Credit and Climate Risk in Green Debt Markets: Corporate Bonds and Energy Efficient Securitisation

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"Suddenly, you could no longer imagine a berry that would appear one day on a gooseberry bush, but only see the thorn that was there right now."

– Narrator

Declaration

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

Massimo Dragotto

December 1, 2025

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Acknowledgements

I'll keep this short, but that doesn't mean I'm any less grateful.

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This thesis was shaped slowly, with care and patience. It is for anyone who keeps going quietly in the background, even when no one is watching, even if it does not go as planned, "even if it's just growing gooseberries."

To all of you: thank you.

Abstract

This thesis explores how environmental information affects credit risk and pricing in fixed-income markets. It focuses on three areas: corporate green bonds, Green RMBS, and mortgage loans with energy performance data. The aim is to understand whether markets respond to environmental signals, and under what conditions these signals matter most.

The first empirical investigation examines corporate green bonds in the secondary market. The analysis shows that the negative yield differential of green over conventional bonds is dynamic and reacts to climate policy events. Certified green bonds in environmentally material industries enjoy a larger premium, while non-certified issues often face scepticism over greenwashing. Certified bonds also maintain narrower spreads during natural disasters and heightened media coverage of climate change.

The second empirical investigation studies Green Residential Mortgage-Backed Securities (RMBS) deals. Using detailed loan and tranche data, it finds that deals labelled as green are backed by loans with lower delinquency risk and are more likely to produce investment-grade tranches. Moreover, stress simulations confirm that green-labelled structures absorb smaller losses under adverse conditions.

The third empirical investigation shifts focus to property-level energy efficiency. It harmonises Energy Performance Certificate (EPC) data from multiple countries to test whether buildings' energy performance predicts loan-level delinquency. The results show that less efficient homes are associated with higher arrears and default risk, especially for lower-income borrowers and during periods of high energy inflation. These findings underline the importance of energy efficiency for loan-level credit risk assessment and its relevance to EU goals on the green transition and energy security.

Overall, the thesis shows that environmental features can enhance markets' assessment of risk, with three key insights: environmental factors are financially relevant, credibility is critical, and effects are context-dependent.

Keywords: Climate risk; Green bonds; Green RMBS; Energy efficiency; Mortgage delinquency.

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Chapter 1

Introduction

1.1 Background and motivation

Climate and energy risks now feature prominently in credit markets. Physical hazards (e.g., floods, heat, storms) and transition forces (e.g., policy shifts, new technologies, disclosure regimes) can alter cash flows, collateral values, and loss expectations. Fixed–income instruments sit at the centre of this transmission: yields and spreads respond to perceived risk; securitisation structures redistribute that risk; and borrower outcomes ultimately determine realised losses.

Three recent developments make a unified empirical assessment both timely and feasible. First, labelled *green* bonds have grown rapidly, often with third–party certification. This raises a pricing question: do markets reward credible environmental attributes, and is that reward stable or time–varying with climate salience and policy news? Second, green securitisation has emerged in Europe alongside new templates and labels. Residential mortgage–backed securities (RMBS) provide a clear link from borrower performance to tranche outcomes; if green deals package stronger collateral or structures, this should be visible in ratings and expected losses. Third, energy price volatility since 2021 has stress–tested household resilience. Energy Performance Certificates (EPCs) now allow standardised, EU–wide measurement of building efficiency at loan level, enabling tests of whether inefficiency raises delinquency risk and whether this effect is stronger for lower–income borrowers or during periods of high energy inflation.

This thesis studies how climate and energy information is reflected in prices and risk across three connected settings: corporate green bonds (Chapter 3), European Green RMBS and tranche outcomes (Chapter 4), and loan–level mortgage performance using EPCs (Chapter 5). A common theme is dynamics under salient conditions: the greenium moves with climate attention and certification; tranche resilience is assessed under stress; and borrower vulnerability rises when energy costs surge. The analysis uses secondary–market bond data, supervisory loan–level records from the European DataWarehouse (EDW), and tranche information from Refinitiv Eikon. Methods are standard and transparent (panel models with rich fixed effects; event–style analyses; simple, clearly stated loss simulations) to emphasise comparability and practical relevance.

1.2 Contributions to climate finance and credit risk

This thesis contributes to climate finance by examining how climate change, environmental credibility, and building energy efficiency are reflected in prices and risk across three parts of fixed–income markets: corporate green bonds (Chapter 3), European green residential mortgage–backed securities (RMBS) and tranche outcomes (Chapter 4), and loan–level mortgage performance using Energy Performance Certificates (EPCs) (Chapter 5). The overarching aim is to clarify when environmental information is priced, which forms of credibility matter, and how energy efficiency translates into credit outcomes. Three core questions motivate the empirical work: (1) how is environmental credibility priced in corporate bond markets, and how does this pricing move with climate attention and disaster news? (2) do green securitisations differ in collateral performance and tranche resilience once standard drivers are controlled for? (3) does property energy efficiency predict mortgage delinquency across the EU, and how do borrower income and energy price inflation shape this relationship?

The main contributions are both conceptual and empirical. First, Chapter 3 shifts the focus from issuance yields to secondary–market corporate spreads and treats the greenium as a time–varying object rather than a constant. Using issuer–level panels with rich fixed effects, the analysis separates the baseline green label from the incremental effect of certification, links green premia to climate–attention cycles and to climate–related disasters, and shows that certification strengthens pricing effects when attention is high. The chapter also brings sectoral environmental materiality into the pricing test: in industries where environmental issues are financially material, certified green bonds earn the largest spread advantage, while non-certified issues in the same sectors can even face a discount consistent with greenwashing concerns. Together, these results underline a simple message for corporate debt markets: credibility and context matter; verified environmental signals are rewarded, and the reward is stronger when climate risk is pressing.

Second, Chapter 4 provides the first systematic evidence on European Green RMBS performance and structure under the emerging EuGB and ESMA disclosure regime. Using loan–level data (EDW) matched to tranche records, the chapter documents that loans securitised in green–labelled deals are associated with lower delinquency and that this collateral advantage is reflected at the tranche level: green deals are more likely to be investment grade and display lower expected losses in scenario–based loss allocations. The analysis distinguishes deal-level labelling from collateral quality and shows that, even without a fully *all-green* asset pool, the combination of disclosure, selection, and structuring yields more resilient outcomes. Overall, the chapter links green labels to observable credit performance and offers a simple stress framework that highlights relative resilience across the capital structure.

Third, Chapter 5 uses the enhanced ESMA template to harmonise EPC information into a common consumption metric (kWh/m^2/year) and delivers the largest EU-wide study to date on energy efficiency and mortgage risk. The chapter shows a clear efficiency–risk gradient: loans on inefficient properties are more likely to become delinquent. The gradient is economically stronger for below-median income borrowers, consistent with tighter budget constraints, and it steepens in periods of elevated energy inflation. Methodologically, the contribution is to move from label categories to a harmonised energy efficiency measure at loan level and to test the mechanism under a natural stress episode (the 2021–2023 energy price surge). For banks and supervisors, the results speak directly to underwriting, provisioning, and model development: incorporating EPC-based efficiency improves risk differentiation, especially under energy–cost stress.

Across chapters, the thesis brings a coherent empirical design to different market layers: secondary–market bond pricing, securitisation structure, and loan–level performance. It combines widely used datasets (Bloomberg/Refinitiv for bonds, EDW for loans, Refinitiv Eikon for tranches) with standard panel models, fixed effects, and stress scenarios that emphasise relative differences rather than heavy model assumptions. The collective implication is that environmental credibility and energy efficiency are increasingly reflected in credit markets: certification and sectoral materiality shape corporate green premia; green securitisations transmit better collateral performance into stronger tranche outcomes;

and property efficiency reduces household credit risk, particularly when energy costs are high. These findings have direct relevance for issuers and originators (timing and design of labelled issuance, collateral selection), investors (pricing, portfolio construction, and stress management), and policymakers (the role of certification, disclosure, and EPC integration in aligning capital with climate objectives).

1.3 Structure of the thesis

Chapter 2 reviews the related literature. It introduces climate finance and climate risk (physical and transition), surveys the evidence on green bonds (green premia, stock market reactions, environmental performance, investor base shifts, and the role of certification), outlines the regulatory and market context for securitisation and Green RMBS in Europe, and summarises the links between energy efficiency, mortgages, and credit risk.

Chapter 3 (*Greenium Fluctuations and Climate Awareness in the Corporate Bond Market*) examines whether green bonds trade at a discount in secondary–market spreads, how that discount varies over time, and how certification, industry materiality, and salient climate events relate to the premium. It uses issuer fixed effects, controls for bond characteristics and liquidity, sovereign benchmarks, and time–varying interactions. This chapter is based on a peer-reviewed article published in the *International Review of Financial Analysis* (Dragotto et al., 2025).

Chapter 4 (*Energy Efficient Securitisation and Tranche Resilience in Mortgage–Backed Securities*) studies whether green–labelled RMBS deals are associated with lower loan–level delinquency and stronger tranche outcomes. It combines EDW loan records with tranche ratings and applies ordered logit models (in rating bands with recency weighting) and transparent loss simulations under moderate and severe Loss Given Default (LGD) settings.

Chapter 5 (*EPC Ratings and Delinquency Risk under Energy Inflation and Income Vulnerability*) uses the EPC–populated subset of EDW to test whether energy–inefficient collateral increases delinquency risk, and whether the effect is stronger for lower–income borrowers and when energy inflation is high. It implements panel logit models with extensive controls and explores arrears balances under continuous energy–inflation interactions. Chapters 4 and 5 build on a separate working paper (Billio et al., 2025).[1]

Chapter 6 concludes. It summarises the main findings, sets out limitations for each empirical chapter, and outlines directions for future research. For ease of reference, Table 1.1 summarises the empirical chapters, datasets, methods, and headline results.

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

Table 1.1. Overview of empirical chapters, data, methods, and main findings.

Ch.	Market & data	Core question	Main approach	Key findings
3	Corporate bonds; secondary-market spreads; certification data; disasters (EM-DAT); climate attention (MeCCO); sector materiality (SASB)	Do markets price green attributes persistently, and how do certification, sector materiality, climate attention, and disasters shape the greenium over time?	Panel models with issuer FE; spreads over sovereign curves; month-varying green $\times$ MeCCO; certification and sector-materiality interactions; 5-day post-event windows for EM-DAT	The greenium is time-varying and widens when climate attention is high; certification amplifies the effect and supports resilience after disasters. In environmentally material sectors, certified bonds earn the largest premia, while non-certified bonds can trade at a discount (greenwashing concern).
4	European RMBS; EDW loan–level data linked to deals; tranche ratings (Refinitiv Eikon)	Are green–labelled deals associated with better loan performance and more resilient tranche outcomes, and how does this show up in ratings and losses?	Panel logit for delinquency; ordered logit for rating bands with recency weighting; static loss allocation under LGD scenarios; robustness with Deal$\times$Quarter FE and benchmark-rate controls.	Green–labelled deals show lower delinquency, stronger rating profiles, and lower simulated losses across the capital stack; senior and mezzanine remain protected even under extreme default/LGD.
5	EU mortgages with EPC fields (EDW); macro indicators incl. energy inflation	Does energy inefficiency raise delinquency risk, and is the effect stronger for lower income borrowers and during high energy inflation?	Harmonised EPC kWh/m^2/year and efficiency tiers; panel logit with rich controls; interactions with income and energy inflation; arrears–balance models	A clear efficiency–risk gradient: low–efficiency loans are riskier; effects are stronger below median income and when energy inflation is high; results support a cash–flow channel and inform bank risk models and stress tests.

Chapter 2

Literature Review

2.1 Climate finance and climate risk

Climate change effects are arising in terms of climate patterns that are slowly changing over time (i.e., *chronic*), such as global warming, melting glaciers, sea level rise, but also in the form of (*acute*) meteorological phenomena or extreme weather events, such as floods, droughts, storms (BIS, 2021; Financial Stability Board, 2017). The repercussions on societal and economic dynamics are tangible: increasing damages caused by natural disasters, costs to be borne by exposed businesses, environmental migrations and so on (Miles-Novelo & Anderson, 2019). The magnitude and capillarity of the resulting consequences suggest that protection from climate risk is of public interest, thereby warranting public sector intervention (Noy, 2020) and global cooperative climate policies capable of overcoming (cross-country and inter-generational) free-riding (Nordhaus, 2015). Timely consideration of adaptation and mitigation measures by policymakers may help limit further losses and stabilise the trend. However, if investors were willing to pay a premium for financing the transition to a net-zero economy (Preclaw & Bakshi, 2020), then green finance would play a dual role, both as an adjunct to the public sector and partially bypassing it (Fatica &

Panzica, 2021; Henide, 2021). Nevertheless, it must be noted that investors "do not acquire any additional or superior claims" on potential positive externalities by holding green assets (Henide, 2021). Therefore, the reasons *why* they would pay such a premium deserve deeper investigation. Possible explanations could be tied to shifts in investor sentiment and to their anticipation of losses caused by climatic events, shocks due to changing policies and market dynamics, or an interaction of the two. More recent work stresses that climate risk affects the entire financial system through channels such as asset repricing, credit risk deterioration, and macroeconomic shocks (ECB, 2021). These channels blur the line between public and private risk-bearing and underline why climate finance has become central to debates on financial stability.

