logistic regression outputs from the optimal models identified for each target variable are scaled into rating classes, facilitating the interpretation and practical application of the rating model outputs.

5 **Model performance analysis:** The final rating model's discriminatory power is evaluated by comparing its predictive performance with and without the inclusion of EPC ratings. Metrics such as the Gini coefficient, the Kolmogorov-Smirnov (KS) statistic, and rating score distributions are used to quantify the impact of EPC ratings on mortgage risk assessment.

This modelling approach is grounded in widely accepted credit risk modelling practices and aligns with both academic literature and regulatory expectations. The use of Gini and IV for initial screening is standard in credit scorecard development, providing a reliable measure of univariate discriminatory power (Lessmann et al., 2015). Weight of Evidence

(WoE) transformations are commonly used in industry to produce stable, interpretable, and monotonic predictors that are well-suited to logistic regression models (Crook et al., 2007; Siddiqi, 2012). Variables are then integrated using a structured stepwise procedure, consistent with best-practice that emphasise parsimony, transparency, and control of overfitting (Hand & Henley, 1997). Model performance is evaluated using the Gini coefficient, a metric explicitly recommended by regulators such as the Bank of England to assess discriminatory power in PD models (Prudential Regulation Authority, 2013), and complemented by the KS statistic, which provides an intuitive measure of score distribution separation (Baesens & Smedts, 2023; Lessmann et al., 2015). Overall, each step of the methodology reflects industry-standard modelling techniques, ensuring that the results are both interpretable and robust within the context of mortgage default risk assessment.

As a complementary analysis, we also examine the influence of EPC ratings on the predicted probabilities of delinquency. This exercise is based on a logistic regression model aligned with the one used in the scoring framework, but shifts the focus from overall model performance metrics to the estimated probabilities of arrears and defaults. Importantly, this specification does not apply WoE transformations to the explanatory variables, allowing for a more direct interpretation of the marginal effect of the energy consumption variable (kWh/m²/year), which is kept in its continuous form. This modelling approach is widely adopted in the credit risk and securitisation literature, as shown by studies such as Campbell et al. (2008), Chava and Jarrow (2004), Crook (2002), and Elul et al. (2010). It provides additional insight into whether, and to what extent, energy efficiency contributes to explaining credit risk outcomes. In doing so, it reinforces the findings on the role of EPC ratings in enhancing rating model performance.

Each of these steps is detailed in the following subsections. The results are then presented in Section 4.3.

4.2.2.1 Initial variable selection and ranking

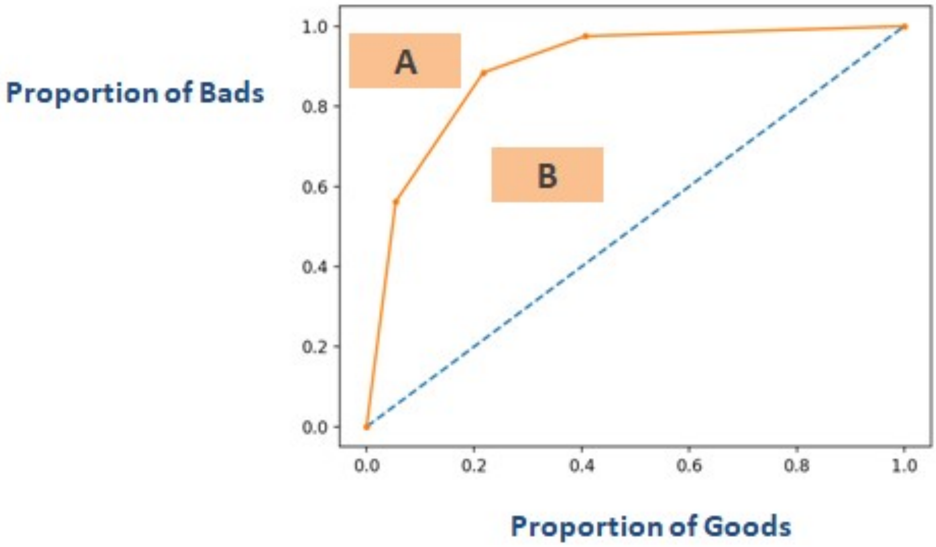
The first step involved selecting a set of potential risk drivers from the dataset that could predict the likelihood of residential mortgage arrears and defaults. The initial list of risk drivers was derived from the available variables in the European DataWarehouse (EDW), with exclusions applied to variables that were generally not populated to ensure data completeness and reliability. These selected risk drivers were then ranked based on their predictive power, as measured by Information Value (IV) and the Gini coefficient, for the four different target variables. The Information Value (IV) and the Gini coefficient are commonly used in credit risk modelling to evaluate how well a variable can distinguish between loans that become delinquent and those that remain performing (see, for instance, Siddiqi (2012)).

Gini coefficient

The Gini coefficient measures the discriminatory power of a variable in differentiating between loans that become delinquent (e.g., arrears or defaults) and those that remain performing. Graphically, the Gini coefficient can be represented by plotting the cumulative proportion of goods against the cumulative proportion of bads at different values of the variable, which are ordered by increasing risk. An example is illustrated in Figure 4.3.

In this figure, the **solid orange line** represents the proportion of goods and bads ranked by increasing risk according to the selected variable, while the **dashed diagonal line** denotes a random allocation, indicating no discriminatory power. The Gini coefficient is based on the idea that a variable with strong predictive power will exhibit a steep increase in the

Figure 4.3. Gini coefficient as a measure of variable discrimination



number of bads for riskier values of the variable. The greater the separation between the variable's curve and the random baseline, the better is the variable's ability to distinguish between performing and non-performing loans.

Mathematically, the Gini coefficient is defined as:

$$Gini = \frac{B}{(A+B)} \tag{4.2}$$

where **B** represents the area between the variable's Gini curve and the diagonal (random baseline), while **(A + B)** is the total area under the curve of a variable with no discriminatory power (random assignment of goods and bads). Higher Gini values indicate greater predictive power in assessing mortgage risk. For this reason, to identify the variables with the strongest relationship with the target variables, a ranking will be established based on the Gini coefficient.

Information value (IV)

Similarly to Gini, the Information Value (IV) is another commonly used metric in credit risk modelling to assess the predictive power of categorical and binned continuous variables in distinguishing between two possible outcomes, such as arrears versus non-arrears. A higher IV value indicates a stronger relationship between the variable and the binary target outcome, making it a more effective predictor.

For a given risk driver with n categories or bins, the IV is calculated as:

$$IV = \sum_{i=1}^{n} \left((\%\text{Goods}_i - \%\text{Bads}_i) \times \ln \left(\frac{\%\text{Goods}_i}{\%\text{Bads}_i} \right) \right) \tag{4.3}$$

where:

- $\%\text{Goods}_i$ represents the share of non-delinquent loans in bin i, relative to the total number of non-delinquent loans in the sample.
- $\%\text{Bads}_i$ represents the share of delinquent loans in bin i, relative to the total number of delinquent loans in the sample.

As described in Siddiqi (2012), IV values above 0.1 indicate that a variable has a meaningful relationship with mortgage delinquency, making it a useful predictor in the analysis. Variables with an IV between 0.02 and 0.1 provide only limited discriminatory power, meaning they contribute some predictive value but are relatively weak indicators of arrears and defaults. Conversely, variables with an IV below 0.02 are considered not predictive, as they lack sufficient differentiation between delinquent and non-delinquent loans. Given its ability to quantify the predictive strength of variables, IV is used alongside the Gini coefficient to rank risk drivers and determine which variables have the strongest association with mortgage arrears and defaults. Specifically, risk drivers with an IV below 0.02 are excluded from the analysis.

Variable binning

To compute the Information Value (IV) and the Gini coefficient, it is necessary to apply binning, particularly for numerical variables. Binning transforms continuous variables into discrete categories, ensuring that comparisons between different risk drivers remain meaningful and interpretable (see, for instance, Siddiqi (2012)). Specifically, numeric variables are divided into ten bins, simplifying the calculation while preserving their predictive power. This approach helps stabilise the estimates of IV and Gini by preventing outliers or extreme values from disproportionately influencing the results.

For categorical variables, all available categories are retained, as these variables are inherently discrete. Since IV and Gini assess the separation between delinquent and non-delinquent loans across different categories, maintaining their natural structure allows for an accurate evaluation of their predictive ability.

4.2.2.2 WoE transformation

Building upon the results from the initial variable selection and ranking, the next step involved applying a Weight of Evidence (WoE) transformation to the key predictive variables. The WoE transformation converts categorical and continuous predictors into numeric values that clearly capture their predictive relationship with mortgage arrears and defaults. This process significantly improves model stability, interpretability, and alignment with the logistic regression framework utilised in the subsequent steps of the analysis, as described in Section 4.2.2.3.

The WoE metric quantifies both the strength and direction of the relationship between each category of a given predictor and the occurrence of the target event. Specifically, WoE evaluates the relative likelihood of observing adverse outcomes (such as arrears or defaults) compared to positive outcomes within each bin or category of the predictor. Formally, the WoE for each category i is defined as:

$$\text{WoE}_i = \ln\left(\frac{\frac{\text{Good}_i}{\text{Total Good}}}{\frac{\text{Bad}_i}{\text{Total Bad}}}\right) \tag{4.4}$$

where:

- Bad_i and Good_i denote the number of observations classified as 'bad' and 'good' within category i, respectively.

- Total Bad and Total Good represent the total counts of 'bad' and 'good' observations across the entire sample.

For numeric variables, an initial binning process was performed by splitting observations into five quantile-based buckets, ensuring balanced distribution and comparability. To satisfy the crucial requirement of monotonicity, essential for the interpretability and robustness of credit risk models, variables exhibiting non-monotonic WoE patterns underwent manual re-binning. Adjacent buckets exhibiting similar WoE values were merged, reducing the original five bins to three where necessary. Variables that continued to demonstrate a non-monotonic relationship with the target outcome after manual adjustments were excluded from further analysis. Non-monotonic relationships imply ambiguous or inconsistent associations with the target, potentially diminishing model clarity and predictive accuracy.

Interpretation of WoE is straightforward: positive WoE values indicate categories with lower risk (associated with better loan performance), whereas negative WoE values indicate higher-risk categories, associated with adverse outcomes such as arrears or default.

4.2.2.3 Stepwise variable integration

Following the Weight of Evidence (WoE) transformation, we developed logistic regression rating models for each of the target variables: Arrears, Material Arrears, Default, and Material Default. This approach aligns with industry standards, as detailed in Thomas (2000) (among others). Each logistic regression model estimates the log-odd of an adverse event (e.g., arrears or default) based on the WoE-transformed risk drivers. Formally, the logistic regression model is expressed as:

$$\log\left(\frac{P(\text{adverse event})}{1-P(\text{adverse event})}\right) = \beta_0 + \beta_1 \text{WoE}_1 + \beta_2 \text{WoE}_2 + \cdots + \beta_n \text{WoE}_n \tag{4.5}$$

where WoE_1 to WoE_n represent the WoE-transformed predictor variables, and β_0 to β_n are the regression coefficients estimated from the data.

Variables were integrated into the logistic regression models using a stepwise procedure, incorporating predictors sequentially based on their ranking from the initial selection stage. Each variable was introduced individually and assessed according to the following criteria:

- *Performance improvement:* Inclusion of the variable had to increase the model's discriminatory power, as measured by a minimum 1% improvement in the Gini coefficient.[5]
- *Statistical significance:* The variable needed to show a statistically significant relationship with the target variable (p-value < 0.05).
- *Expected direction of association:* WoE-transformed variables were expected to demonstrate negative regression coefficients, consistent with the interpretation that

[5] See Section 4.2.2.5 for a detailed explanation of how the Gini coefficient is used to assess model performance.

higher WoE values indicate a lower likelihood of default or arrears. Variables exhibiting positive coefficients, which could imply multicollinearity or inconsistent directional associations, were excluded.

The principal objective of the stepwise integration process was to determine whether incorporating the EPC band variable enhanced model performance sufficiently to warrant its inclusion in the optimal predictive models for each of the four delinquency and default outcomes.

4.2.2.4 Scaling and rating transformation

Following the identification of optimal logistic regression models for each of the target variables (Arrears, Material Arrears, Default, and Material Default), the next step involves converting the model outputs into credit rating scores. This transformation enhances the interpretability of the model results by aligning them with standard industry practices (as described, for instance, in Thomas (2009) and Siddiqi (2012)).

Logistic regression models generate outputs in the form of log-odds, which quantify the likelihood of the adverse outcome. However, log-odds are not intuitive for practical applications. Therefore, these outputs are transformed into predicted probabilities and subsequently scaled into rating scores, a common approach in credit scoring models. The transformation process consists of two stages.

First, the model's log-odds are converted into predicted probabilities for each loan i, using the logistic function:

$$\hat{P}_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \mathrm{WoE}_{1,i} + \beta_2 \mathrm{WoE}_{2,i} + \cdots + \beta_n \mathrm{WoE}_{n,i})}} \tag{4.6}$$

where $\hat{P}i$ represents the predicted probability of the adverse event for loan i, and $\beta_0, \beta_1, \ldots, \beta_n$ are the estimated logistic regression coefficients associated with the WoE-transformed risk drivers ($\mathrm{WoE}_{1,i}, \ldots, \mathrm{WoE}_{n,i}$).

Second, these predicted probabilities are scaled into standardised rating scores according to the following formula:

$$\mathrm{Score}_i = \mathrm{Offset} + \mathrm{Factor} \times \ln\left(\frac{1-\hat{P}_i}{\hat{P}_i}\right) \tag{4.7}$$

where the parameters *Factor* and *Offset* are defined by:

$$\mathrm{Factor} = \frac{\mathrm{PDO}}{\ln(2)} \tag{4.8}$$

$$\mathrm{Offset} = \mathrm{Base\_Score} - (\mathrm{Factor} \times \ln(\mathrm{Base\_Odds})) \tag{4.9}$$

In this formulation, Points-to-Double-Odds (PDO) specifies the number of score points corresponding to a doubling of the odds of default, *Base_Odds* represents the reference odds of default associated with a predetermined benchmark score (for example, base odds of 50:1 means there is one default for every 50 non-defaults at the base score), and *Base_Score* denotes the rating score aligned with these base odds.

In this study, we adopt standard industry parameters (see, for instance, Siddiqi (2012)) to ensure the practical interpretability of scores. Specifically, we set the base score to 600 and assume a base odds of 50:1, with a PDO of 20. This results in the following scoring formula:

$$\mathrm{Score} = 487.123 + 28.8539 \times \ln\left(\frac{1-\hat{P}}{\hat{P}}\right) \tag{4.10}$$

This transformation ensures that the model's outputs are intuitive, aligned with established credit scoring frameworks, and suitable for practical application in credit risk analysis. The resulting scores are inversely related to credit risk, whereby higher scores correspond to lower predicted probabilities of default.

4.2.2.5 Model performance analysis

To evaluate the performance of the rating models developed in this analysis, we rely on two widely used metrics in credit risk modelling: the Gini coefficient and the Kolmogorov–Smirnov (KS) statistic. Both measures are standard tools for assessing a model's discriminatory power (see, for instance, Fang and Chen (2019); Hand and Henley (1997)). We compute these metrics on the final rating scores produced through the scaling transformation described in the preceding section.

The Gini coefficient is used here to evaluate the discriminatory power of the final rating model. While in the initial variable selection phase the Gini was applied to individual risk drivers, it is now computed over the model scores, which aggregate information from all included predictors. It quantifies the model's ability to distinguish between loans that become delinquent and those that remain performing. Graphically, as previously shown in Figure 4.3, the Gini is obtained by plotting the cumulative proportion of goods against the cumulative proportion of bads, where loans are ranked by decreasing model-predicted risk (increasing score). A perfectly random model would produce a diagonal line, whereas a strong model will show a curve that rises steeply for the riskiest scores, indicating that defaults are concentrated among lower-rated loans. The greater the separation between the model's curve and the random baseline, the higher the Gini. Higher Gini values indicate that the rating model has greater discriminatory power in separating risky loans from safe ones.

The KS statistic quantifies the maximum difference between the cumulative distribution functions of the predicted scores for the "bad" (e.g., defaulted) and "good" (non-defaulted) loans. Formally, it is defined as:

$$\text{KS} = \max_{x} \left| F_{\text{good}}(x) - F_{\text{bad}}(x) \right| \tag{4.11}$$

where $F_{\text{good}}(x)$ and $F_{\text{bad}}(x)$ are the empirical distribution functions of the scores for good and bad loans, respectively. The KS statistic provides a measure of the model's separation capability, with higher values indicating better differentiation between risk classes.

To quantify the specific contribution of the EPC band variable, we compare the performance of each final model (for Arrears, Material Arrears, Default, and Material Default) both with and without the inclusion of the EPC-related information. This comparison reveals the marginal value added by incorporating energy efficiency into the credit risk assessment framework.

In addition to the baseline evaluation, we conduct a focused analysis during a period of elevated energy prices: from 2022-Q1 to 2023-Q1. This timeframe is economically significant. The first quarter of 2022 marks the onset of the war in Ukraine, which led to sharp increases in global energy prices. In contrast, 2023-Q1 coincides with a substantial decline in energy prices, as supply constraints eased and energy markets stabilised. This window captures both the escalation and partial resolution of the energy crisis, providing an ideal context for assessing whether energy efficiency (proxied by the EPC rating) plays a more critical role in predicting mortgage risk during periods of price volatility.

To ensure that the models accurately reflect the economic dynamics of this period, they are recalibrated using only observations within this timeframe. Recalibration involves re-estimating the logistic regression coefficients using the restricted sample, allowing the model to adjust for potential shifts in the relationships between predictors and target outcomes due to changing macroeconomic conditions. This exercise enables a more targeted evaluation of the EPC variable's relevance under energy market stress.

4.3 Results

This section presents the main empirical findings. Sections 4.3.1 to 4.3.3 report the results of the modelling process and assess the contribution of the EPC variable to credit risk model performance. Section 4.3.4 provides a complementary analysis on the marginal impact of the collateral's energy consumption on the predicted probability of delinquency.

4.3.1 Variable ranking and WoE transformation

The following tables present the variable ranking results for each of the four target variables, based on the methodology outlined in Section 4.2.2.2. As previously discussed, variables are ranked according to their Gini coefficient, where higher values indicate greater discriminatory power. In addition, variables with an Information Value (IV) below 0.02 are excluded from further consideration, as they are not deemed predictive. The aim of this step is to identify the most relevant predictors for each outcome, which will be used to construct the optimal logistic regression models. The results are presented in Table 4.3 and Table 4.4.

Table 4.3. Variable ranking based on Gini and Information Value (IV) for Arrears target variables. This table presents the ranking of variables based on their predictive power as measured by Gini. As an additional measure, the Information Value (IV) is also presented. Variables with IV > 0.1 are considered strong predictors (highlighted in Green), those with $0.1 \geq$ IV > 0.02 are considered medium predictors (Yellow), and variables with IV ≤ 0.02 are deemed not predictive (Red). Variables with IV ≤ 0.02 will not be considered further in the analysis.

Rank	Variable	Gini	IV
Panel A: Arrears			
1	Quarter since reporting	0.1837	0.1341
2	Employment status	0.1818	0.1161
3	Loan to Value at reporting	0.1706	0.1023
4	Interest rate at reporting	0.1426	0.0676
5	Time to maturity	0.1340	0.0599
6	EPC Kwh efficiency	0.1239	0.0557
7	Customer type	0.1084	0.0407
8	Income at reporting	0.1049	0.0400

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Table 4.3 – continued from previous page

Rank	Variable	Gini	IV
9	Interest rate type	0.0956	0.0398
10	Property value	0.0828	0.0225
11	Loan purpose	0.0577	0.0334
12	Property type	0.0124	0.0046
13	Occupancy type	0.0101	0.0054
Panel B: Material Arrears			
1	Employment status	0.3148	0.3664
2	EPC Kwh efficiency	0.2708	0.3036
3	Time to maturity	0.2514	0.2614
4	Interest rate type	0.2487	0.3316
5	Interest rate at reporting	0.1851	0.1115
6	Income at reporting	0.1641	0.0925
7	Customer type	0.1508	0.0812
8	Property value	0.1472	0.0683
9	Quarter since reporting	0.1091	0.0613
10	Loan to Value at reporting	0.0781	0.0268
11	Loan purpose	0.0769	0.0820
12	Occupancy type	0.0428	0.0293
13	Property type	0.0312	0.0131

Table 4.4. Variable ranking based on Gini and Information Value (IV) for Default target variables. This table presents the ranking of variables based on their predictive power as measured by Gini. As an additional measure, the Information Value (IV) is also presented. Variables with IV > 0.1 are considered strong predictors (highlighted in Green), those with $0.1 \geq$ IV > 0.02 are considered weak predictors (Yellow), and variables with IV ≤ 0.02 are deemed not predictive (Red). Variables with IV ≤ 0.02 will not be considered further in the analysis.

Rank	Variable	Gini	IV
Panel A: Default			
1	Loan to Value at reporting	0.2063	0.1486
2	Employment status	0.2059	0.1548
3	Interest rate at reporting	0.1994	0.1273
4	EPC Kwh efficiency	0.1890	0.1487
5	Quarter since reporting	0.1619	0.0981
6	Interest rate type	0.1571	0.1102
7	Income at reporting	0.1340	0.0609
8	Time to maturity	0.1194	0.0565
9	Customer type	0.1043	0.0374
10	Property value	0.1018	0.0334
11	Loan purpose	0.0716	0.0531

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Table 4.4 – continued from previous page

Rank	Variable	Gini	IV
12	Property type	0.0247	0.0131
13	Occupancy type	0.0203	0.0099
Panel B: Material Default			
1	Employment status	0.2838	0.2949
2	EPC Kwh efficiency	0.2689	0.3242
3	Interest rate type	0.2524	0.3274
4	Time to maturity	0.2204	0.2014
5	Income at reporting	0.2183	0.1559
6	Interest rate at reporting	0.1835	0.1101
7	Property value	0.1754	0.1046
8	Quarter since reporting	0.1425	0.0747
9	Loan purpose	0.1017	0.1375
10	Property type	0.0987	0.0561
11	Loan to Value at reporting	0.0878	0.0368
12	Customer type	0.0854	0.0283
13	Occupancy type	0.0377	0.0252

The results indicate that the EPC rating variable (measured as EPC kWh efficiency) consistently exceeds the minimum threshold of 0.02 in Information Value (IV) across all four target variables, justifying its inclusion in the models. Notably, for two of the four outcomes (Material Arrears and Material Default) the EPC variable emerges as a strong predictor, with an IV exceeding 0.3. In these cases, it ranks as the second most important risk driver. These findings suggest that properties with lower energy efficiency are more prone to significant arrears balances or defaults, potentially reflecting the financial strain imposed by higher energy costs. Among the most influential predictors across all models are *Employment Status*, *Interest Rate at Reporting*, and *Interest Rate Type*, each of which demonstrates consistently high Gini coefficients and IV values.

The relationship between the selected risk drivers and the target variables is further explored through the Weight of Evidence (WoE) transformation. This transformation not only improves the interpretability of the variables but also facilitates a consistent and robust input format for logistic regression modelling. The results of the WoE transformation for the Arrears target variable are presented in Table 4.5, while additional results for the Default target variable are provided in Appendix 4.B. WoE values offer a clear indication of the relationship between each risk driver category and the probability of delinquency. A positive WoE value implies that the corresponding category is associated with a lower likelihood of the adverse event, whereas a negative WoE value indicates a higher risk of the adverse outcome.

Table 4.5. Weight of Evidence (WoE) transformation for the Arrears target variable. This table presents Weight of Evidence (WoE) values and Observed Default Rates (ODR) by bin calculated on the Arrears target variable. Numeric variables are initially divided into five quantile-based buckets (0=low, 4=high), with WoE calculated for each. To improve monotonicity, some variables are further reduced to three buckets by combining those with similar WoE values. Negative WoE values are highlighted in red (higher likelihood of arrears), while positive WoE values are highlighted in green (lower likelihood of arrears).