Climate finance seeks to translate climate risk into financial terms and its consequences into pricing implications. To model climate risk between the two main sources of risk. On the one hand, *physical risk* stems from a direct channel, namely climatic events (storms, sea rise level etc.) that can damage physical assets and reduce their value and productivity. On the other hand, *transition risk* refers to the changing path of the economic system in the attempt to find a solution to climate change. This channel may (in)directly trigger financial losses for institutions unable to adapt to policy and regulatory shifts, technological innovations, changes in investor taste and market sentiment (ECB, 2021; Giglio et al., 2021). The promptness and intensity of the "corrective transition response" is likely to determine the prevalence of the former or the latter risk. A limited effort to transition is linked to growing future physical risks. On the other hand, the stronger the corrective response, the higher the transition risk (Colas et al., 2019).[1] Thus, delayed policy action increases systemic losses while abrupt policy shifts can trigger financial instability.

In the following pages, we briefly review a handful of papers that study if financial markets reflect these risks. We divide them into two main strands, based on whether they discuss the impact of physical risk (Section 2.1.1) or transition risk (Section 2.1.2).

2.1.1 Physical risk

Measuring physical risk requires considering multiple factors, such as (i) the probability and intensity of the climatic event and (ii) the exposure of the institution that is affected. As far as climatic events are concerned, either meteorological data (observational records, projections, climate indices, etc.) are used (Addoum et al., 2020; Balvers et al., 2017; Hong et al., 2019; Tankov & Tantet, 2019), or, alternatively, natural disaster datasets (Huynh & Xia, 2021), which are particularly useful because they provide a direct view of the economic damage caused by climatic events.

The exposure of the entity whose climate risk is measured requires, instead, the use of data that are specific to that entity, such as the value of its assets, the geographical location, and the adaptability potential.

It is not always possible to find a link between general physical risks and their impact on firms' fundamentals. Using historical daily data on temperatures in the United States and establishments data (1990–2015), Addoum et al. (2020) test the existence of a causal

[1] For instance, as Isabelle Schnabel, Member of the Executive Board of the ECB, highlighted with regard to the ongoing energy crisis, green policies and green finance are contributing to the rise in carbon price. While this price change is desirable, it can weigh on the economy if firms and households cannot promptly replace more expensive carbon-intensive energy with cleaner, cheaper alternatives. See "Looking through higher energy prices? Monetary policy and the green transition," *Panel on Climate and the Financial System*.
URL: https://www.ecb.europa.eu/press/key/date/2022/html/ecb.sp220108~0425a24eb7.en.html.

relation between anomalies in the temperature and firms' fundamentals. They do not find a link between these shocks and firm performance in terms of sales and profitability.

However, when hypotheses are tested on specific sectors that are more plausibly affected by certain types of climatic events, results seem to confirm such a relation. Hong et al. (2019) find that food companies' profit growth is affected by droughts and further hypothesise that there are repercussions on stock returns in the food sector of countries exposed to such climatic events. To model their assumption on droughts' effect, they use the Palmer Drought Severity Index (PDSI), which estimates local relative dryness by means of temperature and rainfall data. The strategy employed is to construct a portfolio shorting stocks with undesirable values of PDSI and buying those with high PDSI. They conclude that since their portfolio produces excess returns, the implied predictability of such returns indicates that the market is underestimating climate change risks. Another example comes from Rao et al. (2021), where Indian monsoon data are shown to depress rain-sensitive companies' market value.

Balvers et al. (2017) add to the Fama and French (1996)'s factor model a temperature shock factor, finding that the risk premium for it is significantly negative, causing the cost of capital to be 0.22 bps higher as a result of temperature uncertainty. Moreover, including such a factor raises the average cross-section R^2 in industry-sorted portfolios. A very different approach to proxy physical risk is adopted by Nagar and Schoenfeld (2019). Using data-mining techniques on companies' annual reports, they build an index capturing the recurrence of the word *weather*. Not only is the index found to be a good proxy for physical exposure, since it assumes significantly higher values after a business is hit by a severe storm, but it is also shown to be priced as a risk factor in the cross-section of returns. Huynh and Xia (2021) use data about companies' establishments hit by natural disasters. They find that when companies' sales are weakened after a disaster occurs, investors' overreaction in the U.S. bond and stock market decreases current prices and causes future returns to be higher. They also find that securities of companies with strong environmental profiles are more resilient and experience lower selling, even when their fundamentals are hit. More recent studies highlight heterogeneity in the pricing of physical risk. For instance, Bansal et al. (2016) show that long-run temperature risk is priced in equities but varies strongly by industry, geography and firm-resilience.

2.1.2 Transition risk

The category of transition risks is relatively new in the field of climate finance.[2] Transition risk is associated with the change in strategy, policy, or investment as society and industry work to reduce carbon dependence and its impact on climate.

While the variables used to identify physical risk exposure are harder to find and require some degree of specificity in order to be significant, transition risk proxies are typically easier to construct. For example, proxies for involvement in polluting activities are often used, since polluting sectors are more exposed to transition shocks. One obvious case concerns fossil fuel energy suppliers: they are increasingly exposed to the risk of future policies on carbon emissions and more likely to bear the costs of technological change. This eventually translates into higher return premia associated with growing rates of carbon emissions, which are shown to increase when domestic climate policies are stricter (Bolton & Kacperczyk, 2020). On this topic, several studies suggest that the so-called "carbon premium" is related to the emergence of environmental policy uncertainties, ruling out other possible explanations such as institutional divestment (Bolton & Kacperczyk, 2021b),

[2]See, for instance, "Climate change: what are the risks to financial stability?", Bank of England. URL: https://www.bankofengland.co.uk/knowledgebank/climate-change-what-are-the-risks-to-financial-stability

existing systematic risks, investors' preference, and market sentiment (Hsu et al., 2020). Other studies consider that, similarly to the dynamics determining that non-sin stocks are outperformed by sin stocks (Hong & Kacperczyk, 2009), stocks of companies with higher environmental scores are outperformed by the "browner" — i.e., the greener stocks have negative "alphas" (Pástor et al., 2021). The reason is that, on one hand, investors enjoy holding green assets; on the other hand, in case of climate shocks, brown assets may lose value relative to green ones and investors must be offered higher returns to compensate.

It follows that ESG scores can be used to proxy climate risk exposures to build strategies to dynamically hedge climate change risk exposures (Engle et al., 2020). Subsequent work shows that spikes in climate-related media coverage, proxied by MeCCO news indexes, are followed by capital reallocation toward greener assets and stronger pricing of transition risk, consistent with investors updating beliefs about regulation and technology (Bua et al., 2022; Chen & Takahashi, 2024; Cornelli et al., 2025). These findings highlight the interaction between policy signals, investor sentiment, and financial markets in shaping transition risk pricing.

2.2 Green bonds in climate finance

Born in 2007,[3] green bonds have become central to climate finance, channelling private capital into environment-related projects such as renewable energy, energy efficiency, waste management, green buildings, and biodiversity conservation. The rationale is that proceeds are earmarked for green activities, thereby supporting the transition to a net-zero economy. Since 2014, the market has expanded rapidly, with cumulative issuance surpassing USD 2 trillion by 2023 (Climate Bonds Initiative, 2024). This growth has been

[3] See "EIB issues inaugural sterling green bond," Financial Times, March 26, 2016.

underpinned by voluntary market standards (ICMA Green Bond Principles, GBPs) and more recently by regulatory initiatives such as the EU Green Bond Standard (EUGBS) formally adopted in 2023. The EUGBS aims to create a unified regime, addressing concerns about inconsistent definitions and greenwashing, and requiring alignment with the EU Taxonomy of sustainable activities. Nevertheless, green bonds and green finance more broadly raise a number of questions. The literature on impact investing explores whether social and environmental (i.e., non-pecuniary) motives enter the utility function of investors. In light of the growing attention to climate change, social issues, and their consequences, investors' tastes for Environmental, Social, and Governance (ESG) instruments and Corporate Social Responsibility (CSR) are playing an increasingly important role in investment decision-making. In relation to green bonds, key research questions include the existence of a "greenium" (or green bond premium), stock price reactions, the role of external certifications, the impact on issuers' environmental performance, and the extent to which issuers genuinely pursue green goals after issuance rather than engaging in greenwashing. Recent studies have also examined the role of climate news and investor sentiment in shaping the pricing of green bonds, highlighting "halo effects" whereby positive environmental reputation spills over to issuers' conventional securities (Bae et al., 2019; Caramichael & Rapp, 2024; Sangiorgi & Schopohl, 2021).

2.2.1 Previous studies on green bonds

Green bonds are potentially valuable tools to finance green projects and, thus, the green transition. Perhaps this is also one of the reasons why the percentage of issuers belonging to polluting sectors is (up to four times) higher in the green bond market compared to the overall bond market (Ehlers & Packer, 2017) and there is survey evidence that asset managers "prefer green bonds by non-financial corporates in the industrials, automotive and utilities sectors," notably amongst the most polluting ones (Sangiorgi & Schopohl, 2021).

However, many questions have arisen with reference to this financial instrument. In this section, we focus on few of the most relevant empirical studies regarding green bonds. Amongst the main topics investigated in this area are the existence of a "greenium" (Baker et al., 2018; Fatica et al., 2021; Flammer, 2021; Gianfrate & Peri, 2019; Hachenberg & Schiereck, 2018; Karpf & Mandel, 2018; Larcker & Watts, 2020; Pastor et al., 2021; Zerbib, 2019) and a post-announcement stock price reaction (Flammer, 2021; Tang & Zhang, 2020), the improvement of issuers' environmental performance after the issue (Dorfleitner et al., 2020; Fatica & Panzica, 2021; Fatica et al., 2021; Flammer, 2021), the role of certifications (Dorfleitner et al., 2020; Fatica & Panzica, 2021; Flammer, 2021; Gianfrate & Peri, 2019; Pietsch & Salakhova, 2022) and the change in issuers' investor base (Flammer, 2021; Tang & Zhang, 2020).

2.2.1.1 Green bond premium and stock market reaction

Green bond premium. One of the main hypotheses tested is whether green bonds sell on average at a higher price ("greenium") than conventional bonds. From a purely theoretical point of view, the only difference between the two types lies in the specification of green "use of proceeds" and, therefore, for same credit profiles, they should respond to flat pricing dynamics (i.e., holding other factors constant, green bonds should not sell at a higher price).[4] Despite this "pari passu" principle, investors' taste may still shift equilibrium prices (Fama & French, 2007). Since investors consider commitments with environment and society as value-enhancing (Chava, 2014), in the specific case of the green

[4] See "Explaining green bonds," *Climate Bonds Initiative*. URL: https://www.climatebonds.net/market/explaining-green-bonds.

bond market, they may be willing to accept lower yields for holding sustainable instruments, potentially lowering the cost of debt financing for issuers. Findings regarding this kind of phenomenon are mixed. They vary according to the market where the analysis is carried on, the time frame and the definition of green bond considered.

Analysing a sample of green municipal bonds (according to the label assigned by Bloomberg), Baker et al. (2018) and Karpf and Mandel (2018) find differing results: a premium and a discount respectively. However, Flammer (2021) and Larcker and Watts (2020) believe that this discordance of results derives from methodological flaws. The model used in the former (pooled fixed effects) does not sufficiently account for the differences between green and non-green bonds and biases the estimates towards the discovery of a greenium. The latter study, instead, finds a "green discount" because it ignores tax implications in the municipal bond market.[5]

Furthermore, Larcker and Watts (2020) employ a matching strategy to compare the yield at issue of municipal green and non-green securities. Their results contradict the presence of the premium: green and conventional bonds appear to be flat-priced. Also Flammer (2021), applying the same methodology, but on a sample of corporate bonds, finds no differential. However, Flammer (2021) hypothesises that this pattern could change in the years to come because, once the market expands and the set of profitable green projects narrows, future green investors will have to settle for lower yields.

Zerbib (2019) broadens the sample to various types of bonds (corporate, financial, municipal, sovereigns, supranational & agencies) and pairs every green bond to a conventional bond with similar characteristics. A small, albeit significant premium in favour of green bonds is found. According to the author, a possible explanation for such a premium lies in

[5]Many green bonds in the sample were actually taxable, thus, not surprisingly, paid higher yields. In fact, after-tax yields could have been lower.

the reduction financial risk due to the creation of intangible (reputational) value. Using the same methodology, Hachenberg and Schiereck (2018) and Ehlers and Packer (2017) examine bonds that meet a more strict definition of green (i.e., those certified by CBI) and both detect a statistically significant premium.

Fatica et al. (2021) draw on the Dealogic database and find that supranational and non-financial green bonds sell at a premium if compared to conventional ones. However, despite being more frequently certified, this is not true in relation to bonds issued by the financial sector. They argue that investors' difficulty to directly link financial bonds to green activities is responsible for this inconsistency.

Finally, Pastor et al. (2021) discover a greenium in the German sovereign bond market. Comparing two bonds with identical characteristics, except for the green label, they find that the green bond always has a lower yield to maturity. By building a portfolio that goes long the 10-year green bond and short the non-green twin, the cumulative realised returns accrue stably, in spite of the lower promised yield. They attribute this phenomenon to a shift in investor taste that pushes up the price of green securities, presumably due to growing concerns related to climate change issues.