Variable	Bin	Good %	Bad %	WoE	ODR bin
EPC band (kWh)	Low eff.	16.725%	18.684%	-0.111	0.006
EPC band (kWh)	Medium eff.	50.936%	52.887%	-0.038	0.005
EPC band (kWh)	High eff.	32.338%	28.429%	0.129	0.004
Interest rate type	Floating	3.311%	5.639%	-0.532	0.008
Interest rate type	Fixed	59.916%	65.955%	-0.096	0.005
Interest rate type	Other	36.773%	28.406%	0.258	0.004
Loan purpose	Other	0.165%	0.746%	-1.512	0.023
Loan purpose	Construction	8.600%	9.587%	-0.109	0.006
Loan purpose	Purchase	78.473%	81.658%	-0.040	0.005
Loan purpose	Renovation	2.769%	1.844%	0.407	0.003
Loan purpose	Remortgage	9.993%	6.165%	0.483	0.003
Customer type	Existing	27.063%	35.561%	-0.273	0.007
Customer type	New	40.631%	39.104%	0.038	0.005
Customer type	Other	32.307%	25.335%	0.243	0.004
Employment type	Unemployed	0.898%	2.212%	-0.901	0.012
Employment type	Self-employed	7.985%	13.837%	-0.550	0.009
Employment type	Employed-private	38.412%	46.515%	-0.191	0.006
Employment type	Other	1.033%	1.160%	-0.116	0.006
Employment type	Employed-unknown	33.435%	24.620%	0.306	0.004
Employment type	Employed-public	13.921%	8.971%	0.439	0.003

Table 4.5 continued from previous page

Variable	Bin	Good %	Bad %	WoE	ODR bin
Employment type	Pensioner	4.315%	2.685%	0.475	0.003
Occupancy type	Buy to Let	8.103%	9.218%	-0.129	0.006
Occupancy type	Owner Occupied	90.067%	89.716%	0.004	0.005
Occupancy type	Holiday	1.811%	1.066%	0.530	0.003
Quarter since reporting	0	20.715%	27.372%	-0.279	0.007
Quarter since reporting	1	22.172%	28.186%	-0.240	0.006
Quarter since reporting	2	20.587%	20.982%	-0.019	0.005
Quarter since reporting	3	15.886%	13.900%	0.134	0.004
Quarter since reporting	4	20.640%	9.560%	0.770	0.002
Time to maturity	2	20.634%	25.816%	-0.224	0.006
Time to maturity	1	19.890%	20.960%	-0.052	0.005
Time to maturity	3	19.089%	19.179%	-0.005	0.005
Time to maturity	4	20.358%	19.696%	0.033	0.005
Time to maturity	0	20.029%	14.340%	0.334	0.004
Loan to Value at reporting	4	35.779%	47.351%	-0.280	0.007
Loan to Value at reporting	3	21.682%	24.134%	-0.107	0.006
Loan to Value at reporting	2	19.225%	15.154%	0.238	0.004
Loan to Value at reporting	1	15.437%	9.142%	0.524	0.003
Loan to Value at reporting	0	7.877%	4.218%	0.625	0.003
Property value	0	42.254%	46.897%	-0.104	0.006
Property value	1	31.951%	32.148%	-0.006	0.005
Property value	2	25.795%	20.955%	0.208	0.004
Interest rate at reporting	4	21.526%	28.995%	-0.298	0.007
Interest rate at reporting	3	24.456%	27.143%	-0.104	0.006
Interest rate at reporting	2	27.131%	24.984%	0.082	0.005
Interest rate at reporting	1	19.329%	13.720%	0.343	0.004
Interest rate at reporting	0	7.558%	5.158%	0.382	0.003
Income at reporting	0	17.333%	20.267%	-0.156	0.006
Income at reporting	1	39.045%	44.244%	-0.125	0.006
Income at reporting	2	43.622%	35.489%	0.206	0.004

The results indicate that most variables exhibit a monotonic relationship with the target variable, supporting their inclusion in the logistic regression model and confirming their predictive stability. For example, in the case of Loan to Value at reporting, the highest two quintiles (namely, 4 and 3, corresponding to higher LTV values), are associated with negative WoE values, suggesting a higher likelihood of arrears within these groups. Conversely, the lowest three LTV quintiles (2, 1, and 0) display positive WoE values, with the WoE increasing as the LTV decreases, indicating lower credit risk. A similar pattern is observed for other variables. For Interest rate at reporting, lower interest rate buckets correspond to progressively higher WoE values, reflecting reduced delinquency risk for lower-rate loans. Likewise, the Income variable shows increasing WoE values across higher income categories, consistent with expectations that higher-income borrowers are less likely to fall into arrears. The only exception is Time to maturity, which failed to demonstrate a clear monotonic pattern across buckets. Due to this lack of consistent directional association, the variable was excluded at this stage of the analysis.

With respect to the variable of primary interest, EPC band, the WoE transformation reveals a clear and consistent trend. Collaterals with low energy efficiency are associated with negative WoE values, indicating elevated credit risk. As the energy efficiency improves, the WoE values increase, pointing to a lower likelihood of arrears and defaults. This trend underscores the relevance of energy efficiency in predicting mortgage risk, with more efficient properties showing reduced likelihoods of arrears and defaults.

4.3.2 Stepwise logistic regression results

Following the WoE transformation, variables were integrated into the logistic regression models using a stepwise procedure, where predictors were added sequentially based on their ranking from the initial selection stage. As described in Section 4.2.2.3, variables were retained in the final model if they satisfied three conditions: they improved model performance (with at least a 1% increase in the Gini coefficient), showed statistical significance (p-value < 0.05), and exhibited the expected direction of association with the target variable (i.e., a negative coefficient after WoE transformation).

The results of this stepwise selection process are presented in Table 4.6 for the Arrears and Material Arrears target variables, and in Table 4.7 for the Default and Material Default target variables.

Table 4.6. Stepwise variable selection results for Arrears target variables. This table presents the stepwise selection process for the Arrears and Material Arrears target variables. Variables that increase the performance of the model by at least 1% are retained (highlighted in green), whilst variables that do not achieve a Gini increase of 1% are removed (highlighted in red).

Iteration	Variable	Gini	Rel. Change	Outcome
Panel A: Arrears				
1	Quarter since reporting	0.171	-	-
2	Employment status	0.275	60.82%	Include
3	Loan to Value at reporting	0.325	18.18%	Include
4	Interest rate at reporting	0.352	8.31%	Include
5	EPC Kwh efficiency	0.356	1.14%	Include
6	Customer type	0.365	2.53%	Include
7	Income at reporting	0.375	2.74%	Include
8	Interest rate type	0.380	1.33%	Include
9	Property value	0.380	0.00%	Remove
10	Loan purpose	0.381	0.26%	Remove
Panel B: Material Arrears				
1	Employment status	0.315	-	-
2	EPC Kwh efficiency	0.340	7.94%	Include
3	Interest rate type	0.372	9.41%	Include
4	Interest rate at reporting	0.432	16.13%	Include
5	Income at reporting	0.437	1.16%	Include
6	Customer type	0.438	0.23%	Remove
7	Property value	0.450	2.97%	Include
8	Quarter since reporting	0.470	4.44%	Include
9	Loan to Value at reporting	0.472	0.43%	Remove
10	Loan purpose	0.472	0.43%	Remove
11	Occupancy type	0.473	0.64%	Remove

In both arrears specifications, the EPC band proves to be a strong and relevant predictor, meeting all inclusion criteria. Its contribution is particularly noteworthy for the Material Arrears model, where its addition leads to a 7.94% increase in the Gini coefficient. This aligns with previous findings from the variable ranking step, where EPC band was identified as the second most important predictor for this outcome, confirming the robustness of its predictive value in identifying material arrears.

Table 4.7. Stepwise variable selection results for Default target variables. This table presents the stepwise selection process for the Default and Material Default target variables. Variables that increase the performance of the model by at least 1% are retained (highlighted in green), whilst variables that do not achieve a Gini increase of 1% are removed (highlighted in red). Variables that exhibit a negative coefficient are also removed, as this indicates a high correlation with other predictors.

Iteration	Variable	Gini	Rel. Change	Outcome
Panel A: Default				
1	Loan to Value at reporting	0.193	-	-
2	Employment status	0.291	50.78%	Include
3	Interest rate at reporting	0.357	22.68%	Include
4	EPC Kwh efficiency	0.368	3.08%	Include
5	Quarter since reporting	0.402	9.24%	Include
6	Interest rate type	0.419	4.23%	Include
7	Income at reporting	0.423	0.95%	Remove
8	Customer type	0.426	1.67%	Include
9	Property value	0.427	0.23%	Remove
10	Loan purpose	0.427	0.23%	Remove
Panel B: Material Default				
1	Employment status	0.284	-	-
2	EPC Kwh efficiency	0.340	19.72%	Include
3	Interest rate type	0.378	11.18%	Include
4	Income at reporting	0.380	0.53%	Remove
5	Interest rate at reporting	0.443	17.20%	Include
6	Property value	0.459	3.61%	Include
7	Quarter since reporting	0.475	3.49%	Include
8	Loan purpose	0.482	1.47%	Include
9	Property type	0.486	0.83%	Remove
10	Loan to Value at reporting	0.482	0.00%	Remove
11	Customer type	0.488	1.24%	Remove (sign)
12	Occupancy type	0.485	0.62%	Remove

Similarly, for the default target variables, the EPC band proves to be a strong predictor and is retained in both model specifications. Notably, for the Material Default outcome, incorporating the EPC band results in a substantial improvement in model performance, with a 19.7% increase in the Gini coefficient.

Overall, the final models achieve a Gini coefficient above 40% in three out of four cases, indicating a relatively good model performance.[6] Across all four specifications, the inclusion of the EPC band consistently enhances the model's predictive ability. The improvement is particularly pronounced in the Material Default specification, highlighting the EPC band's value in distinguishing high-risk loans and supporting its relevance as a key risk driver in mortgage credit assessments. A few variables were excluded from the final models, likely because their predictive contribution is already captured by other, more dominant risk drivers. Among these, the most commonly excluded variables across the four specifications are *Loan purpose*, *Customer type*, and *Occupancy type*.

The logit regression results for the *Material Default* target variable (the model that achieved the highest peformance) are presented in Table 4.8. This table reports the estimated coefficients and associated statistics for the variables retained in the final model following the stepwise procedure. Results for the remaining target variables are provided in Appendix 4.C.

[6] It is worth noting that the European DataWarehouse (EDW) dataset does not include behavioural borrower-level variables typically obtained from credit bureaus, which are often used in internal credit rating models to enhance predictive accuracy. As a result, the performance achieved here is particularly notable given the more limited set of explanatory variables.

Table 4.8. Regression results for Material Default. This table reports the regression estimates, standard errors, Wald Chi-Square statistics, and p-values for the estimated model. The results are based on a logistic regression framework using Weight of Evidence (WoE) transformed variables.

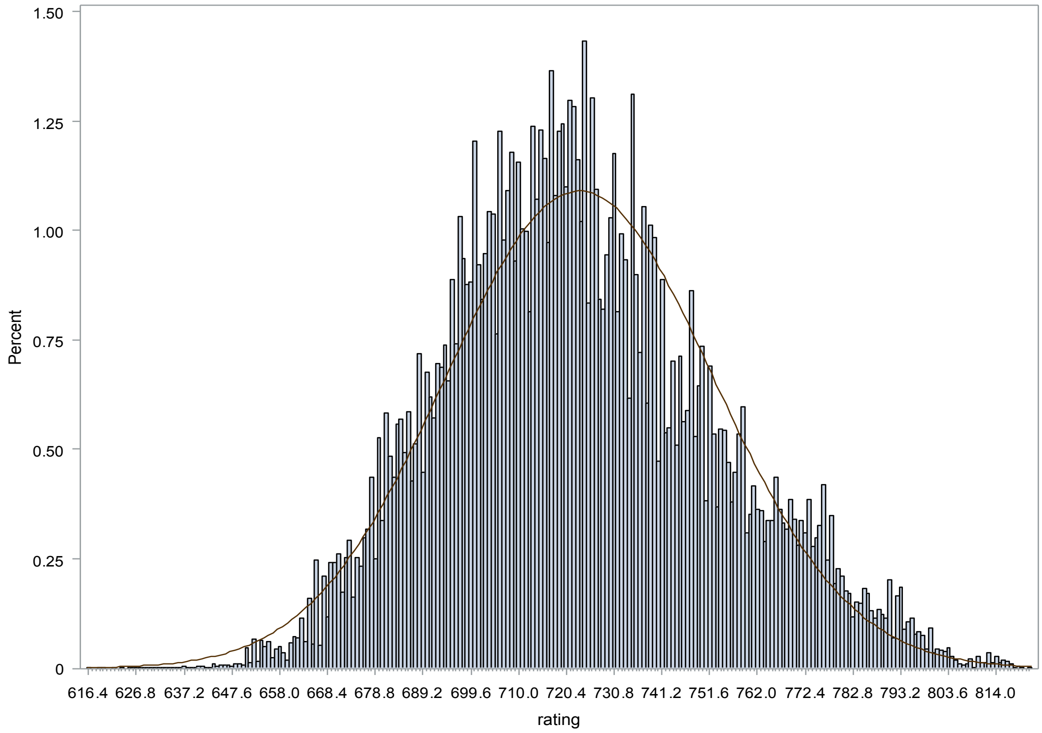
Variable	Estimate	Std. Error	Wald Chi-Square	p-value
Intercept	-7.73	0.03	95395.97	<.0001
Employment status	-0.65	0.06	124.68	<.0001
EPC kWh efficiency	-1.01	0.09	134.27	<.0001
Interest rate type	-0.78	0.06	176.40	<.0001
Interest rate at reporting	-1.37	0.07	341.42	<.0001
Property value at reporting	-0.93	0.09	114.17	<.0001
Quarters since reporting	-1.09	0.09	132.43	<.0001
Loan purpose	-0.56	0.09	38.18	<.0001

The results align with expectations, as all coefficients are negative, confirming that higher WoE values correspond to a lower probability of default. Among the predictors, the EPC variable exhibits a particularly strong association with default risk, with a coefficient of -1.01, making it the third most influential variable in absolute terms. This highlights the relevance of energy efficiency in mortgage risk assessment, suggesting that loans secured by more energy-efficient properties are less likely to default. These findings support the importance of both borrower characteristics (e.g., employment status and interest rate terms) and property-related factors (e.g., EPC rating) in accurately predicting default probabilities.