Stock price reaction. The results regarding investors' consideration of the green signal sent by green bond issuers are more consistent. Tang and Zhang (2020) and Flammer (2021) use an event study methodology to examine the stock price reaction around the announcement date of a green bond issue. Both find that in the time window containing the date of the announcement, companies experience positive cumulative abnormal returns (CARs). When compared with previous studies in corporate finance showing no significant stock price reaction following the announcement of (conventional) bonds (e.g. Eckbo et al., 2007), it becomes more evident that the CARs are observed precisely because of the *green nature* of the bond. This result is in harmony with the works in the ESG literature supporting that investors perceive environmental commitment as value-enhancing (Klassen & McLaughlin, 1996; Krüger, 2015).

2.2.1.2 Environmental performance

A major concern for sustainability-oriented lenders is that borrowers' declared intentions will not be subsequently fulfilled. We refer to non-compliance with sustainable "use of proceeds" by issuers of green bonds as a form of "greenwashing". Especially in absence of strict regulations and enforcement schemes, issuers may decide to attract investors with a taste for sustainability, take advantage of the reputational effect stemming from green bond issuance and then divert the proceeds to other-than-green activities.

Few studies examine whether companies do undertake actions to actually improve their environmental performance following the issue of green securities. Flammer (2021) builds a sample of green and comparable non-green bond issuers through a matching approach. The matched control is a firm as similar as possible to the green bond issuer *ex ante*[6] to overcome potential endogeneity concerns.[7] To estimate the post-issue difference in performance between the two groups, a difference-in-differences specification is implemented. Results indicate that green bond issuers improve their environmental performance, both in terms of higher ASSET4 Environment rating (Thomson Reuters) and lower direct (Scope 1) CO_2 emissions. The improvements are unlikely to be driven solely by the projects financed through green bonds, but, again, this is consistent with a signalling argument and, on the contrary, it rules out the validity of the "greenwashing" argument.

[6] Tobin's Q, ROA, leverage, size, company's ESG ratings at time (t-1) and (t-2) w.r.t. the green bond issue date are used to compute the Mahalanobis distance. The company with the shortest Mahalanobis distance is the one chosen as comparable to perform the counterfactual analysis.

[7] The choice of issuing a green security may be endogenous with respect to the environmental performance, thus potentially inducing a spurious relation.

Fatica and Panzica (2021) investigate whether non-financial corporations improve their performance both in terms Scope 1 and overall CO_2 emissions after the issue of green bonds. They find a reduction of the emissions, and the effect is stronger when green bonds use of proceeds is not for refinancing purposes (but for financing new projects only). Fatica et al. (2021) analyse how financial institutions' syndicated lending policies change after the issuance of green bonds. They find that financial institutions make their balance sheet greener not only in the liability side (by issuing green securities), but also in the asset side (by reducing lending towards highly polluting sectors).

2.2.1.3 Shifts in the investor base

Some studies have examined the role of green bonds in bringing in different types of investors. According to Chiang (2017), green bonds attract eco-friendly investors, which helps diversify the investor base. To test this hypothesis, Larcker and Watts (2020) draw on the MSRB transaction database to build two measures: a proxy for institutional ownership and a Herfindal-Hischer concentration index (HHI) to quantify ownership concentration. Their goal is to investigate whether any differences are found between green and non-green bonds. Although no statistically significant differences are found with regards to institutional ownership, green bonds have substantially lower HHI ownership (thus, a more diverse investor base).

Tang and Zhang (2020) focus on the presence of institutional investors amongst shareholders. They find that after issuing a green bond, companies enjoy a greater presence of institutional investors in their ownership structure. However, by adding a dummy that differentiates the type of institutional investors between domestic and foreign, they find the relation to be affected by a domestic bias, i.e., the effect is positive and statistically significant with respect to domestic investors only. They link this effect to the media exposure to which green bond issuers are generally subject to.

Moreover, Flammer (2021) inspects the change in the percentage of long-term and green investors in the ownership structure of green bond issuers. She adopts two different measures to identify long-term investors: i) those whose duration measure[8] is above the median and ii) those whose churn rate is below the median across all investors. Running a difference-in-differences regression, she confirms that the percentage of long-term investors increases. The same holds if the measure of long-term investors is replaced by a measure of green shareholders.[9]

2.2.1.4 The role of certifications

To partially tackle potential concerns about the authenticity of the eco-friendly commitment, green bond issuers can obtain a certification, subject to the positive assessment of an external reviewer. There seems to be consensus on the role of certifications and their effectiveness: they are linked to higher improvements in the post-issuance environmental performance (Fatica & Panzica, 2021; Fatica et al., 2021; Flammer, 2021). Consistent with the findings about investors' positive response towards voluntary disclosure of green investments (e.g. Martin & Moser, 2016), the announcement of a *certified* green bond issue induces a more pronounced positive stock price reaction and, subsequently, greater participation of long-term investors in the ownership structure (Flammer, 2021).

Dorfleitner et al. (2020) match green and non-green bonds to test the existence of a "greenium." In the overall sample the greenium is absent, but, when the bond is certified, the greenium appears and its magnitude positively depends on the "shade of green" the

[8]The duration measure captures the holding horizon of investors and it is computed following the methodology in Cremers and Pareek (2016).

[9]Green investors are identified by Flammer (2021) as those who are members of the Ceres Investor Network on Climate Risk and Sustainability.

external review ascribed to the bond: the darker the shade (i.e., the greener the investment), the larger the spread between green and non-green bonds. However, one may suspect this cheaper financing effect may be offset by the additional cost that the external review entails. Gianfrate and Peri (2019) overcome such a concern and find that, notwithstanding the additional cost for the external review, green bonds still provide cheaper financing. Conversely, Larcker and Watts (2020) find that the certification for municipal bonds does not produce "incremental yield benefits" with respect to non-certified green bonds and conventional bonds in general.

2.3 Securitisation, regulation, and Green RMBS

Securitisation pools granular loans and transforms them into tranched securities. By slicing cash flows into notes with different levels of subordination, banks can reduce their regulatory capital burden, while investors have the flexibility to choose securities that match their risk–return preferences. Research shows that securitisation acts as a mechanism for transferring credit risk, and its use tends to increase when the regulatory framework and institutional conditions are favourable (DeMarzo, 2005; Loutskina, 2011; McGowan & Nguyen, 2023). However, before the 2008 financial crisis, securitisation was also used in ways that undermined financial stability. In particular, tranching and off-balance-sheet structures were sometimes employed to reduce capital requirements without meaningfully transferring risk, raising concerns about regulatory arbitrage and systemic fragility (Acharya et al., 2013). In response to these failures, European policymakers introduced a single securitisation rulebook along with the Simple, Transparent, and Standardised (STS) framework. This framework establishes minimum requirements for risk retention, due diligence, and transparency, and includes comparability criteria designed to limit structural complexity and enhance supervisory oversight (The EU Parliament and Council, 2017; Varouchakis, 2024). At the heart of these reforms is a strengthened role for disclosure, aimed at improving market discipline and restoring trust in securitisation markets. Empirical evidence suggests that the reforms have been effective: the new rulebook produced deals with lower delinquency rates and greater resilience during economic downturns, reflecting both better underlying loan quality and simpler, more transparent deal structures (Billio et al., 2023).

Green RMBS add an environmental layer to the transparency rules that govern securitisation, aligning this financial tool with the EU's wider strategy for sustainable finance. By directing private capital towards building renovation and energy-efficient housing, Green RMBS support the EU's energy policy objectives to reduce emissions, lower household energy bills, and improve energy security. These goals are particularly relevant in the building sector, which accounts for a large share of the EU's energy use and carbon emissions (European Commission, 2020a, 2020b; The EU Parliament and Council, 2023a). From a financing perspective, securitisation plays a practical role by recycling capital: it allows lenders to transfer existing loans off their balance sheets and use the freed-up capacity to issue new green mortgages. At the same time, it offers investors exposure to diversified loans with different levels of credit risk. This mechanism helps address the EU's substantial green investment gap, with annual funding needs estimated at over €300 billion (European Commission, n.d. European Investment Bank, 2023; Fitch Ratings, 2022a). Recent regulatory developments have clarified how green standards apply to structured finance. Under the European Green Bond Regulation (EuGB), securitisations that use the official green label must meet the use-of-proceeds requirement. This means that the underlying pool of loans does not need to be entirely green, but the capital raised must still finance projects that comply with the EU Taxonomy. Transparency requirements are still evolving, and the expectation is that, as the stock of energy-efficient loans grows, future green-labelled securitisations will also need to show stronger environmental performance at the asset level (The EU Parliament and Council, 2023b).[10] In parallel, the EU Securitisation Regulation requires securitisations backed by residential mortgages or auto loans to disclose any available environmental performance information on the underlying assets. This improves transparency, supports investor due diligence, and reduces the risk of greenwashing (The EU Parliament and Council, 2017). Taken together, these elements position Green RMBS as a scalable and policy-aligned financing tool to attract private investment in support of the EU's 2030 climate targets and the transition to a more energy-efficient housing stock (Andersson et al., 2025). Whether and to what extent a green label affects RMBS pricing, credit performance, or investor perception is ultimately an empirical question, which is examined in the analysis that follows.

2.4 Energy efficiency and credit risk

Energy performance affects credit risk through the affordability channel. Inefficient homes tend to have higher and less flexible energy bills. When income is disrupted by shocks, these households have less room to adjust, increasing the likelihood of missed payments (Kaza et al., 2014). This channel operates alongside typical drivers of mortgage risk, such as income, employment status, interest rate, house price movements, etc. At the borrower–property level, energy efficiency influences both the flow and the stock of credit risk. On the flow side, higher utility bills reduce affordability margins, making marginal borrowers more vulnerable to arrears during adverse conditions (Bell et al., 2023; Kaza

[10] Guidance and legal summaries confirm this interpretation. However, as more energy-efficient mortgages enter the market, the flexibility currently allowed for mixed pools is expected to be reduced (Commission de Surveillance du Secteur Financier (CSSF), 2024; The EU Parliament and Council, 2023b).

et al., 2014). On the stock side, expected energy costs are capitalised into property prices. Inefficient homes tend to sell at a discount compared to similar efficient ones (Aydin et al., 2020; Hyland et al., 2013). Evidence on environmental certifications and advanced building technologies points in the same direction, showing stronger price and rent performance and lower turnover for better-performing properties (Devine & McCollum, 2022; Sanderford et al., 2015). Lower collateral values, combined with fixed debt obligations, reduce equity buffers and may lead to higher losses if default occurs (Aydin et al., 2020; Hyland et al., 2013). At the policy level, energy efficiency is a central tool in the EU's strategy for climate goals and energy security. The 2023 Energy Efficiency Directive outlines measures to reduce greenhouse gas emissions, lower energy bills and import dependence, and address energy poverty while improving air quality and economic resilience (The EU Parliament and Council, 2023a). Targets include at least a 55% cut in emissions by 2030 relative to 1990, a fully decarbonised building stock by 2050, and a 32.5% improvement in energy efficiency by 2030 compared to 2007 levels (European Commission, 2020a, 2020b).[11] Meeting these goals requires significant investment. Annual investment needs exceed €300 billion, with a financing gap of around €165 billion. While public funding has increased, most capital must come from private sources (European Commission, n.d. European Investment Bank, 2023).

In practice, Energy Performance Certificates (EPCs) provide a common metric for building efficiency and a basis for disclosure, valuation, and regulatory monitoring. Ongoing efforts to expand and harmonise EPC coverage will improve data quality and comparability for lenders and researchers (The EU Parliament and Council, 2024). Efficiency also interacts with transition risk. Poorly performing homes face higher running costs and

[11] Earlier 2020 targets, including a 20% cut in emissions and a 20% gain in efficiency, were exceeded (European Commission, 2022; European Environment Agency et al., 2021).

retrofit needs as environmental standards tighten, increasing the risk of becoming stranded. In contrast, efficient homes offer some protection from these risks (Ferentinos et al., 2023). Despite this, there is still limited evidence that lenders systematically incorporate energy efficiency into mortgage pricing (Bell et al., 2023). From a modelling perspective, the key question is whether energy-related variables improve predictions of credit risk beyond standard drivers. In probability-of-default models, this can be tested by examining the incremental contribution of EPC-based indicators after accounting for loan-to-value, income, employment, and other relevant factors (Kaza et al., 2014). Existing evidence is supportive but scattered across countries. In the United States, ENERGY STAR homes are associated with lower default and prepayment risk (Kaza et al., 2014). In the United Kingdom, mortgages on more efficient homes are less likely to enter arrears, even after controlling for income (Guin & Korhonen, 2020). In the Netherlands, more efficient properties are linked to lower default probabilities (Billio et al., 2021).

Chapter 3

Greenium Fluctuations and Climate Awareness in the Corporate Bond Market

3.1 Introduction

Climate change has become one of the most pressing challenges of our time, and its potential impact on the global economy is increasingly being recognised by academics and policymakers alike. A growing body of literature literature in Environmental, Social, and Governance (ESG) finance, and more specifically in climate finance, has been focusing on the role of green bonds as financial tools for funding green projects and, thus, facilitating the green transition. One of the most debated topics in this area is whether green bonds sell at a higher price, the so called "greenium," than conventional bonds. This phenomenon has profound implications for companies, investors, and policymakers. The existence of a greenium could potentially encourage companies to adopt more environmentally friendly investments, thus accelerating the shift towards a net-zero economy. However, this also introduces a risk: firms could potentially leverage the greenium to secure cheaper financing while indulging in greenwashing—that is, issuing green bonds without a genuine commitment to environmental responsibility. For policymakers, this underscores the importance of regulatory oversight and transparency in the green bond market to foster authentic green investments and curb potential misuse.

Standard theoretical models suggest that, if identical except for their 'green' label, green and conventional bonds should be priced equally.[1] Thus, a discrepancy in pricing could point to a market inefficiency. Alternatively, this difference could suggest that investors value environmental sustainability more, indicating a shift in their investment preferences. Existing research provides conflicting evidence regarding the presence, magnitude and sign of the greenium (e.g., Baker et al., 2018; Karpf & Mandel, 2018; Larcker & Watts, 2020).

To the best of our knowledge, ours is the first paper to present empirical evidence for the impact on the greenium of increased climate awareness due to major climate policy discussions, political events, natural disasters, and media coverage.

Building on the seminal work of Flammer (2021), which explores the yield differences between green and conventional bonds at issuance, we adopt a distinct approach and arrive at different results. Flammer (2021)'s study employs a univariate difference-in-means approach and concludes that there is no significant difference in yields between green and conventional bonds at issuance. In contrast, we compare the performance of green versus conventional bonds over time within a multivariate regression framework and identify a discernible greenium. Additionally, by focusing our analysis on the yield spread over treasury yields, rather than solely on the yield itself, we effectively minimise potential biases from fluctuating interest rate conditions. This methodological shift enables a comprehensive analysis of the dynamics of the greenium over time and in relation to changes in climate

[1] Given that the credit profile of green bonds mirrors that of conventional bonds from the same issuer, the pricing dynamics of these two should theoretically align, keeping other factors constant. As such, green bonds and conventional bonds are "pari passu" in their pricing structures. See *Explaining green bonds*, *Climate bonds initiative*. : https://www.climatebonds.net/market/explaining-green-bonds.

awareness and market sentiment. The identification of a sentiment-driven greenium has practical implications. First, it allows investors to align their investment strategies more effectively with market sentiment. Secondly, it presents an opportunity for companies to coordinate the timing of their green bond issuances with periods of heightened climate awareness.

We contribute to the existing literature in three main ways. Our first contribution is an analysis of the influence of natural disasters on the performance of green bonds. While we note that natural disasters typically have an adverse effect on bond performance, this is not the case with certified green bonds. The result of a negative financial performance when disasters strike aligns with existing studies which have highlighted how such calamities can cause infrastructure damage, property losses, economic activity disruptions, and uncertainty about future prospects in impacted regions (Lanfear et al., 2019; Nagar & Schoenfeld, 2019; Pankratz & Schiller, 2022). This leads to increased risk-aversion and higher yields. However, we show that certified green bonds defy this trend, exhibiting a positive return during such events. Moreover, we find a direct correlation between the severity of the disaster and the divergence in the return of certified green bonds versus conventional bonds. For instance, we observe that as we transition from the scenario with no climate damage to the 99% quantile of the dollar damage distribution, uncertified green bonds demonstrate an increase in yield spread of 8 basis points (bps) (equivalent to 10.5% of the average yield spread in the matched sample). On the other hand, certified bonds experience a decline of 13.2 bps (17.4% of the average yield spread). Our results emphasise the significance of disaster risk for bond pricing while also highlighting the potential hedging advantages for certified green bond holders. This corroborates previous research on the resilience of financial instruments with strong environmental profiles in the aftermath of natural disasters (e.g., Huynh & Xia, 2021; Yang, 2021).

Our second contribution is an examination of the influence of heightened climate awareness on the greenium. We identify two distinct effects linked to a one standard deviation increase in a popular climate awareness indicator, the Media and Climate Change Observatory (MeCCO) World index. First, we see an overall modest reduction in yield spreads of 2.1 bps for bonds issued by green issuers. Second, we find a greater reduction of 6.25 bps, equivalent to 8.23% of average yield spreads, for certified green bonds. Both are statistically significant at the 1% level. Our findings are consistent with Huynh and Xia (2020) who show that investors are prepared to pay a premium for bonds issued by companies with high E-scores during periods of heightened climate awareness. This phenomenon can be attributed to a shift in investor sentiment driven by increased media coverage of climate change.

Our research also adds new insights into the role of certifications and external reviews within the green bond market. The literature has yielded various findings on this topic. Prior studies highlight how green bond certifications can lead to a spike in the borrower's stock price post bond-issuance and ignite interest from long-term and green investors (Flammer, 2021). Moreover, only green bonds that have undergone certification are associated with lower borrower's emissions (Fatica & Panzica, 2021) and a persistent greenium (Pietsch & Salakhova, 2022). Building upon these findings, our analysis reveals that certified green bonds are associated with an up to fivefold larger average greenium than uncertified bonds. Furthermore, our findings show that certified green bonds in high environmental impact industries[2] enjoy a significantly larger greenium compared to those in less impactful

[2] High environmental impact industries are defined as those classified by the Sustainability Accounting Standards Board (SASB) with a materiality score of 3 or higher. These include Chemicals, Coal Operations, Construction

industries. This reflects investors' preference for credible environmental improvements in environmentally material sectors (Ehlers & Packer, 2017; Sangiorgi & Schopohl, 2021). Conversely, non-certified green bonds in these sectors are often viewed with scepticism and may even face a discount, likely due to concerns over greenwashing. These findings have important policy implications. By advancing rigorous certification standards, policymakers can boost investor confidence and help direct capital to high-impact sectors, where it could have the greatest effect in reducing pollution. Therefore, certification could play an important role in achieving environmental targets and supporting the credibility of climate-focused investments.

Our third contribution is a more comprehensive analysis of the dynamic nature of the greenium relative to previous studies (Pietsch & Salakhova, 2022; Zerbib, 2019). We uncover that the fluctuations in the greenium are closely correlated to momentous shifts in climate change policies. For example, in the months following the 2015 Paris Agreement, the greenium broadened from an average of 2 bps to nearly 15 bps, which accounts for 19.76% of the average yield spread in the sample. Conversely, the election of United States (US) President Trump and his subsequent decision to withdraw the US from the Paris Agreement coincided with a period in which the greenium gradually declined and eventually faded.

These findings have practical implications for investors aiming to build resilient portfolios. Certified green bonds, in particular, offer greater stability against climate related risks, often holding or increasing in value during extreme weather events.

In the subsequent sections of this paper, we will review previous studies and develop testable hypotheses (Section 3.2). We will then delve into the description of our data and

Materials, Pulp & Paper Products, Metals & Mining, Electric Utilities & Power Generators, Oil & Gas – Exploration & Production, Oil & Gas – Refining & Marketing, Semiconductors, Hotels & Lodging, and Waste Management.

methodology (Section 5.4) and discussion of our results (Section 3.4). Finally, we will conclude the paper by summarising the main findings and their implications (Section 3.5).

3.2 Hypotheses development

As illustrated in the previous section, the existence of the greenium is a focal question in the literature.[3] However, its existence remains a point of debate. Findings on this phenomenon are mixed and vary according to the market analysed, time frame, type of issuing entity (Fatica & Panzica, 2021), entity characteristics (Liaw, 2020), and methodology employed (Larcker & Watts, 2020).

Given the lack of consensus on the existence of the greenium in the literature, we first test its presence with the most comprehensive sample of green and conventional bonds to date. This leads to our first hypothesis:

Hypothesis 3.1 *Corporate green bonds trade at a lower yield spread compared to matched conventional counterparts in the secondary market.*

Due to the contradictory findings in the literature, we hypothesise that the nature of the greenium may be dynamic and that external factors influence its appearance and disappearance over time. In the literature, the factors that determine the fluctuation of greenium over time have not been studied in depth. However, the concept of a fluctuating greenium could be inferred from several papers. Pietsch and Salakhova (2022) find that the emergence of the greenium in the secondary market in recent years can be attributed to the increased participation of retail investors, who are presumably driven by heightened

[3] See, for example, Baker et al. (2018), Caramichael and Rapp (2024), Fatica and Panzica (2021), Flammer (2021), Gianfrate and Peri (2019), Hachenberg and Schiereck (2018), Karpf and Mandel (2018), Larcker and Watts (2020), Pástor et al. (2021), Pietsch and Salakhova (2022), and Zerbib (2019).

awareness and concerns regarding climate-related issues.[4] This interpretation aligns with broader evidence on investors' shifting preferences during periods of heightened uncertainty. Kinateder et al. (2021) highlight the role of safe-haven assets in systemic crises, showing that investors tend to reallocate capital into traditionally safer asset classes during episodes of extreme volatility. In this context, Arat et al. (2023) find that while green bonds exhibit a persistent greenium in normal market conditions, this premium more than doubles during times of extreme market stress. Furthermore, Seltzer et al. (2022) indicate that firms with poor environmental profiles have higher yield spreads, particularly when stricter regulatory enforcement is in place and when climate regulatory risks are present. Therefore, we argue that green bonds, representing financial instruments with a relevant environmental component, may exhibit lower yield spreads in correspondence of major climate events. Thus, our second hypothesis is:

Hypothesis 3.2 *The greenium varies over time as investors revise their expectations about climate policy credibility and the salience of climate risks. In particular, shifts in policy signals and increases in climate-risk salience are expected to influence both the magnitude and the direction of the greenium.*

A major concern for sustainability-oriented investors interested in green bonds is that borrowers' commitment to green projects will not be upheld. We refer to non-compliance with the declared use of proceeds by issuers of green bonds as greenwashing. Especially in absence of strict regulations and enforcement schemes, issuers may decide to attract investors with a taste for sustainability, take advantage of the reputational effect stemming from green bond issuance and then divert the proceeds to other-than-green activities.

[4] One might expect the greenium to decline as issuance expands and scarcity diminishes. However, the growth in green bond supply was matched and, in some period, overcome, by the expansion of ESG assets under management, particularly in Europe. As a result, demand for green-labelled securities has remained strong relative to supply, preventing the greenium from fully dissipating

To partially tackle potential concerns about the authenticity of green bonds, issuers can obtain a certification, subject to the positive assessment of an external reviewer. There is consensus regarding the function and efficacy of certifications. Certified green bonds are associated with greater improvements in the post-issuance environmental performance of issuers (Fatica & Panzica, 2021; Fatica et al., 2021; Flammer, 2021). Moreover, consistent with the findings regarding investors' positive response to voluntary disclosure of green investments (e.g., Martin & Moser, 2016), the announcement of a certified green bond issue causes a more pronounced positive stock price reaction and a greater participation of long-term investors in the ownership structure (Flammer, 2021).

Finally, the size of the greenium strongly depends on the level of greenness determined by the external reviewer (Dorfleitner et al., 2021). With these findings in mind, we consider certification a determining factor in our analysis and test whether certification continues to influence the greenium even when controlling for its market sentiment-driven fluctuations over time:

Hypothesis 3.3 *Certification leads to a larger greenium for green bonds in the secondary market even when controlling for variations in market sentiment.*

We also scrutinise the influence of natural disasters on green bond performance. We predict that the infrastructural damage and property losses, consequential disruptions in economic activity, and uncertainty over future prospects in disaster stricken regions might promote risk-aversion among investors. This 'risk-off' environment, may stimulate demand for higher returns to offset perceived risk (Johar et al., 2022). In such circumstances, heightened investor alertness to climate risks could stimulate increased demand for environmentally responsible investments (IMF, 2021). Thus, certified green bonds, signalling environmental sustainability, could become increasingly attractive to investors in the aftermath of natural disasters. Investors may view such bonds as vehicles for reducing the frequency (via climate risk mitigation projects) and impact (through climate adaptation initiatives) of future calamities.

Hypothesis 3.4a *The occurrence of a natural disaster increases the greenium, as climate-related events raise the salience of climate risks and strengthen investors' demand for environmentally friendly investments.*

Hypothesis 3.4b *The magnitude of natural-disaster damages is positively associated with the size of the greenium, as more severe events further increase climate-risk salience and amplify the relative attractiveness of environmentally friendly investments.*

Furthermore, we focus on the potential impact of heightened public attention to climate change on the greenium. First, we hypothesise that heightened public attention to climate change may lead to a decrease in the yield spread for all bonds (including conventional bonds) issued by green bond issuers. This mechanism can be interpreted through the lens of a *halo effect*, whereby the issuance of a green bond sends a credible signal of environmental commitment that extends beyond the specific instrument to the issuer's entire debt portfolio. This hypothesis stems from the credible signal that green issuers send to the market by issuing green bonds, indicating their commitment to environmental sustainability. As public attention to climate change increases, this commitment may increase the perceived value of all the bonds, green or conventional, issued by these green issuers, leading to a reduction in the yield spread of both types of bonds.

Hypothesis 3.5a *Both conventional and green bonds issued by green issuers experience a decrease in the yield spread during periods of heightened public attention to climate change.*

It is important to note that the climate news captured by the index largely consists of policy conferences (such as the COPs), regulatory announcements and institutional commitments that frequently involve dedicated funding flows or enhanced policy support for low-carbon activities. These events raise climate attention in a way that improves the prospects of firms engaged in environmental initiatives, reducing the spreads on both their green and conventional bonds. Second, we postulate that events related to climate change, captured by the media (e.g., international climate summits, the emergence of new transition policies, significant advancements in green technology etc.) may further increase the interest towards certified green instruments. Our last hypothesis is that certified green bonds exhibit superior performance during periods of amplified public awareness of climate change relative to non-certified green bonds.