The distribution of rating scores for the Material Default model is presented in Figure 4.4. This figure follows the rating transformation process described in Section 4.2.2.4, where predicted probabilities were scaled into intuitive, standardised credit scores. The remaining score distributions for the other target variables are reported in Appendix 4.D.

The graph displays the distribution of final rating scores across the sample for the Material Default variable, with values ranging from 616 to 827. The distribution exhibits a bell-shaped pattern, with most scores concentrated around the centre, indicating a relatively

Figure 4.4. Rating distribution for Material Default.

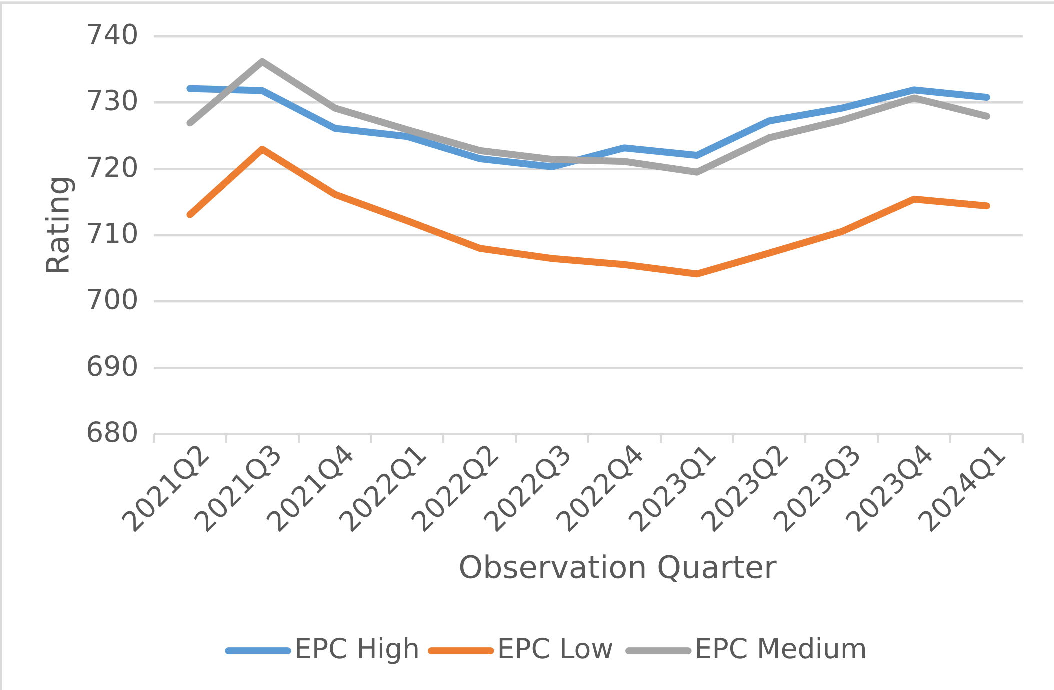


symmetric spread of ratings. Importantly, all scores lie above 600, suggesting that the overall sample is low risk. This outcome is consistent with expectations, given that the data originates from the European DataWarehouse and pertains to loans securitised into RMBSs eligible for repurchase agreements with the ECB. These transactions are subject to stringent credit quality requirements and must achieve a minimum rating of A3. As a result, the concentration of scores in the higher range reflects a lower predicted probability of default within the sample, as higher scores correspond to stronger credit quality.

As an additional analysis, we plot in Figure 4.5 the average rating by EPC band for the Material Default variable. The figure shows that the model consistently assigns higher ratings to loans associated with High and Medium EPC efficiency bands, reflecting their lower risk profile. In contrast, loans with Low EPC efficiency receive substantially lower ratings across time, indicating their higher likelihood of default.

However, in this case, no clear score differentiation is observed between the High and Medium EPC bands. This could be attributable to overlapping risk profiles that are not fully disentangled in this specific model. It is worth noting that in other cases (such as the model for Default) a clearer separation is observed across all three EPC bands. Specifically, loans with High EPC efficiency consistently exhibit higher average scores than both Medium and Low EPC categories, indicating better risk differentiation. Further details can be found in Appendix 4.E.

Figure 4.5. Average rating by EPC Efficiency band for Material Default.

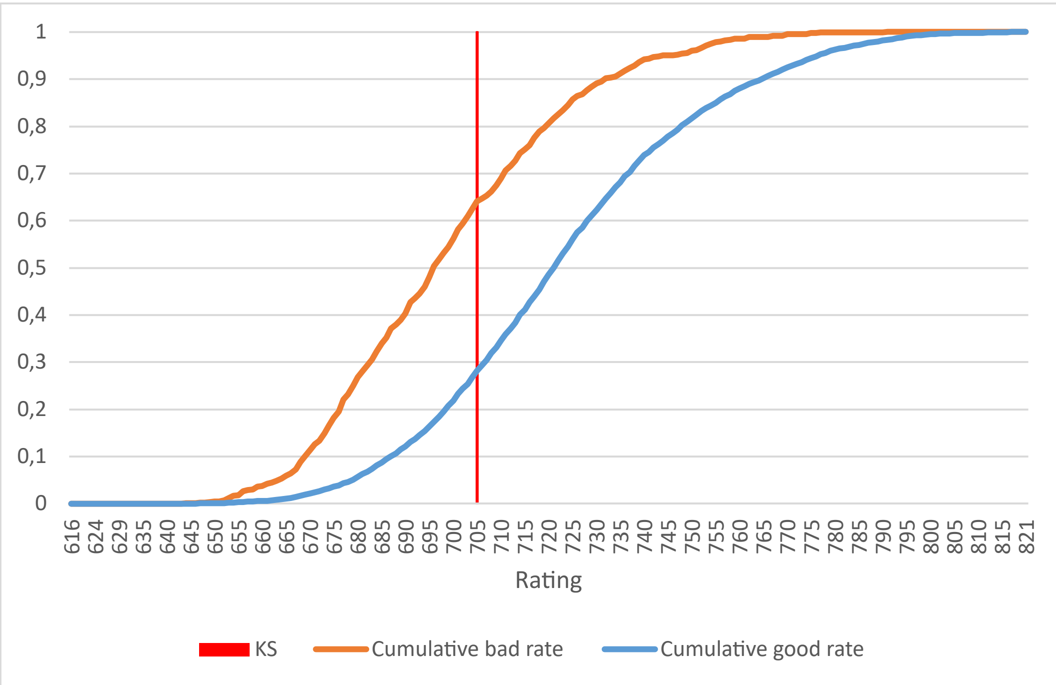


4.3.3 Impact of EPC ratings on model performance

To evaluate the impact of incorporating EPC ratings into the logistic regression models, we compare the predictive performance of each model with and without the inclusion of the EPC band variable. Performance is assessed using two widely recognised metrics: the Gini coefficient and the Kolmogorov–Smirnov (KS) statistic. These are calculated on the final rating scores obtained through the scaling procedure described in Section 4.2.2.4.

As an initial illustration, Figure 4.6 presents the KS statistic for the model predicting Material Default. The KS statistic quantifies the maximum separation between the cumulative distributions of goods (non-defaults) and bads (defaults), offering a visual measure of the model's ability to distinguish between the two classes. In this case, the model achieves a KS statistic of 35.5%, indicating strong discriminatory performance. As a reminder, the corresponding Gini coefficient for this model is 48.5%, as previously reported in Table 4.7. Additional KS plots for the other target variables are provided in Appendix 4.F.

Figure 4.6. Kolmogorov-Smirnov (KS) statistic for Material Default.



Following this graphical analysis, Table 4.9 presents a comprehensive summary of the Gini and KS statistics for all four target variables, comparing model performance with and without the inclusion of the EPC band variable. This comparison enables us to quantify the incremental contribution of the EPC information across different dimensions of mortgage delinquency and default risk.

Table 4.9. Model performance comparison with and without EPC variable. This table reports the Gini coefficient and KS statistic for different target variables, comparing the baseline model to a model excluding the EPC variable. The relative change column represents the percentage variation when EPC is removed. Green cells indicate the highest impact of excluding EPC for both Gini and KS statistic.

Target variable	Gini			KS statistic		
	Baseline	Without EPC	Rel. Change	Baseline	Without EPC	Rel. Change
Arrears	38.0%	37.7%	0.80%	27.4%	27.2%	0.62%
Material Arrears	47.0%	46.8%	0.43%	34.6%	34.2%	1.17%
Default	42.6%	41.8%	1.91%	31.6%	31.0%	2.09%
Material Default	48.2%	46.8%	2.99%	35.5%	35.3%	0.77%

The results show performance improvements for all four target variables when the EPC band is included. The impact is most pronounced for the default-related variables, with a 2.99% increase in the Gini coefficient for *Material Default* and a 1.91% increase for *Default*, demonstrating the variable's importance in predicting high-severity outcomes.

To further evaluate the impact of the EPC band variable, the models were tested over a specific period of elevated energy prices, spanning from 2022-Q1 to 2023-Q1. This timeframe holds particular economic significance: the first quarter of 2022 marks the onset of the war in Ukraine, which precipitated a sharp increase in global energy prices. In contrast, the first quarter of 2023 witnessed a notable decline in energy costs, as supply constraints eased and markets began to stabilise. This window thus captures both the peak and the early resolution phase of the energy crisis, offering a meaningful context to assess whether energy efficiency, proxied by the EPC band, becomes more relevant for mortgage risk prediction under conditions of energy price volatility.

To account for the specific dynamics of this period, the models were recalibrated using only the subset of data from 2022-Q1 to 2023-Q1. Recalibration entails re-estimating the logistic regression coefficients on this restricted sample, allowing the model to adjust for potential changes in the relationships between risk drivers and delinquency outcomes during the crisis. The results of this analysis are reported in Table 4.10.

Table 4.10. Model performance during high energy inflation (Jan 2022 – Mar 2023). This table presents model performance during the high energy inflation period (Jan 2022 – Mar 2023). The models were recalibrated using data from this time frame to capture the impact of energy price volatility. The relative change column shows the performance drop when EPC is removed. Green cells highlight the most significant declines in predictive performance for both Gini and KS metrics.

Target variable	Gini			KS statistic		
	Baseline	**Without EPC**	**Rel. Change**	**Baseline**	**Without EPC**	**Rel. Change**
Arrears	33.6%	33.1%	1.51%	25.3%	24.9%	1.64%
Material Arrears	45.7%	45.3%	0.88%	34.0%	33.3%	1.98%
Default	41.1%	39.8%	3.27%	31.9%	30.6%	4.42%
Material Default	49.2%	47.6%	3.36%	37.4%	36.6%	2.26%

The results for the high energy inflation period demonstrate a consistent improvement in model performance across all four target variables when the EPC band variable is included. These findings reinforce the earlier results and further underscore the EPC band's relevance, particularly in predicting defaults. Notably:

- For *Material Default*, the improvement in the Gini coefficient rises to 3.36% (compared to 2.99% in the full sample), emphasising the growing predictive value of the EPC band during periods of elevated energy costs.

- For *Default*, the improvement in the KS statistic more than doubles to 4.42% (from 2.09%).

- For *Arrears* and *Material Arrears*, although the gains are more modest, the Gini improves by 1.51% and 0.88% (up from 0.80% and 0.43%, respectively), confirming that the EPC band continues to enhance model performance even in the case of less severe delinquency outcomes.

These results suggest that the relevance of energy efficiency becomes more pronounced during times of heightened energy price pressure, with the EPC band acting as a valuable risk differentiator across all stages of delinquency.

4.3.4 Impact of energy consumption on probability of default

As a complementary analysis, this section examines the influence of EPC ratings on the predicted probabilities of arrears and default. This analysis is based on a logistic regression model that mirrors the structure used in the rating score framework but shifts the focus from model performance metrics to predicted probabilities. Importantly, unlike the previous models, this version does not apply Weight of Evidence (WoE) transformations. Additionally, the models directly employ a continuous measure of energy consumption (kWh/m²/year). This allows for a more intuitive interpretation of the marginal effects, making it easier to understand how increases in the collateral's energy consumption relate to delinquency risk. The results are presented in Table 4.11, which shows the estimated effect of EPC efficiency on the four target outcomes.