Hypothesis 3.5b *Certified green bonds perform better than non-certified green bonds during periods of heightened public attention to climate change.*

3.3 Data and methodology

Our goal is to examine the existence and evolution of the greenium between January 2014 and July 2022 in the secondary market.[5] To this end, we collect information on green and conventional bonds issued by green issuers from the Bloomberg Fixed Income securities database and Refinitiv Datastream. In order to facilitate the comparison process, we limit our sample to bonds with fixed coupon and without embedded options. This results in

[5]We gather data for green and conventional bonds issued from January 2014 to December 2021. We track secondary market trading for these bonds until July 2022. This ensures that bonds issued towards the end of 2021 have enough observations for the panel regression analysis.

15,786 bonds issued by green issuers between 2014 and 2021, of which 790 are green bonds. For each bond, we retrieve the issuer Identifier (ID), green label (identifying whether a bond is green or not), coupon rate, maturity date, issue date, amount issued in US dollars, rating at issue, and yield spread. Table 3.1 provides a comprehensive overview of the variables that have been employed in our analysis. Table 3.2 shows the descriptive statistics of the bond sample. On average, the bonds in the sample have a maturity of 5.90 years and a coupon rate of 1.56%. The credit rating assigned at the time of issue averaged 22.7, which falls within the range of A+ to AA- on the Standard and Poor's (S&P) scale. The average amount issued is $416.6 million, with a minimum of $5.5 million and a maximum of $2 billion. The average yield spread is 75.9 bps.

Our analysis of the greenium is based on a sample in which each green bond is matched to an equivalent conventional bond. To determine the most suitable conventional match for each green bond, we use the Mahalanobis Distance (MD) method.[6] The use of MD is particularly suitable for our analysis, as it outperforms other matching techniques when the number of covariates is relatively small and ensures robustness in different settings (King & Nielsen, 2019; Rubin, 1979; Stuart, 2010; Zhao, 2004). Furthermore, MD has been successfully employed in other studies on green bonds (e.g., Bedendo et al., 2023; Flammer, 2021), making it a well-established method in this context.

In order to ensure that green and conventional bonds are comparable across different sectors and issuers, we specifically match bonds with the same issuer. This ensures that sector-specific and issuer-specific characteristics are consistent between the matched pairs. The use of MD also ensures that the selected bonds are closely comparable on key bond-level attributes such as coupon rate, issue date, maturity, and issuance amount. However,

[6] Ideally, a perfect matching approach would be used, but applying such a methodology would drastically reduce the sample size, as many bonds would not find a match. Using the MD and the matching criteria we applied, ensures a high-quality match while preserving a sufficient sample size.

Table 3.1. Description of variables used in the regression analysis.

Variable	Type	Description
Dependent		
Yield spread	Continuous	The spread of a corporate bond expressed as the difference between the bond's yield to maturity and the yield to maturity of the associated benchmark government bond. The spread is expressed in bps.
Variables of interest		
Green Bond	Dummy	A variable that takes the value of 1 if the bond is green, and 0 otherwise.
Certified	Dummy	A variable that takes the value of 1 if the bond is both green and certified and 0 otherwise. Certified bonds' adherence to specific standards and guidelines established by recognised third-party organisations, such as the Climate Bonds Initiative, is verified by independent auditors to ensure transparency.
ESG Score	Categorical	A time-varying measure ESG performance obtained from Refinitiv, categorised into four levels, from 'A' to 'D', where 'A' represents the highest performance and 'D' the lowest.
Dummy 5 days post-disaster	Dummy	A binary variable that takes a value of 1 in the five days following a natural disaster related to climate change (i.e., excluding geological disasters) in the country of the bond issuer, and 0 otherwise.
Log(Damages in $m)	Continuous	The natural logarithm of the damages in adjusted million dollars caused by a natural disaster related to climate change in the country where the bond issuer is located.
Rel. Δ MeCCO index	Continuous	A variable representing the relative change (in decimals) in the Media and Climate Change Observatory (MeCCO) World index, which monitors media coverage of climate change and related issues across various forms of media in different countries and regions..
Innovations on MeCCO index	Continuous	A variable representing the innovations on the MeCCO World index, derived from the residuals of an AR1 model on the index.
Control variables		
Bid-ask spread	Continuous	It represents a measure of market liquidity. It is computed as the difference between the ask price and bid price of a bond as a percentage of the mid-price. It is expressed in bps.
Years to maturity	Continuous	The number of years until the bond reaches maturity.
Amount issued	Continuous	The natural logarithm of the amount issued for the bond.
Coupon rate	Continuous	The coupon rate of the bond, expressed as a percentage.
Rating	Categorical	A set of fixed effects representing the bond rating changes over time.
Currency	Categorical	A set of fixed effects representing the currency denomination of the bond.
Issuer	Fixed Effect	A set of dummies identifying each issuer.
Month	Fixed Effect	A set of fixed effects for each specific month and year.
Quarter	Fixed Effect	A set of fixed effects for each specific quarter and year.
Day	Fixed Effect	A set of fixed effects for each specific day.
Additional Variables		
Market Illiquidity	Continuous	The weighted average bid-ask spread across all bonds in the market, adjusted by outstanding amounts, capturing market-level liquidity.
Issuer Illiquidity	Continuous	The daily average bid-ask spread of bonds issued by each issuer, reflecting issuer-specific liquidity characteristics.
Gamma Illiquidity	Continuous	A bond-specific liquidity measure based on the covariance of consecutive log price changes, as per Bao et al. (2011).
Impact	Dummy	Indicates industries with at least one environmental materiality topic, as per SASB, scoring above zero.
High Impact	Dummy	Indicates industries with a high environmental materiality (SASB score of 3 or higher), signifying significant environmental impact.

Table 3.2. Summary statistics of the bond sample. This table provides a summary of the descriptive statistics for the variables used in the regression analysis. Panel (A) reports the time-varying variables. *Bid-ask spread* indicates the relative bid-ask spread of the bond prices. "Dummy 5 days post-disaster" is a binary variable indicating the immediate aftermath of a disaster. *Rel. Δ MeCCO index* refers to the monthly changes in the Media and Climate Change Observatory (MeCCO) index and *Innovations on MeCCO index* represents the first-order autoregressive model innovations. Panel (B) reports the variables measured at issue. *Yield to Maturity (YTM)* is the Yield to Maturity at issue. *Log(issue amount)* is the natural logarithm of the amount issued. Maturity is the maturity of the bond (in years). *Coupon* is the coupon rate in percentage. *Impact* and *High Impact* are dummies that activate if SASB score is ≥ 1 and ≥ 3 respectively. *Rating at Issue* refers to the credit rating assigned to a bond, converted into an integer representing a specific S&P rating. The average rating at issue is 22.7, which corresponds to a rating between A+ and AA-, where 22 represents S&P rating A+ and 23 represents S&P rating AA- (Table 3.A.1 of the Appendix displays the full conversion of S&P credit ratings into numerical values). Panel (C) measures the disaster variables when extreme weather events occur. *Damages (in $bn)* represents the total damages in billions of dollars caused by a disaster, while *Log(Damages in $m)* is the natural logarithm of these damages. Panel (D) presents additional variables utilised in the robustness tests, including liquidity measures, and sectoral environmental impact indicators.

Panel (A): time-varying variables						
Variable	**Obs**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**
Yield spread (bps)	346,418	75.9	57.7	68.0	-102.0	741.3
Bid-ask spread	346,418	24.25	19.08	19.05	0.00	115.87
Dummy 5 days post-disaster	346,418	0.04	0.19	0.00	0.00	1.00
Rel. Δ MeCCO index	102	0.03	0.21	0.03	-0.51	0.73
Innovations on MeCCO index	102	40.34	1124.23	43.65	-5170.48	2908.64
Panel (B): variables measured at issue						
Variable	**Obs**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**
YTM (%)	688	1.58	1.37	1.22	0.00	7.50
Amount issued ($m)	688	416.63	425.50	245.87	5.52	2000
Maturity (years)	688	5.90	3.35	5	1	30
Coupon rate (%)	688	1.56	1.37	1.22	0.11	7.38
Impact	688	0.38	0.48	0.00	0.00	1.00
High Impact	688	0.12	0.33	0.00	0.00	1.00
Rating at issue	688	22.7	2.5	23	17	26
Panel (C): variables measured when extreme weather events occur						
Variable	**Obs**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**
Damages (in $bn)	350	2.76	8.26	0.85	0.0002	105.02
Log(Damages in $m)	350	6.45	1.86	6.75	0.79	11.56
Panel (D): additional variables for robustness tests						
Variable	**Obs**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**
Market Illiquidity	346,418	22.45	6.36	22.94	0.43	64.01
Issuer Illiquidity	346,418	24.25	14.94	20.97	0.00	115.87
Gamma Illiquidity	344,310	4.22	11.47	1.40	0.00	35.83

merely minimising the distance between issue dates through the MD method does not ensure an even distribution of issue dates between the groups of green and conventional bonds.[7] This consideration is crucial, as bonds issued at different times can display varying yields influenced by the respective market conditions in those periods. To counter this, we introduce the additional constraint that the issue dates of each pair of matched bonds should not exceed one year. Furthermore, we also refine our regression analysis by focusing on the corporate yield spread over treasury yields, rather than solely on corporate yields. This approach helps us to assess more accurately the relative performance and pricing of green versus conventional bonds, isolating external market influences.

We begin by first selecting conventional bonds that have the same issuer and rating at issue of the selected green bonds. Then, we compute the MD between each green bond and conventional counterparts. Finally, to form each pair, we select the conventional bond with the shortest "distance" to the original green bond. The final matched sample consists of 344 pairs of green and conventional bonds. For each bond in the matched sample, we obtain the following daily variables from Refinitiv Datastream: yield spreads, which measure the yield differential between the bond and the corresponding benchmark government bond with a similar maturity; and relative bid-ask spreads, expressed as a percentage of the mid-price, to account for differences in liquidity across bonds; credit rating history.

To further ensure the quality of our matching, we have provided the differences in means between the matched samples of green and conventional bonds in Table 3.3. This table illustrates the closeness of the two groups after matching, with no statistically significant differences observed between them in terms of the bond characteristics at issue.

Table 3.4 compares the number and amount issued of green bonds between 2014–2022, for each country in both the full and matched samples. While the total quantity and overall

[7]This is because, even when the issue date is incorporated as a dimension in the multi-dimensional MD computation, the minimum MD could still pair bonds that are similar across the other dimensions, such as coupon, maturity, and amount issued, but differ significantly in their issue dates, potentially by a substantial time span.

Table 3.3. Characteristics at issue of green bonds and matched conventional bonds. This table compares the characteristics at issue of the matched green vs conventional bonds in our sample. Yield Spread denotes the yield differential between a corporate bond and the associated benchmark government bond. YTM is the Yield to Maturity at issue. Log(issue amount) is the natural logarithm of the amount issued. Maturity is the maturity of the bond (in years). Coupon is the coupon rate in percentage. Rating at Issue refers to the credit rating assigned to a bond, converted into an integer representing a specific S&P rating. The average rating at issue is 22.7, which corresponds to a rating between A+ and AA-, where 22 represents S&P rating A+ and 23 represents S&P rating AA-. p-value represents the p-value of the difference-in-means. ***, **, and * denote significance at the 1%, 5%, and 10% levels. The sample is made of 688 bonds issued between 2014 and 2021.

Variable	Label	Obs	Mean	Std. Err.	[95% conf.	interval]	p-value
Yield spread (bps)	*(1) Non Green*	344	76.6	2.7	71.4	81.9	
	(2) Green	344	77.6	2.7	72.3	82.9	
Difference (1)-(2)			-1.0	3.8	-8.4	6.5	0.802
YTM (%)	*(1) Non Green*	344	1.61	0.07	1.46	1.76	
	(2) Green	344	1.54	0.07	1.40	1.69	
Difference (1)-(2)			0.07	0.11	-0.14	0.23	0.523
Log(amount issued)	*(1) Non Green*	344	19.26	0.07	19.12	19.39	
	(2) Green	344	19.23	0.06	19.11	19.35	
Difference (1)-(2)			0.03	0.09	-0.15	0.21	0.753
Years to maturity	*(1) Non Green*	344	5.92	0.18	5.55	6.28	
	(2) Green	344	5.87	0.18	5.52	6.22	
Difference (1)-(2)			0.05	0.26	-0.46	0.55	0.862
Coupon rate (%)	*(1) Non Green*	344	1.59	0.08	1.44	1.74	
	(2) Green	344	1.52	0.07	1.38	1.67	
Difference (1)-(2)			0.07	0.11	-0.14	0.27	0.523
Rating at issue	*(1) Non Green*	344	22.7	0.1	22.4	22.9	
	(2) Green	344	22.7	0.1	22.4	22.9	
Difference (1)-(2)			0.0	0.0	0.0	0.2	1.000

value of green bonds are significantly reduced in the matched sample, the proportional contribution of each country to the total remains stable. The relative contributions of each country do not deviate markedly from those in the full sample. This suggests that the matched sample, though reduced in size, reflects the geographic diversity present in the full sample.