Table 4.11. The impact of energy efficiency labels on mortgage arrears. The table presents the marginal effects (in bps) from four specifications of panel logit regressions, where the dependent variables represent different indicators of mortgage delinquency. The dependent variables are: (1) arrears, (2) material arrears (arrears exceed 1% of the loan balance), (3) default, and (4) material default (default where arrears exceed 1% of the loan balance). The key explanatory variable is *Energy consumption (kWh/m²/year)*, measured in increases of 100. Other control variables include loan, borrower and collateral characteristics as well as macroeconomic variables. Robust standard errors are clustered at the regional level (3-digit postcode). Additional macroeconomic and fixed effects are included. The symbols ***, , and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1)	**(2)**	**(3)**	**(4)**
EPC kWh/m²/year:				
Energy consumption (per 100 kWh)	4.36***	1.45***	2.44***	1.03***
	(0.67)	(0.35)	(0.39)	(0.24)
LTV at reporting:				
1st quintile (baseline)	-	-	-	-
2nd quintile	3.69	1.10	1.03	1.47
	(2.86)	(1.46)	(1.73)	(1.06)
3rd quintile	12.23***	5.66**	4.09*	1.57
	(4.08)	(2.39)	(2.32)	(1.23)
4th quintile	24.83***	4.74	8.96***	1.88

Table 4.11 continued from previous page

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1)	**(2)**	**(3)**	**(4)**
	(4.07)	(2.93)	(2.24)	(1.47)
5th quintile	38.79***	6.57**	13.98***	2.15
	(5.63)	(2.68)	(2.59)	(1.41)
Time to Maturity (quarters)	0.22***	-0.12**	0.09***	-0.04
	(0.06)	(0.05)	(0.02)	(0.03)
Loan purpose:				
Purchase (baseline)	-	-	-	-
Construction	1.29	1.74	0.22	2.08
	(4.21)	(1.67)	(2.23)	(1.33)
Other	-3.87	-3.86	-4.30	3.23
	(4.03)	(3.06)	(4.76)	(5.09)
Remortgage	-0.49	-0.81	-1.06	-2.44***
	(3.02)	(2.34)	(2.34)	(0.53)
Renovation	-12.5***	-2.80	-5.71**	-2.56***
	(3.64)	(2.25)	(2.38)	(0.86)
Interest rate at reporting:				
1st quintile (baseline)	-	-	-	-
2nd quintile	-2.35	-4.02**	0.19	1.08
	(4.41)	(1.59)	(1.44)	(0.67)
3rd quintile	-1.45	-3.56**	0.47	1.15*
	(4.89)	(1.80)	(1.49)	(0.67)
4th quintile	12.07*	0.67	7.35***	3.09***
	(6.44)	(1.91)	(2.34)	(1.05)
5th quintile	28.4**	7.00**	14.21***	5.63***
	(11.70)	(3.31)	(5.04)	(1.84)
Interest type:				
Fixed (baseline)	-	-	-	-
Floating	5.63	6.94**	4.49*	1.64
	(8.30)	(3.37)	(2.68)	(1.08)
Other	-10.10	-6.59	-5.20	-4.25**
	(12.71)	(4.25)	(5.50)	(1.84)
Employment:				
Employed – private sector (baseline)	-	-	-	-
Employed – public sector	-18.13***	-5.73***	-5.53***	-1.50***
	(2.05)	(1.09)	(0.97)	(0.57)
Employed – other	3.15	4.04	2.42	1.46
	(3.96)	(3.29)	(4.27)	(1.21)
Other	27.61**	14.17*	12.79	13.87
	(13.45)	(7.67)	(8.71)	(8.68)
Pensioner	-4.05	-0.21	-2.14	0.51
	(4.19)	(1.51)	(1.83)	(1.06)
Self-employed	37.72***	13.86***	11.85***	5.14***
	(4.11)	(2.04)	(2.31)	(1.02)
Unemployed	45.46***	17.4***	19.01***	3.85
	(12.27)	(4.88)	(6.80)	(2.70)
Income at reporting:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-9.87***	-3.60**	-3.66**	-1.46*
	(3.31)	(1.61)	(1.82)	(0.86)
3rd tertile	-22.58***	-7.68***	-8.27***	-3.29***
	(3.27)	(1.97)	(1.73)	(1.12)
Occupancy type:				
Owner occupied (baseline)	-	-	-	-
Buy to Let	2.27	1.32	3.43**	1.05

Table 4.11 continued from previous page

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1)	**(2)**	**(3)**	**(4)**
	(2.06)	(1.06)	(1.45)	(0.91)
Holiday	-7.61	-2.29	-3.00	-1.19
	(7.25)	(2.30)	(4.20)	(1.26)
Other	(omitted)	(omitted)	(omitted)	(omitted)
	-	-	-	-
Property type:				
Residential flat (baseline)	-	-	-	-
Other	-15.43***	-2.99	-4.59	-0.83
	(5.62)	(2.30)	(3.79)	(1.82)
Residential house	-0.55	-0.14	1.01	-1.11
	(2.88)	(1.50)	(1.48)	(0.94)
Residential terrace	6.79	7.61**	0.85	2.54
	(7.60)	(3.26)	(2.08)	(2.28)
Property value:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-4.40**	-3.56***	-2.37**	-1.28**
	(1.75)	(1.28)	(1.07)	(0.56)
3rd tertile	-2.63	-3.81***	-1.63	-1.77***
	(2.94)	(1.19)	(1.50)	(0.65)
Macro variables	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0581	0.0726	0.0636	0.0728
Observations	4,479,471	4,372,063	4,419,642	4,270,893

Across all four target variables (Arrears, Material Arrears, Default, and Material Default) there is clear evidence that properties with lower energy efficiency (i.e., higher energy consumption) are associated with significantly higher delinquency risk. Specifically, the probability of arrears increases by 4.36 basis points (bps) when the collateral's energy consumption increases by 100 kWh/m². Given the sample mean arrears rate of 49.57 bps, this corresponds to an approximate 8.8% increase for each additional 100 kWh/m². Similarly, for Material Arrears, the marginal effect is 1.45 bps, amounting to a 11.6% increase relative to the 12.58 bps sample mean. The pattern continues across default-related outcomes: Default increases by 2.44 bps (a 14.8% increase over the 16.77 bps mean), while Material Default rises by 1.03 bps, a 23.4% increase compared to the mean rate of 4.40 bps.

These effects remain statistically significant even after accounting for a rich set of control variables capturing borrower, loan, and property characteristics, as well as macroeconomic indicators. Fixed effects at the quarter and deal level are also included to account for time-varying and transaction-specific heterogeneity. As for the controls, the direction and magnitude of the coefficients are consistent with expectations. Loans with higher LTV values are associated with higher delinquency risk, and both self-employed and unemployed borrowers exhibit elevated default probabilities. Borrower income is also a strong determinant of performance: compared to the lowest income tertile (baseline), loans to borrowers in the second and third income tertiles experience progressively lower delinquency rates. For example, being in the top income tertile reduces the probability of arrears by 22.58 bps and material arrears by 7.68 bps.

To verify the robustness of the main results, two complementary analyses were performed.[7] The first test, presented in Table 4.G.1, extends the baseline specification by introducing interaction terms between Deal and Quarter fixed effects (Deal × Quarter FE). This specification accounts for time-varying shocks specific to each securitised transaction, thereby controlling for unobserved deal-level dynamics over time. The inclusion of these interaction terms does not alter the key findings: the impact of Energy consumption on delinquency remains both economically and statistically significant across all target variables.

The second robustness test, reported in Table 4.G.2, investigates the effect of using the raw EPC labels directly, without harmonising them across countries through energy consumption mappings. In this alternative specification, the labels A and B are treated as the high-efficiency reference group, while the medium-efficiency group comprises labels C, D,

[7] Untabulated results confirm that the estimated effects remain materially unchanged when the analysis is conducted using annual observations instead of quarterly data, suggesting that the relationship between EPC ratings and mortgage risk is robust to the choice of temporal aggregation.

and E, and the low-efficiency group includes labels F and G. The results confirm that loans associated with F/G-rated properties continue to display significantly higher delinquency risk relative to A/B-rated properties. In contrast, the medium-efficiency group does not exhibit a statistically significant difference. These findings reaffirm the original conclusion that poor energy efficiency, especially at the lowest end of the EPC spectrum, is strongly associated with increased mortgage risk.

Altogether, these results highlight that energy efficiency, as captured by EPC ratings and corresponding energy consumption levels, is a significant and robust determinant of mortgage delinquency. Properties with higher energy needs are consistently more likely to experience repayment difficulties, even after controlling for a comprehensive set of risk factors.

4.4 Conclusions

This chapter has examined the role of energy efficiency, as captured by Energy Performance Certificate (EPC) ratings, in predicting mortgage delinquency and default. Using a comprehensive dataset of 4.5 million loan-level quarterly observations sourced from the European DataWarehouse, we built and evaluated a series of rating models designed to assess whether the inclusion of EPC information enhances credit risk assessment. Model performance was then assessed using the Gini coefficient and the Kolmogorov–Smirnov (KS) statistic, both in the full sample and during a period of heightened energy inflation (2022–Q1 to 2023–Q1).

The results consistently show that EPC ratings contribute positively to model performance across all specifications. The EPC variable meets the criteria for inclusion in the final model in every case, demonstrating both statistical significance and the expected negative relationship with credit risk (i.e., higher energy efficiency corresponds to lower default probability). For the material default outcome, which represents the most severe form of delinquency, including the EPC band increases the Gini by 2.99% in the full sample and by 3.36% during the high energy inflation period. These improvements underscore the EPC variable's robustness as a predictor, particularly under conditions of energy price volatility.

To further explore the EPC band's contribution, we conducted a complementary that focused on the marginal effect of the collateral's energy consumption on predicted probabilities of delinquency. The results showed substantial differences in credit risk across EPC tiers, even after controlling for a rich set of loan, borrower, and macroeconomic characteristics. For instance, an increase in the collateral's average energy consumption of 100 kWh/m^2 is associated to a 23.4% higher probability of material default.

Taken together, the evidence presented in this chapter demonstrates that energy efficiency is not merely an environmental or regulatory concern, but also a financially material dimension of mortgage credit risk. EPC ratings provide valuable forward-looking information about a borrower's ability to meet their debt obligations, particularly in contexts where energy costs form a significant share of household expenditure. As the mortgage and securitisation markets increasingly grapple with climate-related risks, the integration of EPC ratings into rating frameworks may offer a meaningful enhancement to the predictive accuracy and resilience of credit risk models. These findings have important implications for regulators and lenders seeking to align risk management practices with sustainability objectives in the European housing finance ecosystem.

Appendices to Chapter 4

4.A Variable list

Table 4.A.1. Description of variables used in the regression analysis.

Variable	Type	Description
Delinquency		
Arrears	Dummy	A variable that takes the value of 1 if the loan is one quarter in arrears, and 0 otherwise.
Material Arrears	Dummy	A variable that takes the value of 1 if the loan is one quarter in arrears and the arrears balance is greater than or equal to 1% of the current loan balance, and 0 otherwise.
Default	Dummy	A variable that takes the value of 1 if the loan is two consecutive quarters in arrears, and 0 otherwise.
Material Default	Dummy	A variable that takes the value of 1 if the loan is two consecutive quarters in arrears and the arrears balance is greater than or equal to 1% of the current loan balance, and 0 otherwise.
Energy Efficiency		
EPC kWh/m²/year	Categorical	Categorises the energy efficiency of the loan based on the average kWh consumption per m² per year across all the collateral. The variable is divided into three ranges: the highest consumption third is categorised as Low Efficiency, the middle third as Medium Efficiency, and the lowest third as High Efficiency.
EPC Label	Categorical	Categorises properties based on their EPC label. Categories include EPC A/B (high), EPC C/D/E (medium), and EPC F/G (low).
Loan Characteristics		

Table 4.A.1 continued from previous page

Variable	Type	Description
Loan Purpose	Categorical	The purpose of the loan, categorised into Purchase, Construction, Remortgage, Renovation, or Other.
Interest Rate	Continuous	Interest Rate applied to the loan at the time of the first reporting date.
Interest Type	Categorical	The type of interest rate applied to the loan, which can be Fixed, Floating, or Other.
Loan-to-Value (LTV)	Continuous	The loan-to-value ratio at the time of the first reporting date.
Time to maturity	Continuous	Number of quarters to maturity.
Quarter since reporting	Continuous	Number of quarters since the first reporting date.
Borrower Characteristics		
Employment	Categorical	Employment status of the borrower, which can be Employed in the private sector, public sector, or unknown sector, as well as Pensioner, Self-employed, Unemployed, or Other.
Income	Continuous	The borrower's income at the time of the first reporting date.
Customer type	Categorical	Identifies whether the borrower is a new or existing customer.
Collateral Characteristics		
Occupancy Type	Categorical	The type of occupancy of the property, which can be Owner Occupied, Buy to Let, Holiday, or Other.
Property Type	Categorical	The type of property, categorised as a Residential Flat, Residential House, Residential Terrace, or Other.
Property value	Continuous	The value of the property at the time of the first reporting date.
Macro Variables		
House price index change (%)	Continuous	The percentage change in the house price index over the previous 12 months.
Unemployment rate change (%)	Continuous	The percentage change in the unemployment rate over the previous 12 months.
Inflation change (%)	Continuous	The percentage change in the inflation rate over the previous 12 months.
Energy inflation change (%)	Continuous	The percentage change in energy inflation over the previous 12 months.

4.B WoE results for default target variable

Table 4.B.1. Weight of Evidence (WoE) transformation for the Default target variable. This table presents Weight of Evidence (WoE) values and Observed Default Rates (ODR) by bin calculated on the Default target variable. Numeric variables are initially divided into five quantile-based buckets (0=low, 4-high), with WoE calculated for each. To improve monotonicity, some variables are further reduced to three buckets by combining those with similar WoE values. Negative WoE values are highlighted in red (higher likelihood of arrears), while positive WoE values are highlighted in green (lower likelihood of arrears).

Variable	Bin	Good %	Bad %	WoE	ODR bin
EPC kWh Efficiency	Low Eff	16.73%	20.63%	-0.209	0.002
EPC kWh Efficiency	Med Eff	50.94%	52.01%	-0.021	0.002
EPC kWh Efficiency	High Eff	32.33%	27.36%	0.167	0.001
Interest Rate Type	Floating	3.32%	7.71%	-0.844	0.004
Interest Rate Type	Fixed	59.97%	68.94%	-0.139	0.002
Interest Rate Type	Other	36.71%	23.34%	0.453	0.001
Loan Purpose	Other	0.17%	0.61%	-1.288	0.006
Loan Purpose	Purchase	78.49%	84.29%	-0.071	0.002
Loan Purpose	Construction	8.61%	8.60%	0.001	0.002
Loan Purpose	Renovation	2.76%	1.72%	0.473	0.001
Loan Purpose	Remortgage	9.97%	4.77%	0.737	0.001
Customer Type	Existing Customer	27.13%	35.06%	-0.256	0.002
Customer Type	New Customer	40.60%	39.62%	0.025	0.002
Customer Type	Other	32.26%	25.32%	0.242	0.001
Employment Type	Unemployed	0.91%	2.70%	-1.092	0.005
Employment Type	Self-Employed	8.03%	12.78%	-0.465	0.003
Employment Type	Employed Private	38.47%	50.12%	-0.265	0.002
Employment Type	Other	1.03%	0.97%	0.066	0.002
Employment Type	Employed Public	13.89%	9.82%	0.346	0.001
Employment Type	Employed Unknown	33.37%	21.53%	0.438	0.001
Employment Type	Pensioner	4.30%	2.08%	0.727	0.001
Occupancy Type	Buy to Let	8.12%	10.34%	-0.242	0.002
Occupancy Type	Owner Occupied	90.06%	88.63%	0.016	0.002
Occupancy Type	Holiday	1.81%	1.03%	0.558	0.001
Property Type	Residential Terrace	0.37%	1.22%	-1.182	0.005
Property Type	Residential Flat	27.94%	28.86%	-0.032	0.002

Table 4.B.1 continued from previous page

Variable	Bin	Good %	Bad %	WoE	ODR bin
Property Type	Residential House	69.24%	68.21%	0.015	0.002
Property Type	Other	2.44%	1.71%	0.357	0.001
Quarter Since Reporting	1	22.16%	29.96%	-0.301	0.002
Quarter Since Reporting	2	20.59%	22.80%	-0.102	0.002
Quarter Since Reporting	0	20.69%	20.96%	-0.013	0.002
Quarter Since Reporting	3	15.90%	15.22%	0.044	0.002
Quarter Since Reporting	4	20.66%	11.07%	0.624	0.001
Time to Maturity	2	20.67%	26.76%	-0.258	0.002
Time to Maturity	3	19.08%	19.13%	-0.002	0.002
Time to Maturity	4	20.34%	19.96%	0.018	0.002
Time to Maturity	1	19.91%	18.73%	0.061	0.002
Time to Maturity	0	20.00%	15.42%	0.260	0.001
Loan to Value at Reporting	4	35.84%	49.44%	-0.322	0.002
Loan to Value at Reporting	3	21.70%	24.46%	-0.119	0.002
Loan to Value at Reporting	2	19.21%	14.05%	0.313	0.001
Loan to Value at Reporting	1	15.40%	8.21%	0.629	0.001
Loan to Value at Reporting	0	7.85%	3.84%	0.714	0.001
Collateral Value	0	42.28%	47.59%	-0.118	0.002
Collateral Value	1	31.96%	32.18%	-0.007	0.002
Collateral Value	2	25.76%	20.23%	0.242	0.001
Interest Rate at Reporting	4	21.57%	31.93%	-0.392	0.002
Interest Rate at Reporting	3	24.47%	28.96%	-0.169	0.002
Interest Rate at Reporting	2	27.13%	22.11%	0.204	0.001
Interest Rate at Reporting	1	19.29%	12.38%	0.444	0.001
Interest Rate at Reporting	0	7.54%	4.61%	0.492	0.001
Income at Reporting	0	17.35%	21.99%	-0.237	0.002
Income at Reporting	1	39.08%	44.84%	-0.138	0.002
Income at Reporting	2	43.57%	33.16%	0.273	0.001

4.C Model results

Table 4.C.1. Regression results for the estimated models across different target variables. This table reports the regression estimates, standard errors, Wald Chi-Square statistics, and p-values for the estimated models across different target variables. The results are based on a logistic regression framework using Weight of Evidence (WoE) transformed variables.

Variable	Estimate	Std. Error	Wald Chi-Square	p-value
Panel A: Arrears				
Intercept	-5.302	0.007	550138.822	<.0001
Quarters since reporting	-1.090	0.022	2451.353	<.0001
Employment status	-0.892	0.022	1649.750	<.0001
Loan to Value at reporting	-1.008	0.023	1961.332	<.0001
Interest rate at reporting	-1.320	0.030	1892.136	<.0001
EPC kWh efficiency	-1.015	0.078	167.527	<.0001
Customer type	-0.796	0.033	587.915	<.0001
Income at reporting	-0.748	0.044	287.123	<.0001
Interest rate type	-0.795	0.039	423.270	<.0001
Panel B: Relative Arrears				
Intercept	-6.678	0.015	206321.830	<.0001
Employment status	-0.745	0.029	643.667	<.0001
EPC kWh efficiency	-0.905	0.126	51.753	<.0001
Interest rate type	-0.728	0.035	438.368	<.0001
Interest rate at reporting	-1.466	0.046	1027.867	<.0001
Income at reporting	-0.220	0.049	19.728	<.0001
Property value at reporting	-0.913	0.058	252.464	<.0001
Quarters since reporting	-1.258	0.066	361.901	<.0001
Panel C: Default				
Intercept	-6.388	0.012	263960.080	<.0001
Loan to Value at reporting	-1.016	0.034	890.191	<.0001
Employment status	-0.790	0.035	515.765	<.0001
Interest rate at reporting	-1.320	0.038	1199.100	<.0001
EPC kWh efficiency	-1.208	0.089	185.027	<.0001
Quarters since reporting	-1.125	0.043	683.767	<.0001
Interest rate type	-0.937	0.039	587.400	<.0001
Customer type	-0.748	0.058	165.450	<.0001

4.D Rating distribution

Figure 4.D.1. Rating distribution by target variable.