Subsequently, we conduct a panel OLS regression analysis to test the hypotheses discussion in Section 2. The baseline model is as follows:

$$
\begin{aligned}
Yield\ Spread_{it} = \alpha\ +\ \beta \times \textbf{Green Bond}_i\ +\ \gamma \times Controls_{it} \\
+\ \theta_i +\ \lambda_t +\ \epsilon_{it}
\end{aligned}
\tag{3.1}
$$

where $Yield\ Spread_{it}$ represents the yield spread of bond i at time t over a comparable Treasury security and Green Bond is a dummy the identifies green bonds. The model includes a set of controls, such as the residual maturity, the bid-ask spread, the amount issued, and the coupon rate of the bond. Furthermore, it includes currency fixed effects and credit rating dummies. θ_i and λ_t represent respectively the issuer and time fixed effects.

Table 3.4. Comparison of green bond issuance by country - full vs. matched samples. The table shows the number and percentage of green bonds issued by each represented country in the sample, together with the amount issued in billion dollars. The bonds are classified under two distinct samples: the *Full Sample*, and the *Matched Sample*. The *Full Sample* includes the complete universe of fixed coupon green bonds issued by green issuers and reported by both Bloomberg Fixed Income and Refinitiv Datastream. Bonds with optionality features are excluded. The *Matched Sample* represents the subsample of green bonds resulting from the matching methodology applied to pair green and conventional bond in our analysis. The methodology requires a perfect match on the issuer identifier and bond rating at issue and selects the match based on the minimisation of the Mahalanobis Distance computed on coupon rate, the issued amount, the time to maturity, and the issue date.

	Full Sample				**Matched Sample**			
	Green Bonds		**Amount Issued**		**Green Bonds**		**Amount Issued**	
Country	**No.**	**%**	**B$**	**%**	**No.**	**%**	**B$**	**%**
China	211	26.71%	89.70	32.44%	51	14.83%	21.93	16.02%
France	35	4.43%	29.44	10.65%	27	7.85%	23.22	16.96%
Germany	59	7.47%	23.57	8.53%	29	8.43%	13.41	9.80%
Netherlands	24	3.04%	19.95	7.22%	18	5.23%	14.98	10.94%
Japan	171	21.65%	18.63	6.74%	69	20.06%	12.00	8.77%
South Korea	120	15.19%	17.28	6.25%	77	22.38%	8.55	6.24%
Norway	11	1.39%	9.47	3.43%	6	1.74%	6.36	4.65%
United States	15	1.90%	8.15	2.95%	7	2.03%	3.89	2.84%
Italy	11	1.39%	7.55	2.73%	9	2.62%	6.44	4.70%
Spain	6	0.76%	6.09	2.20%	5	1.45%	5.26	3.85%
Cayman Islands	11	1.39%	5.87	2.12%	2	0.58%	1.20	0.88%
Hong Kong	13	1.65%	4.93	1.78%	2	0.58%	0.63	0.46%
British Virgin Islands	12	1.52%	3.78	1.37%	3	0.87%	0.60	0.44%
Canada	6	0.76%	3.62	1.31%	5	1.45%	3.30	2.41%
India	8	1.01%	3.56	1.29%	3	0.87%	1.36	1.00%
Sweden	12	1.52%	3.39	1.23%	9	2.62%	2.79	2.04%
Austria	6	0.76%	3.12	1.13%	4	1.16%	1.87	1.36%
Australia	5	0.63%	2.92	1.05%	4	1.16%	2.69	1.97%
Finland	6	0.76%	2.40	0.87%	3	0.87%	1.94	1.42%
United Kingdom	8	1.01%	2.23	0.81%	2	0.58%	0.95	0.69%
Other	40	5.06%	10.84	3.92%	9	2.62%	3.50	2.56%
Total	790	100%	276.50	100%	344	100%	136.87	100%

3.4 Results and discussion

3.4.1 Baseline model

First, we investigate whether there are differences in pricing between green and non-green corporate bonds. We begin by examining whether green bonds exhibit a greenium, meaning they trade at consistently lower spreads than conventional bonds (Hypothesis 3.1). Differently from previous studies such as Flammer (2021), which employed a univariate difference-in-means approach, our analysis utilises a multivariate regression approach, allowing for a more comprehensive control of various factors affecting bond pricing. We conduct our analysis through multiple regression specifications. The results in Table 3.5 indicate that green bonds do indeed trade at a slightly lower spread (-2.14 to -1.99 bps), on average, compared to conventional bonds. The result is statistically significant across specifications 1 to 3. This finding holds true when controlling for bid-ask spreads, years to maturity, issue amount, coupon rate, issuer fixed effects and various time fixed effects. Additionally, we rebuild the matched sample by matching conventional bonds with equivalent conventional bonds (rather than green ones) to run a placebo test. The placebo test is implemented by reconstructing the matched sample using only conventional bonds. For each green-conventional pair in the original matched sample, I select a conventional bond that is closest to the matched pair based on the same matching criteria applied earlier (currency, seniority, rating band, industry, time to maturity, and issue amount). A new dummy variable, Placebo, is then assigned a value of one for the first bond in each matched conventional pair and zero for the second bond.

Estimating the baseline specification with this placebo sample tests whether the matching procedure itself generates artificial spread differences. If the method introduced bias, we would observe a statistically significant spread difference between two otherwise comparable conventional bonds. Instead, the placebo coefficients are indistinguishable from zero across all specifications, confirming that the greenium estimated in Columns (1)–(3) is not an artefact of the matching algorithm but reflects an actual pricing difference between green and non-green bonds The results (specifications 4–6) show that there is no statistically significant difference in the yield spread between the newly matched bonds. This provides further support for the hypothesis that green bonds trade at a lower spread compared to conventional bonds.

3.4.2 Fluctuations over time

Following the previous analysis, we investigate whether the greenium effect varies over time (Hypothesis 3.2). To test this hypothesis, we introduce an interaction term between the green bond dummy and each month in the sample period. The interaction term allows the effect of *Green bond* to vary across different time periods. The greenium effect is not constant over time, as displayed by Figure 3.1, which plots the marginal effect of being labelled as green in each month. Notably, the plot shows a marked increase in the greenium effect starting in November 2015, coinciding with the signing of the Paris Agreement, as indicated by the first red line. Similarly, in the following months, December 2015 and January through April 2016, the coefficients are negative and all statistically significant at the 1% level.[8] In this period, the greenium expanded significantly, with yield spreads reducing by about 16 bps. This increase in demand for green bonds highlights how major policy events can drive price appreciation for certified green bonds.

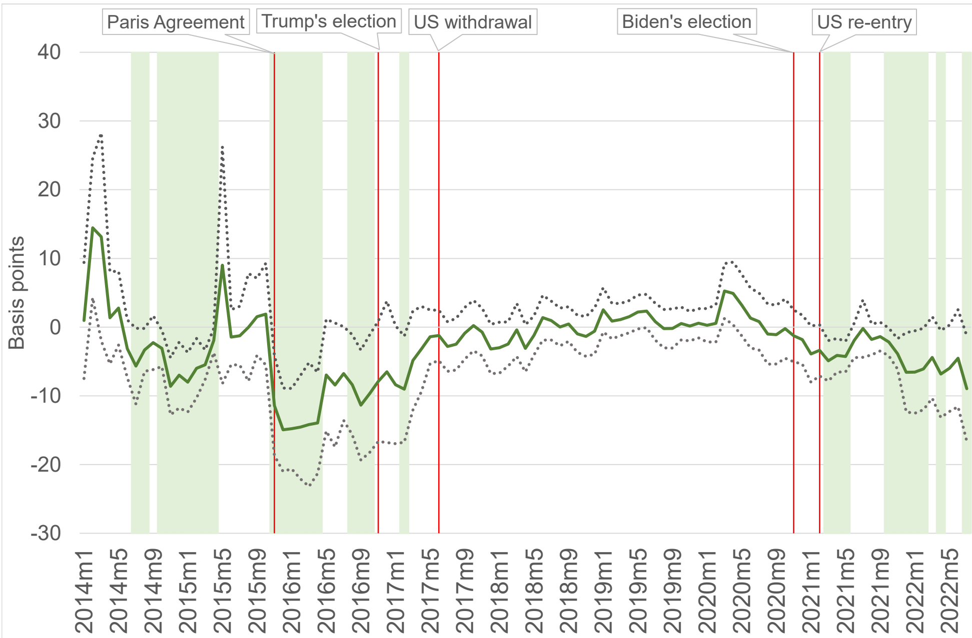
[8]Additionally, we note a green discount in 2014. However, this could potentially be an anomaly given that our temporal analysis sample was just beginning at this point and a limited number of observations could have had a disproportionate effect on the coefficients.

Table 3.5. Determinants of the yield spread (baseline model). This table presents the regression analysis examining the impact of green bond label on corporate bond yield spreads. The analysis employs a Green Bond dummy (which equals 1 for green bonds) in Columns 1–3 and a Placebo dummy (which equals 1 for conventional placebo bonds) in Columns 4–6. Each set of columns tests the relationship under different time fixed effects: quarterly (Columns 1 and 4), monthly (Columns 2 and 5), and daily (Columns 3 and 6), with corresponding standard errors clustered at the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating, issuer and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Green bond	-2.14***	-2.03***	-1.99***			
	(0.61)	(0.38)	(0.09)			
Placebo				-0.01	-0.02	-0.02
				(0.41)	(0.25)	(0.06)
Bid ask spread	0.43***	0.39***	0.37***	0.40***	0.36***	0.34***
	(0.05)	(0.03)	(0.01)	(0.07)	(0.04)	(0.01)
Time to maturity	2.81***	2.95***	3.00***	3.52***	3.69***	3.78***
	(0.20)	(0.13)	(0.03)	(0.30)	(0.19)	(0.05)
Log(Issue amount)	-1.80**	-1.87***	-1.89***	-2.95***	-3.08***	-3.13***
	(0.71)	(0.44)	(0.11)	(1.02)	(0.62)	(0.14)
Coupon rate	-0.19	-0.15	-0.13	-0.10	-0.11	-0.09
	(1.14)	(0.69)	(0.17)	(1.31)	(0.80)	(0.19)
Rating FE (FE)	YES	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	NO	NO	YES	NO	NO
Month FE	NO	YES	NO	NO	YES	NO
Day FE	NO	NO	YES	NO	NO	YES
R-squared	0.6015	0.6168	0.6226	0.665	0.6812	0.6873
Bonds	688	688	688	444	444	444
Observations	346,418	346,418	346,418	298,150	298,150	298,150

From November 2016 onwards, however, we observe a progressive reduction of the yield differential between green and conventional bonds, which corresponds to a decrease in the greenium, ultimately reaching zero. This temporal shift coincides with the election of Donald Trump, whose efforts to downplay the effect of climate change culminated in the United States' withdrawal from the Paris Agreement in June 2017. This period of small or no greenium extended until the end of 2020. In particular, the green premium did not witness an immediate rebound following the election of Joe Biden in November 2020. The

Figure 3.1. Marginal effect of the green bond label on the yield spread. This graph shows the marginal effect of the green bond label on bond yield spreads over time. The effect is estimated through the linear regression model in specification (2) of Table 3.5 with the addition of interaction terms between the green bond dummy and dummies identifying each month within the sample period (January 2014 to July 2022). The solid line represents the estimated effect in bps, while the dotted lines provide the 90% confidence interval. The light green shaded background indicates the months when the greenium is statistically significant at the 10% level. The red lines denote, from left to right, significant events: signing of the Paris Agreement, President Trump's election, the US withdrawal from the Paris Agreement, President Biden's election and the rejoining of the US in the Paris Agreement.



persistent focus on the COVID-19 pandemic during this period may have overshadowed environmental concerns in the media, potentially impacting investor demand for green bonds. Yet, the scenario changed in February 2021, when President Biden announced the US re-entry into the Paris Agreement. At this point, the greenium regained statistical significance. We conjecture that the weight of the US stance on climate change may have swayed the market of green bonds.

These findings suggest that the greenium effect is not static, but rather dynamic and sensitive to a variety of external factors. Market participants' valuation of green bonds and their willingness to pay a premium for them may depend on the political context, shifts in public sentiment on climate issues, changes in regulatory frameworks, and other major global events. Specifically, these patterns indicate that the greenium responds strongly to changes in the credibility and direction of climate policy. Positive policy developments, such as the Paris Agreement, increase investors' confidence in a sustained transition and widen the greenium. Conversely, when climate policy certainty weakens, as during the US withdrawal from the Paris Agreement, investors reassess investments in ESG securities and the greenium narrows. This mechanism suggests that investor preferences for green assets are policy-dependent and become stronger when enforcement appears more credible.

3.4.3 The role of certification

Next, we investigate the strength of the greenium for certified green bonds Hypothesis 3.3.

Data on whether a green bond has undergone certification with an external reviewer is collected from the Climate Bonds Initiative (CBI) and incorporated into the specification. By examining the relationship between certification and greenium, we aim to corroborate the results found in the literature about the impact of external reviews on the pricing of green bonds in the market (Dorfleitner et al., 2021; Fatica & Panzica, 2021; Gianfrate & Peri, 2019). Therefore, we add a *Certified* dummy to our baseline specifications in Table 3.5. Results are reported in Table 3.6. It is important to clarify that this variable functions as an interaction term between the *Green Bond* label and the certification status, capturing the additional effect of certification beyond the baseline greenium of non-certified green bonds. In this specification, the coefficient on *Green Bond* now isolates the greenium for non-certified green bonds only, while the coefficient on *Certified* represents the incremental effect of certification. Since all certified bonds are also green bonds, the total greenium for certified green bonds is computed as the sum of these two coefficients.