FIGURE A: ARREARS

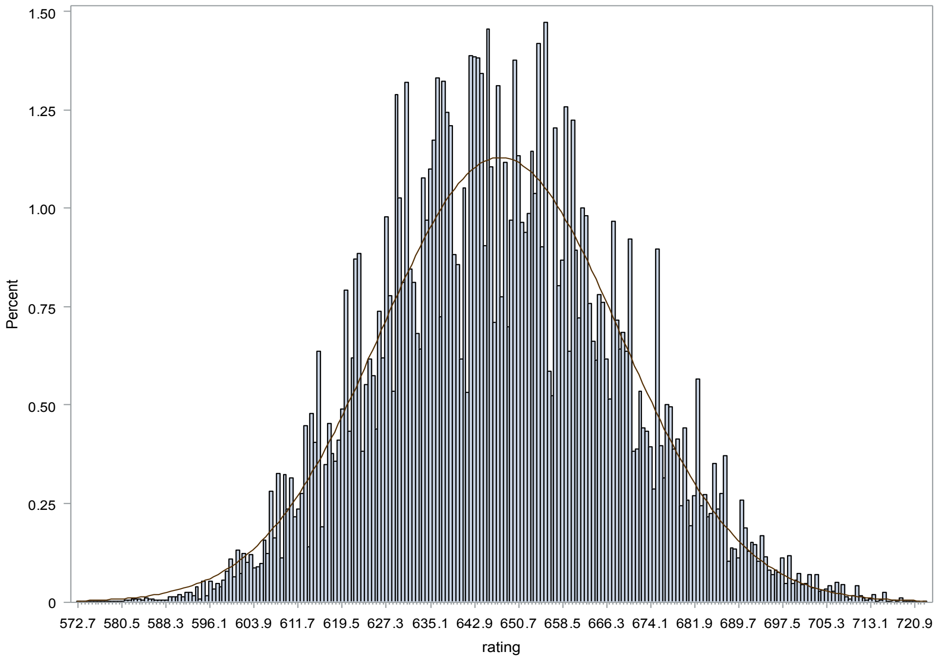


FIGURE B: MATERIAL ARREARS

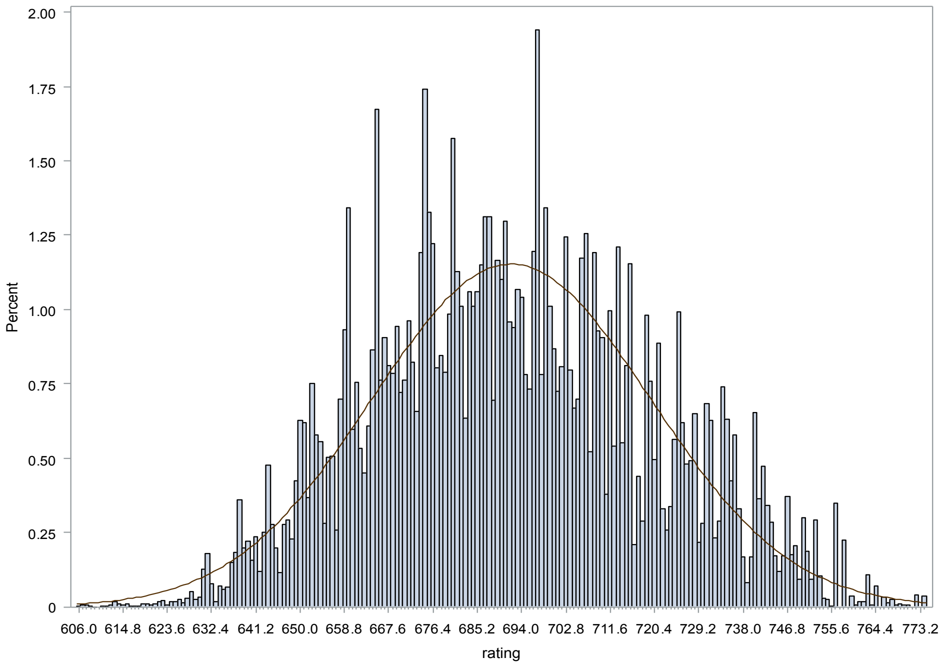


FIGURE C: DEFAULT

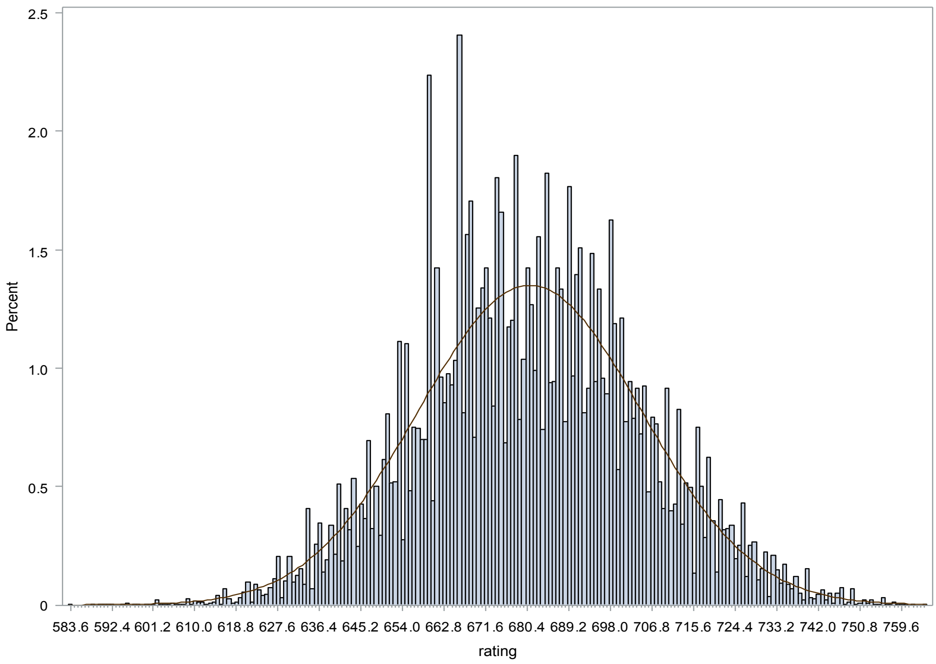
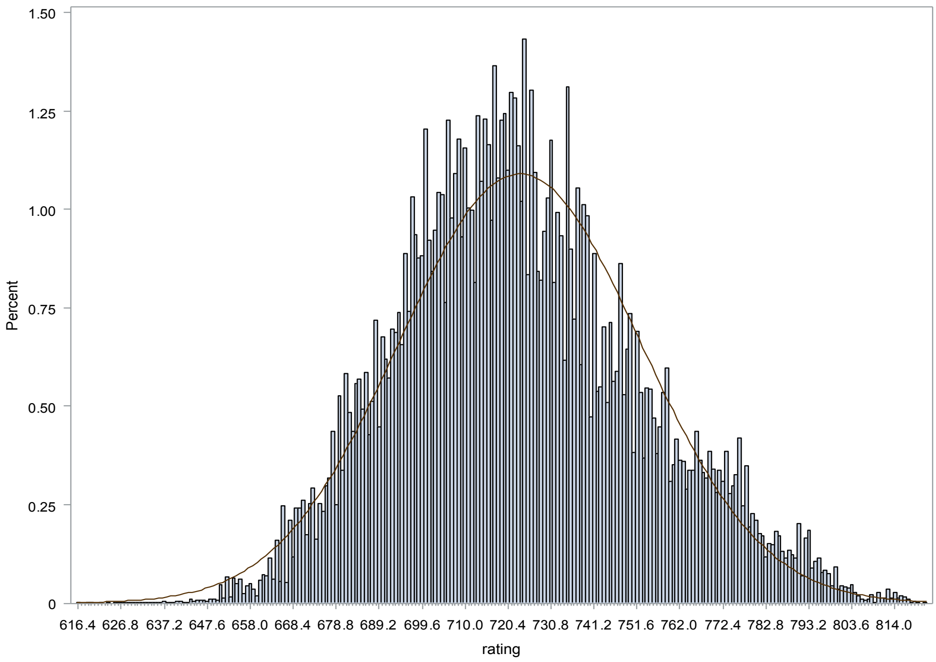


FIGURE D: MATERIAL DEFAULT



4.E Average rating by EPC Band

Figure 4.E.1. Average rating over time by EPC efficiency band.

FIGURE A: ARREARS

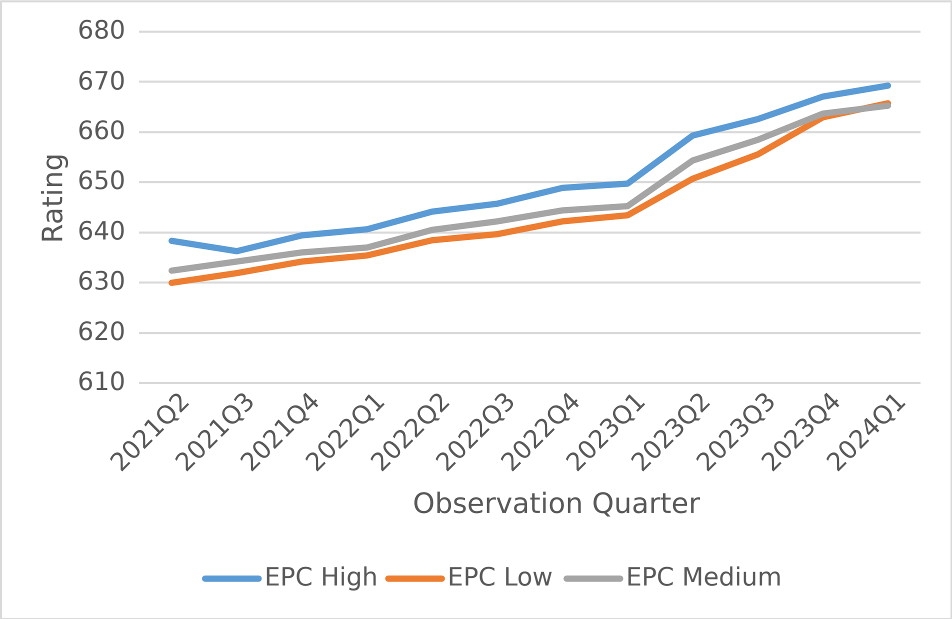


FIGURE B: MATERIAL ARREARS

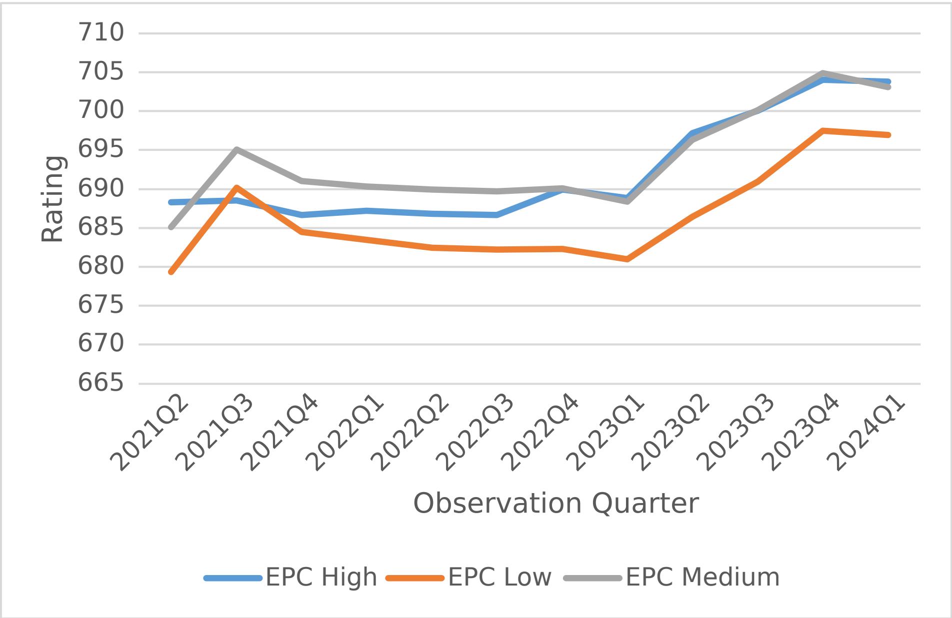


FIGURE C: DEFAULT

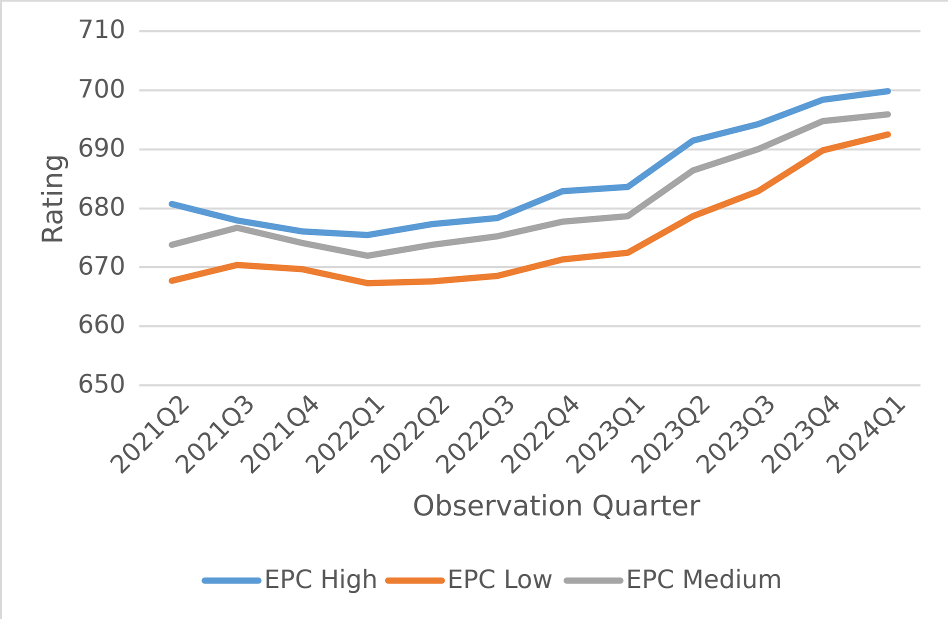
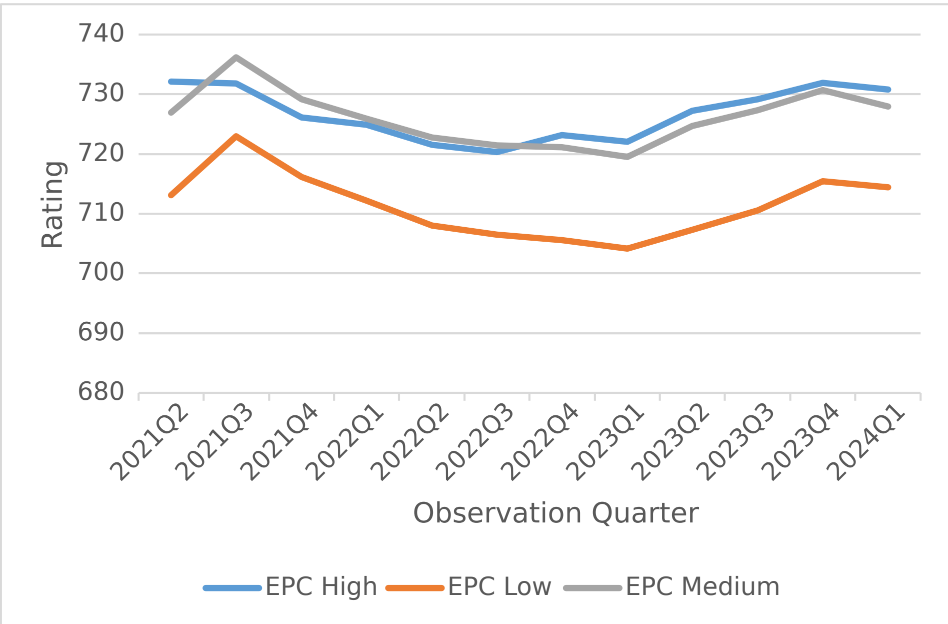


FIGURE D: MATERIAL DEFAULT



4.F Kolmogorov-Smirnov (KS) statistic results

Figure 4.F.1. Kolmogorov-Smirnov (KS) statistic by target variable.

FIGURE A: ARREARS

FIGURE B: MATERIAL ARREARS

FIGURE C: DEFAULT

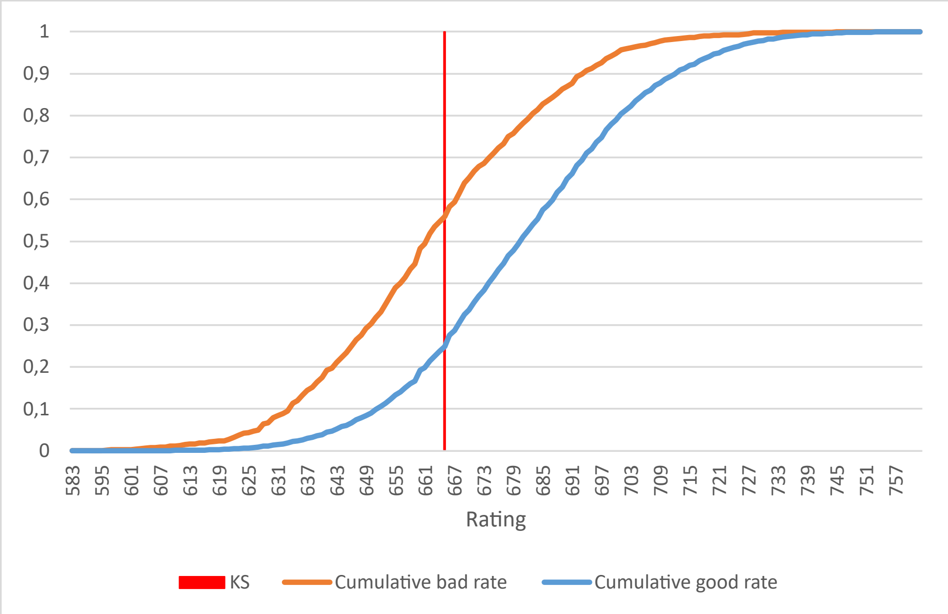
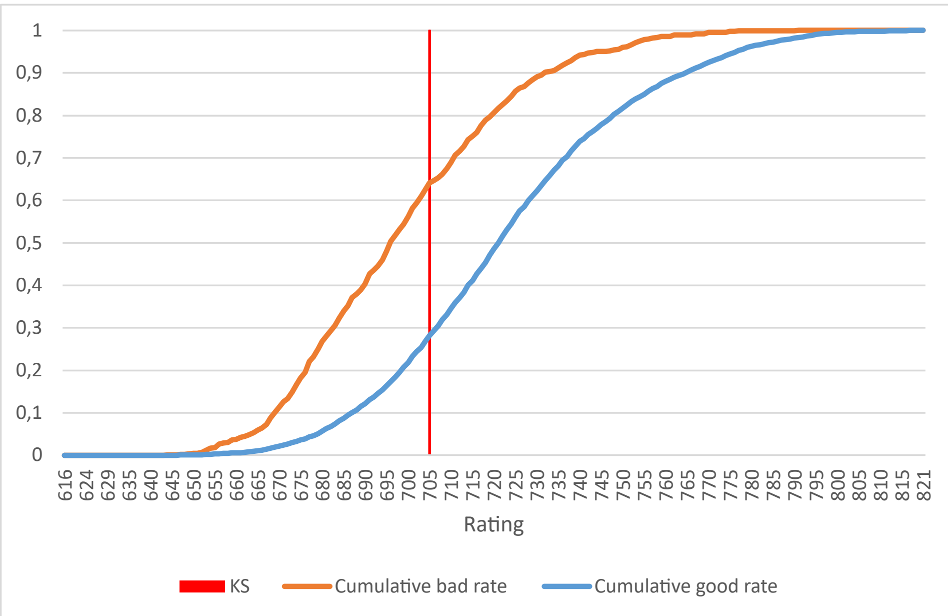


FIGURE D: MATERIAL DEFAULT



4.G Robustness analyses

Table 4.G.1. The impact of energy efficiency labels on mortgage arrears with interaction of quarter and deal FE (robustness). The table presents the marginal effects (in bps) from four specifications of panel logit regressions, where the dependent variables represent different indicators of mortgage delinquency. The dependent variables are: (1) arrears, (2) material arrears (arrears exceed 1% of the loan balance), (3) default, and (4) material default (default where arrears exceed 1% of the loan balance). The key explanatory variable is *Energy consumption*, measured in increments of 100 kWh/m². The interaction of Deal and Quarter Fixed Effects (Deal x Quarter FE) is used for robustness. Other control variables include loan, borrower, and collateral characteristics. Macroeconomic variables are omitted as they are captured by the Deal x Quarter FE. Robust standard errors are clustered at the regional level (3-digit postcode). The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1)	**(2)**	**(3)**	**(4)**
EPC kWh/m²/year:				
Energy consumption (per 100 kWh/m²/year)	4.36***	1.49***	2.48***	1.13***
	(0.69)	(0.36)	(0.40)	(0.26)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Collateral characteristics	Yes	Yes	Yes	Yes
Macro variables	No	No	No	No
Deal x Quarter FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0608	0.0745	0.0682	0.0741
Observations	4,437,702	4,214,721	4,349,998	3,831,518

Table 4.G.2. The impact of EPC labels on mortgage arrears with interaction of quarter and deal FE (robustness). The table presents the marginal effects (in bps) from four specifications of panel logit regressions, where the dependent variables represent different indicators of mortgage delinquency. The dependent variables are: (1) arrears, (2) material arrears (arrears exceed 1% of the loan balance), (3) default, and (4) material default (default where arrears exceed 1% of the loan balance). The key explanatory variable is the *EPC label*, categorized into three groups: A/B, C/D/E, and F/G. Other control variables include loan characteristics, borrower characteristics, and collateral characteristics. Macroeconomic variables are omitted as they are captured by the Deal x Quarter FE. Robust standard errors are clustered at the regional level (3-digit postcode). The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1)	**(2)**	**(3)**	**(4)**
EPC Label:				
EPC A/B (baseline)	-	-	-	-
EPC C/D/E	4.8841	0.6359	1.4911	0.5191
	(3.2952)	(1.6882)	(1.0432)	(0.7676)
EPC F/G	11.2718***	5.2212***	5.9358***	4.0318***
	(3.3505)	(1.6473)	(1.4069)	(1.0667)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Collateral characteristics	Yes	Yes	Yes	Yes
Macro variables	No	No	No	No
Deal x Quarter FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0558	0.0667	0.0589	0.0574
Observations	4,440,249	4,264,802	4,037,700	3,568,412

4.H EPC Rating conversion

Table 4.H.1. Conversion of EPC labels to energy consumption ranges across countries. This table provides the conversion between energy efficiency labels (A-G) and energy consumption ranges (in kWh/m²/year) used across various European countries, including Belgium, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, and the United Kingdom. Each row corresponds to a specific range of energy consumption and shows how that range is classified into energy efficiency labels for each country. This conversion helps standardise the EPC ratings used in the analysis by correlating them with energy consumption levels.

kWh/m²/year	Belgium			France	Germany	Ireland	Italy	Netherlands	Portugal	Spain	UK
	Brussels	Flanders	Wallonia								
≤ 0	A	A	A	A	A	A	A	A	A	A (≤ 36)	A (≤ 32)
0-5											
5-10											
10-15											
15-20											
20-25											
25-30											
30-35											
35-40											B
40-45										B (≤ 63)	
45-50	B										
50-55				B	B				B		
55-60											
60-65											
65-70										C (≤ 103)	C
70-75											
75-80					C	B			B-		
80-85											
85-90			B								
90-95				C							
95-100	C										
100-110		B			D		B		C	D (≤ 161)	D (≤ 135)
110-120											
120-130							C				
130-140					E						
140-150											E
150-160	D			D		C (≤ 175)	D		D		
160-170					F			B			
170-180			C (≤ 255)							E (≤ 291)	F
180-190											
190-200								C			
200-210		C			G		E		E		G
210-220	E (≤ 275)										
220-230											
230-240				E		D					
240-250											
250-260								D	F		
260-270			D				F				
270-280											
280-290	F (≤ 345)										
290-300								E (≤ 335)		F (≤ 367)	
300-310		D				E					
310-320											
320-330											
330-340				F							
340-350			E					F			
350-360	G						G				
360-370											
370-380										G	
380-390						F		G			
400-425		E									
425-450			F								
≥ 450				G		G					

Chapter 5

Conclusions

This thesis has explored how regulatory frameworks, both established and emerging, shape credit risk in the European residential mortgage-backed securities (RMBS) market. It has done so by evaluating the effectiveness of post-crisis securitisation reforms and by investigating the role of energy efficiency in credit risk modelling, particularly under conditions of macroeconomic stress. The three empirical chapters together offer a coherent analysis of how different dimensions of regulation influence the quality, structure, and predictive assessment of credit risk in securitised mortgage portfolios.

Chapter 2 assessed the general provisions introduced by the 2018 European Securitisation Regulation. The findings show that these provisions were successful in improving the overall quality of securitised mortgage loans. Specifically, loans issued under the new regulatory regime exhibited significantly lower delinquency rates. This improvement appears to stem not from changes in individual loan performance alone, but also from a shift in the composition of securitised pools, with a decline in high-risk characteristics such as high loan-to-value ratios and self-employed borrower segments. While the structural design of RMBS deals changed only modestly, we observe a notable increase in the share of AAA-rated tranches, indicating a positive impact on the perceived quality of securitisation structures.

These findings support the view that the general regulatory reforms helped realign incentives in the securitisation chain and encouraged more prudent selection of loans.

Chapter 3 extended the analysis to the STS framework and demonstrated that STS-labelled deals are associated with both stronger credit performance and simpler deal structures. Notably, the resilience of STS transactions became most apparent during the COVID-19 shock, when their delinquency rates remained substantially lower than those of non-STS deals. While concerns have been raised that the STS label might offer a false sense of security, the evidence presented in this thesis suggests the opposite: that greater standardisation and transparency can reinforce risk discipline and support market stability during periods of economic stress. The chapter also shows that STS deals are more likely to receive higher tranche ratings despite their simpler structures, indicating that improvements in the overall quality of the securitised pool outweigh any potential increases in risks linked to the securitisation structure.

Chapter 4 shifts the focus to a more recent regulatory priority: the integration of environmental risk factors into credit assessment frameworks. Using 4.5 million loan-level observations from the European DataWarehouse (2021–2024), this chapter evaluates whether energy efficiency—measured through EPC ratings—improves the predictive accuracy of mortgage credit risk models. Results show that the inclusion of EPC information leads to consistent and significant gains in model performance, particularly for default and material default outcomes. The EPC variable is shown to improve the predictive accuracy by up to 4.4% during the 2022–2023 period of high energy inflation. These findings confirm that energy efficiency is not merely a sustainability metric, but a financially material risk indicator that enhances model discrimination, especially under economic stress. Recognising the lower risk associated with energy-efficient homes can help improve loan pricing, incentivise green lending, and inform the design of policy tools such as subsidies and guarantees, ultimately supporting the green transition while also strengthening credit portfolios.

Taken together, the findings from this thesis show that regulatory design, whether aimed at structural reforms or climate goals, can have a measurable impact on credit risk in the mortgage market. The effectiveness of post-crisis reforms, particularly the STS framework, is reflected in the observed improvements in loan quality, deal structure, and credit performance during downturns. At the same time, growing regulatory attention to environmental risks is well placed: energy efficiency emerges as a key determinant of credit performance in the presence of inflationary shocks. By bridging these dimensions, this thesis contributes to a more integrated understanding of how evolving regulatory frameworks can enhance the resilience of mortgage markets in a changing economic and environmental landscape.

Limitations and avenues for future research

This thesis relies primarily on loan-level data from the European DataWarehouse (EDW), covering securitised mortgages reported between 2013 and 2024. While this dataset offers standardised, high-frequency information across a wide range of jurisdictions, it captures only those loans that meet ESMA disclosure requirements for securitisation. Securitised mortgages may differ from those retained on bank balance sheets in terms of origination standards, documentation, and borrower composition. As such, the findings presented in Chapters 2 and 3 are most directly applicable to the universe of publicly reported European RMBS and may not directly generalise to unsold loans or other geographies. This restricts the ability to assess the broader market-wide impact of regulatory reforms on credit risk and securitisation practices. Future research could address this gap by incorporating supervisory or internal bank datasets that include both retained and securitised exposures.

Another limitation of the regulatory analysis is its focus on the early years following the 2018 Securitisation Regulation, including the immediate onset of the COVID-19 pandemic. While the thesis documents meaningful changes in loan composition and performance, a longer-term assessment, capturing later years of regulatory implementation in more stable macroeconomic conditions, would provide a fuller picture of behavioural responses and structural adjustments across credit cycles.

Chapter 4, which evaluates the role of energy efficiency in credit risk modelling, also presents a few limitations that should be considered when interpreting the findings. First, the external validity of the results is constrained by data availability. A large share of mortgages lack EPC information, and banks that report EPCs may differ systematically from those that do not. Moreover, the analysis focuses on a period of heightened energy price volatility (2021–2024), which may amplify the importance of energy efficiency relative to more stable macroeconomic conditions. Caution is therefore warranted when generalising the results to bank-held portfolios, other EU jurisdictions, or different time periods. Second, while the analysis draws on detailed loan-level data, it lacks information from credit rating agencies (CRA), whose internal models and scores are widely used by lenders to assess retail mortgage risk. The absence of CRA ratings limits our ability to benchmark the incremental value of EPC information against existing proprietary credit assessments. Lastly, an important area for future research is to examine how the introduction of climate-related regulation, such as EPC-linked guarantees, green capital requirements, or disclosure mandates, shapes lender and investor behaviour. Understanding how such policies affect pricing, credit allocation, and securitisation practices will be essential to assess the long-term integration of climate risks into the European mortgage market.

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