Results show that the *Green* dummy coefficients range from -1.51 to -1.47, while the *Certified* dummy coefficients vary from -7.10 to -7.05, as detailed in Table 3.6. All coefficients are statistically significant at the 1% level. This analysis reveals that certified green bonds, validated by an external review, exhibit a reduction in yield spread between 8.41 and 8.52 bps. This effect is over five-fold compared to non-certified green bonds, underscoring the strong market response to external reviews as a means of assuring a green bond's credibility and transparency.

This result may also reflect investors' awareness of the risks associated with greenwashing, where issuers make misleading claims about the environmental benefits of their products or services. The certification process with an external reviewer can help mitigate these risks by providing investors with independent verification of the environmental impact of the bond proceeds.

Furthermore, previous literature suggests that the industry sector of the borrower also plays a significant role in determining the strength of the greenium. Investors demonstrate a marked preference for green instruments issued by environmentally unfriendly sectors (Ehlers & Packer, 2017; Sangiorgi & Schopohl, 2021). To investigate this, we further refine our analysis by incorporating the SASB materiality framework, which categorises industries based on their environmental impact. Specifically, we define two dummy variables:

- **Impact**: for industries with at least one environmental materiality issue identified by SASB,

- **High Impact**: for industries with 3 or more environmental materiality issues, indicating significant exposure to environmental issues.

Table 3.6. Green certification and bond spreads. This table presents the results of a panel regression model examining the determinants of daily yield spread. The explanatory variables include a Green Bond dummy, which equals 1 for green bonds, a Certified dummy, which equals 1 for certified bonds, the bid-ask spread, time to maturity in years, the natural logarithm of the issue amount, and the coupon rate, as well as rating, currency, issuer fixed effects. Column (1) uses quarter fixed effects; Column (2) uses month fixed effects, and Column (3) uses daily fixed effects. Corresponding standard errors clustered at the quarter-issuer, month-issuer, and day-issuer level are reported in parentheses. Sample period: January 2014 to July 2022. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.47**	-1.35***	-1.31***
	(0.65)	(0.40)	(0.09)
Certified	-7.05***	-7.09***	-7.10***
	(1.09)	(0.69)	(0.17)
Bid ask spread	0.43***	0.39***	0.37***
	(0.05)	(0.03)	(0.01)
Time to maturity	2.82***	2.96***	3.02***
	(0.21)	(0.13)	(0.03)
Log(Issue amount)	-1.73**	-1.80***	-1.82***
	(0.71)	(0.44)	(0.11)
Coupon rate	-0.19	-0.15	-0.13
	(1.14)	(0.69)	(0.17)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6019	0.6172	0.6230
Bonds	688	688	688
Observations	346,418	346,418	346,418

To assess whether the greenium differs across industries with varying environmental impacts, we interact these dummy variables with the key variables of interest: *Green Bond* and *Certified*. The inclusion of these interaction terms allows us to explore whether industries with higher environmental relevance exhibit a stronger or weaker greenium relative to less impactful industries.

The results from this extended regression analysis are presented in Table 3.7. It is important to note that the stand-alone variables *Impact* and *High Impact* are omitted from the regression due to the inclusion of issuer fixed effects. From Column (1) of the table, where quarter-by-year fixed effects are used, the yield differential for green, certified bonds in industries with environmental impact can be computed as the sum of the relevant coefficients: -2.22 for the green bond dummy, 1.94 for the interaction between green bonds and environmental impact, -6.22 for the certified bond dummy, and -2.51 for the interaction between certification and environmental impact. These coefficients sum to -9.01 bps (standard deviation: 1.63; p-value < 0.01), indicating that certified green bonds in industries with environmental concerns enjoy a substantial greenium, reducing the yield spread by 9 bps relative to conventional bonds in the same industries. This result highlights the critical role that certification plays in assuring investors of the credibility of green bonds, particularly in environmentally impactful industries. In contrast, green, non-certified bonds in industries with environmental impact in Column (1) show no significant greenium, with the sum of the relevant coefficients (-2.22 for the green bond dummy and 1.94 for the interaction term) equalling -0.28 bps (standard deviation: 1.42). We reach the same conclusion when we use month-by-year fixed effects (Table 3.7, column 2). When focusing on high environmental impact industries, the yield differential of green, certified bonds increases to -15.49 bps (standard deviation: 5.47; p-value < 0.01) with quarter-by-year fixed effects (column 3), and -15.26 bps (standard deviation: 3.33; p-value < 0.01) with month-by-year fixed effects (column 4). Conversely, green, non-certified bonds do not enjoy the same favourable treatment in environmental impact industries, with a yield differential of 3.01 bps (standard deviation: 2.09) and 3.17 bps (standard deviation: 1.30; p-value < 0.05), for quarter-by-year and month-by-year fixed effects respectively, indicating. in the latter case, a statistically significant green discount for non-certified green bonds in high-impact industries.

To facilitate the understanding of these effects, we summarise the greenium calculations in Table 3.A.2 in the Appendix. The results confirm that certified green bonds consistently exhibit a substantial greenium across all specifications, but the magnitude of the greenium is particularly pronounced in industries with high environmental impact (SASB $\geq$ 3). This is evident in both the quarter-year and month-year fixed effects models, where the certification of bonds in these environmentally impactful industries results in a greenium exceeding 15 bps. Conversely, green non-certified bonds do not enjoy the same favourable treatment in environmental impact industries. If we consider the bonds issued in highly environmental impactful industries, in fact, the data suggest that these bonds are viewed with scepticism by investors. For instance, in the quarter-year fixed effects model (Panel A) the spread differential changes sign and becomes positive, albeit it is not significant. In the month-year fixed effects model (Panel B) it even reaches a spread increase of over +3 bps, significant at the 5% level (*green discount*). This result implies that without certification, the green label alone does not suffice to convince investors of the bond's environmental credibility, probably highlighting concerns over greenwashing.

3.4.4 Disaster events

Next, we investigate whether the occurrence of significant climate-related natural disasters in the issuer's country is associated with dynamic fluctuations in the greenium of green bonds. To do so, we introduce two variables in our baseline specification: *Dummy 5 days post-disaster* and *Log(Damages in $m).* The former variable is equal to 1 in the five days following the occurrence of a climate-related natural disaster in the issuer's country, while the latter is the natural logarithm of damages in million dollars caused by disasters, calculated for the 5-day period immediately following each disaster event and set to zero otherwise. We obtain information on the occurrence and damages caused by such disasters from Emergency Events Database (EM-DAT) (Guha-Sapir et al., 2009), a well-known and widely used database on natural disasters. It is important to stress that the disaster variables used in this chapter identify climate-related events at the country level, not at the firm level. The dummy equal to one in the five days following a disaster does not imply that the issuer has suffered direct physical damage. Rather, this measure captures a country-level shock that increases public and media attention to climate risks.[9]

Figure 3.2 displays the cumulative estimated disaster damages by country worldwide in the period studied. By including these variables in our analysis, we aim to test whether not only the occurrence (Hypothesis 3.4a) but also the intensity of climate-related natural disasters (Hypothesis 3.4b) play a role in affecting the magnitude of the greenium.

We carry out three models to scrutinise the effects of the green bond label and disaster events on the yield spread of bonds (Table 3.8). In all our specifications, we include controls for the bid-ask spread, years to maturity, log of issue amount, bond rating, coupon rate, and implemented fixed effects for issuer and currency. In the first model, we include a green bond dummy variable, a certified green bond dummy variable, and a dummy variable marking five days post-disaster events. Certifications significantly diminish the yield spread, whereas uncertified green bonds see a smaller spread reduction. The disaster dummy variable ranges between 4.36 and 5.34 bps, indicating an increase in the yield spreads in the 5 days following a natural disaster for those bonds issued by companies based in the country affected by the disaster. Additionally, across all specifications, the interaction

[9]As such, these events operate as climate-salience shocks, making climate change more visible and less deniable. As such, natural disasters act similarly to positive transition-policy signals, increasing the relative attractiveness of transition-aligned assets and widening the greenium.

between certified green bonds and the post-disaster dummy is negative and statistically significant (ranging from -14.40 to -13.90 across the three specifications). Specifically, in column (1), the overall effect of the occurrence of disasters on certified green bonds can be computed as 4.36 - 14.40 = -10.03 bps (Wald t-test -3.06; p-value: 0.002).[10] This indicates that certification more than compensates for the negative impact of natural disasters on the bond spread. Certified green bonds become more attractive to investors than other bonds in such circumstances. The resilience of certified green bonds—demonstrated by the 10.03 bps reduction in yield spreads following disasters—suggests they are less vulnerable to the impact of disasters on bond prices.

Table 3.9 examines Hypothesis 3.4b by incorporating *Log(Damages in $m)*, which significantly influences the yield spread across all specifications. The interaction between certified green bonds and this measure of damages shows a statistically significant negative impact.

[10] Similarly, in specification (2), the net effect is 4.73 - 13.90 = -9.17 bps (Wald t-test: -3.58; p-value < 0.01), and in specification (3), the net effect is 5.34 - 14.21 = -8.87 bps (Wald t-test: -7.21; p-value < 0.01).

Table 3.7. Environmental impact and bond spreads. This table presents the results of a panel regression model examining the determinants of daily yield spread, focusing on the interaction between green bonds and environmental impact. The explanatory variables include a Green Bond dummy, interaction terms between Green Bond and environmental impact measured as Impact (defined as industries with at least one environmental materiality issue identified by SASB) and High Impact (defined as industries with 3 or more environmental materiality issues identified by SASB), a Certified dummy, and interaction terms between Certified and the impact dummies. Other control variables include the bid-ask spread, time to maturity in years, the natural logarithm of the issue amount, the coupon rate, and various combinations of fixed effects. Sample period: January 2014 to July 2022. Standard errors clustered at the quarter-issuer, and month-issuer levels are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**	**(4)**
*Green bond*Impact*	1.94	1.92**		
	(1.57)	(0.96)		
*Certified*Impact*	-2.51	-2.32		
	(2.53)	(1.57)		
*Green bond*High Impact*			5.15**	5.20***
			(2.16)	(1.34)
*Certified*High Impact*			-12.58**	-12.47***
			(5.85)	(3.57)
Green bond	-2.22***	-2.10***	-2.13***	-2.03***
	(0.61)	(0.38)	(0.66)	(0.41)
Certified	-6.22***	-6.32***	-5.92***	-5.96***
	(1.26)	(0.80)	(1.09)	(0.69)
Bid ask spread	0.43***	0.39***	0.43***	0.39***
	(0.05)	(0.03)	(0.05)	(0.03)
Time to maturity	2.84***	2.98***	2.86***	3.00***
	(0.21)	(0.13)	(0.21)	(0.13)
Log(Issue amount)	-1.82**	-1.89***	-1.84**	-1.91***
	(0.73)	(0.45)	(0.72)	(0.44)
Coupon rate	-0.11	-0.07	-0.27	-0.23
	(1.16)	(0.70)	(1.14)	(0.69)
Rating FE	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES
Quarter FE	YES	NO	YES	NO
Month FE	NO	YES	NO	YES
R-squared	0.6020	0.6172	0.6021	0.6174
Bonds	688	688	688	688
Observations	346,418	346,418	346,418	346,418

Figure 3.2. Global distribution of cumulative climate-related disaster damages by country (2014–2022). This choropleth map displays the cumulative estimated disaster damages in adjusted billion dollars by country worldwide from 2014 to 2022, due to climatological, hydrological, and meteorological natural disasters. The darker the green shade, the greater the damage recorded. Data sourced from the EM-DAT, Centre for Research on the Epidemiology of Disasters (CRED), Université Catholique de Louvain, Brussels, Belgium.

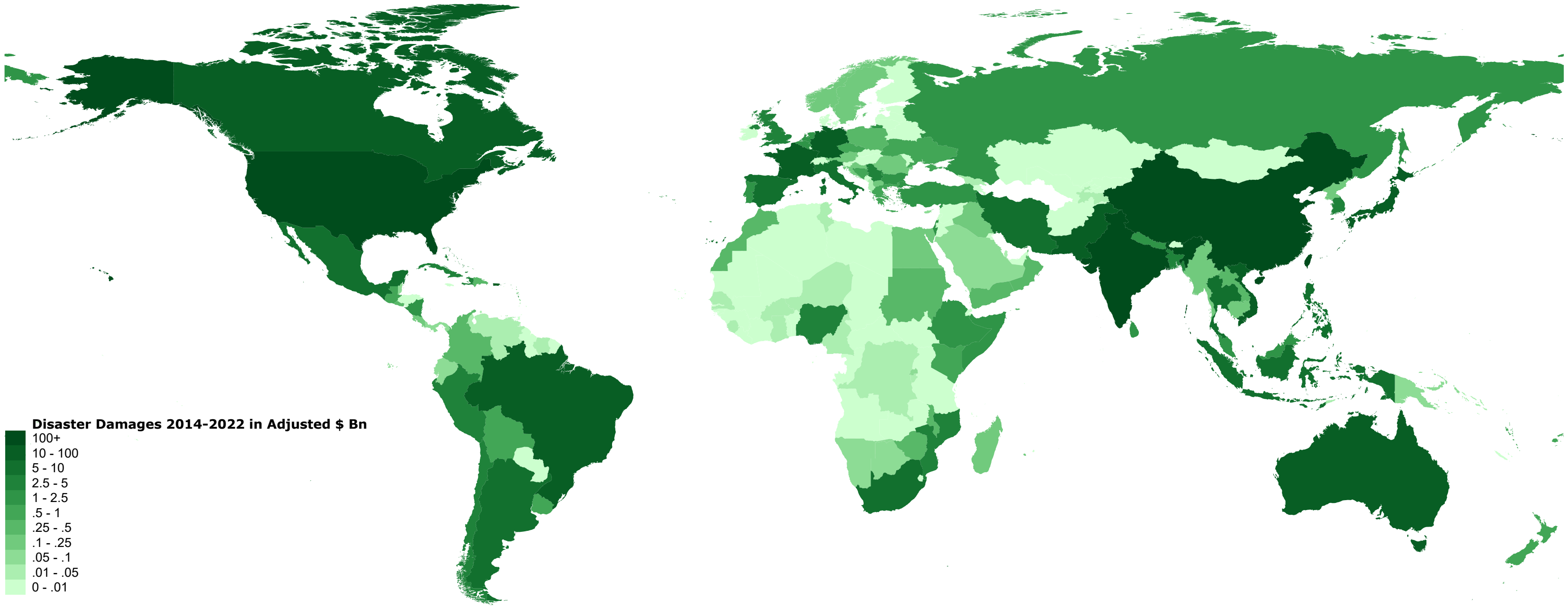


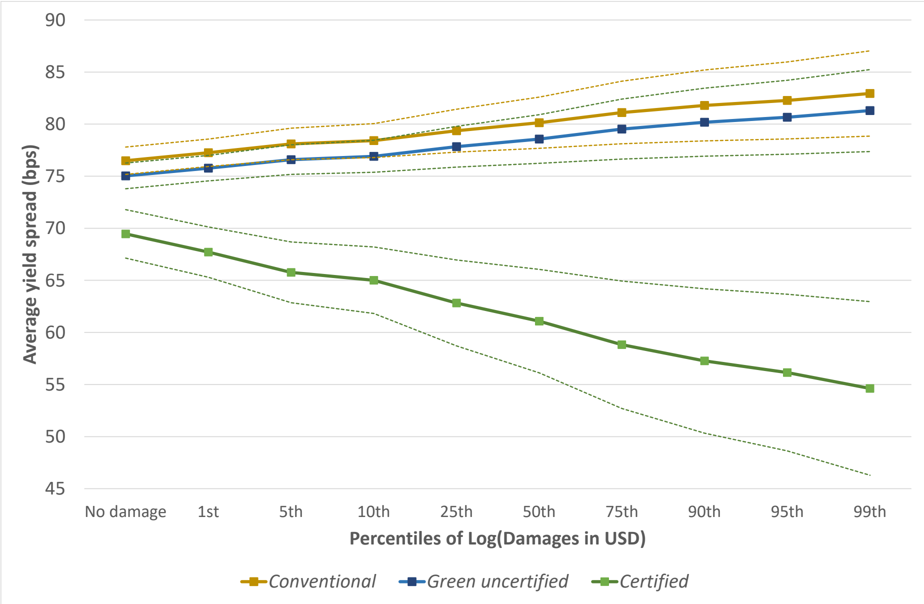
Table 3.8. Extreme weather events and bond spreads. This table presents panel regressions examining the impact of green bond issuance, disaster events, and certification on bond yield spreads. The analysis employs a Green Bond dummy (1 for green bonds), a Certified dummy (1 for certified bonds with external verification), the dummy "5 days post-disaster" that equals 1 in the five days following extreme weather events as reported in EM-DAT. Each column tests the relationship under different time fixed effect: quarterly (Column 1), monthly (Column 2) and daily (Column 3), with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating, issuer and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.47**	-1.34***	-1.30***
	(0.66)	(0.41)	(0.10)
Certified	-6.61***	-6.67***	-6.67***
	(1.09)	(0.69)	(0.18)
5 days post-disaster	4.36***	4.73***	5.34***
	(1.51)	(1.13)	(0.59)
*Green bond*5 days post-disaster*	0.13	-0.07	-0.10
	(1.10)	(0.84)	(0.40)
*Certified*5 days post-disaster*	-14.40***	-13.90***	-14.21***
	(3.23)	(2.53)	(1.21)
Bid ask spread	0.43***	0.39***	0.37***
	(0.05)	(0.03)	(0.01)
Time to maturity	2.82***	2.96***	3.02***
	(0.21)	(0.13)	(0.03)
Log(Issue amount)	-1.73**	-1.80***	-1.82***
	(0.71)	(0.44)	(0.11)
Coupon rate	-0.21	-0.16	-0.15
	(1.14)	(0.69)	(0.17)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6022	0.6175	0.6232
Bonds	688	688	688
Observations	346,418	346,418	346,418

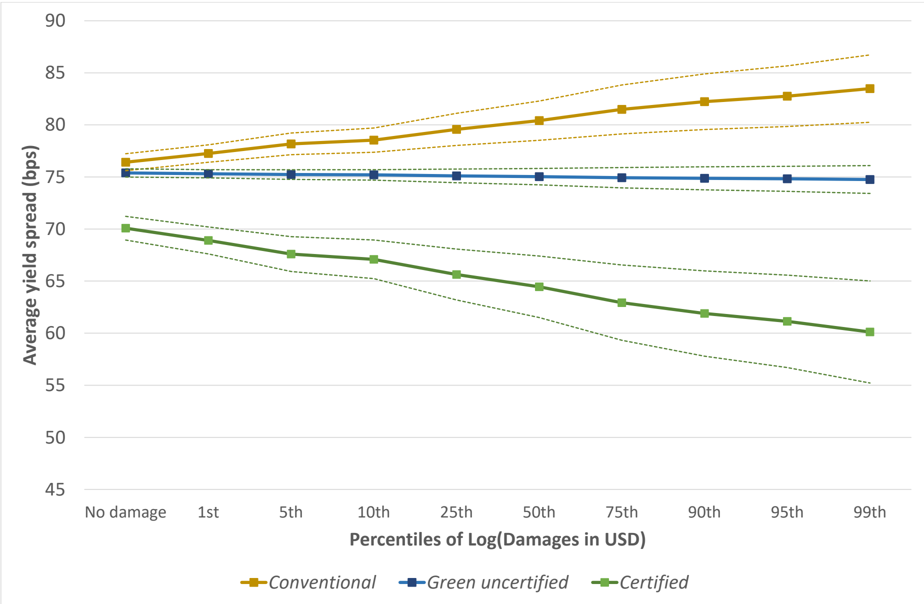
Table 3.9. Intensity of weather events and bond spreads. This table presents panel regressions examining the impact of green bond issuance, disaster events, and certification on bond yield spreads. The analysis employs a Green Bond dummy (1 for green bonds), a Certified dummy (1 for certified bonds with external verification), *Log(Damages in $m)*, which represents the natural logarithm of damages in million dollars caused by disasters, calculated for the 5-day period immediately following each disaster event and set to zero otherwise. Each column tests the relationship under different time fixed effect: quarterly (Column 1), monthly (Column 2) and daily (Column 3), with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating, issuer and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.46**	-1.37***	-1.29***
	(0.66)	(0.40)	(0.10)
Certified	-6.64***	-6.74***	-6.70***
	(1.08)	(0.68)	(0.18)
Log(Damages in $m)	0.72***	0.77***	0.86***
	(0.20)	(0.16)	(0.09)
*Green bond*Log(Damages in $m)*	-0.02	0.08	-0.05
	(0.17)	(0.14)	(0.06)
*Certified*Log(Damages in $m)*	-2.11***	-1.72***	-2.08***
	(0.43)	(0.39)	(0.18)
Bid ask spread	0.43***	0.39***	0.37***
	(0.05)	(0.03)	(0.01)
Time to maturity	2.82***	2.96***	3.02***
	(0.21)	(0.13)	(0.03)
Log(Issue amount)	-1.73**	-1.80***	-1.82***
	(0.71)	(0.44)	(0.11)
Coupon rate	-0.21	-0.16	-0.15
	(1.14)	(0.69)	(0.17)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6022	0.6175	0.6233
Bonds	688	688	688
Observations	346,418	346,418	346,418

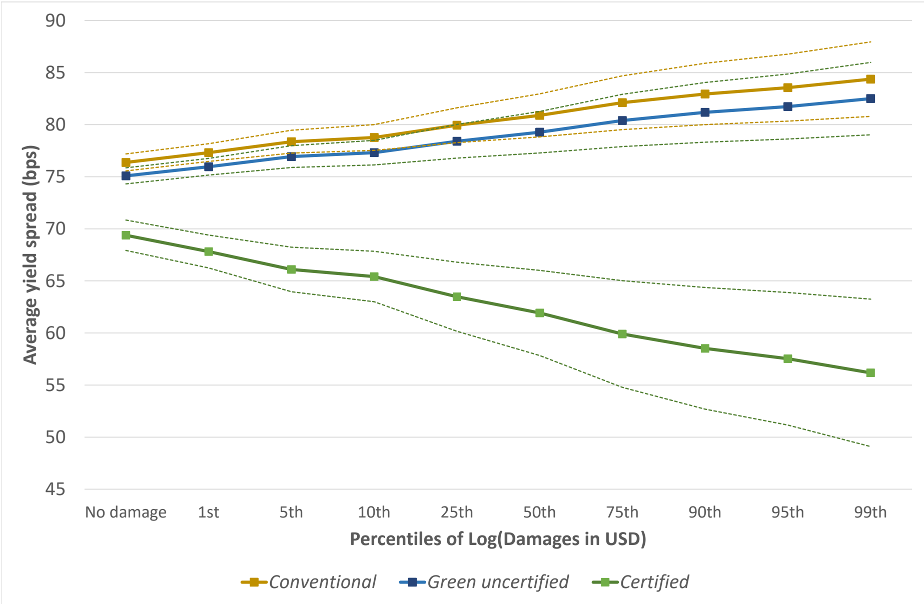
Figure 3.3. Relationship between severity of climate events and average yield spreads. The figure shows the marginal effects of yield spreads for certified bonds, uncertified green bonds and conventional bonds for different percentiles of Log(Damages in m$). Marginal effects are obtained from model specifications (1)–(3) in Table 3.9. The solid lines represent the mean values, while the dotted lines represent the 95% confidence intervals.



(a) Specification (1)



(b) Specification (2)



(c) Specification (3)

Figures 3.3a, 3.3b and 3.3c illustrate the estimated margins from specifications (1), (2), and (3) respectively, comparing yield spreads for certified green, uncertified green, and conventional bonds across different percentiles of the variable Log(Damages in $m). As shown in Figure 3.3a, for uncertified green bonds and conventional bonds, the yield spread increases with the damage percentiles. Specifically, the marginal effect of the yield spread rises from approximately 76 bps with no damages to around 83 bps at the 99th percentile of damages for uncertified green bonds, and to 81 bps for conventional bonds. In contrast, for certified green bonds, the yield spread decreases with increasing damage percentiles, starting at approximately 69 bps with no damages and decreasing to about 55 bps at the 99th percentile of damages. These patterns are consistently observed in Figure 3.3b and 3.3c as well.

Overall, green bonds are seen to enjoy a narrower yield spread, while certified green bonds reap a larger greenium. Disaster events in the issuer's country increase bond spreads in the five days following their occurrence. The size of the damages caused by disasters also play a role in increasing the spread. The positive and statistically significant effect of the variables *Dummy 5 days post-disaster* and *Log(Damages in $m)* on bond spreads can be explained by the increased uncertainty and risk associated with natural disasters. When disasters strike, there is often significant damage to infrastructure and property, which can lead to disruptions in economic activity and uncertainty about the future prospects of the affected country (e.g., Botzen & Van Den Bergh, 2009). Moreover, the occurrence of natural disasters can generate a sense of fear, uncertainty, and negative sentiment among investors, even those who are not directly affected by the disaster (Noy, 2009). This sentiment can lead to a risk-off environment, where investors become more risk-averse and demand higher yields to compensate for the perceived increased risk (Johar et al., 2022). The sustainability aspect signalled by certified green bonds is particularly attractive to investors in the aftermath of natural disasters, as these bonds could potentially curtail the impact of future disaster and contribute to rebuilding efforts (IMF, 2021). The interaction between certification and Log(Damages in $m) suggests that the certification's effect is magnified by the severity of the damages caused by natural disasters.

These results align with the interpretation of other studies (Baker et al., 2018; Bolton & Kacperczyk, 2021a) showing that climate-related events can act as informational shocks that heighten the salience of climate risks. Building on this insight, the interpretation advanced here is that such events may strengthen investors' incentives to rebalance towards assets that are more aligned with the low-carbon transition. Certified green bonds are not physically protected from disasters; rather, they may benefit from being perceived as transition-aligned investments when climate risk becomes more visible. In other words, investors favour environmentally sustainable bonds after disasters as a transition-aligned hedging strategy and, in so doing, can mitigate the negative impact of natural disasters on their bond investments.

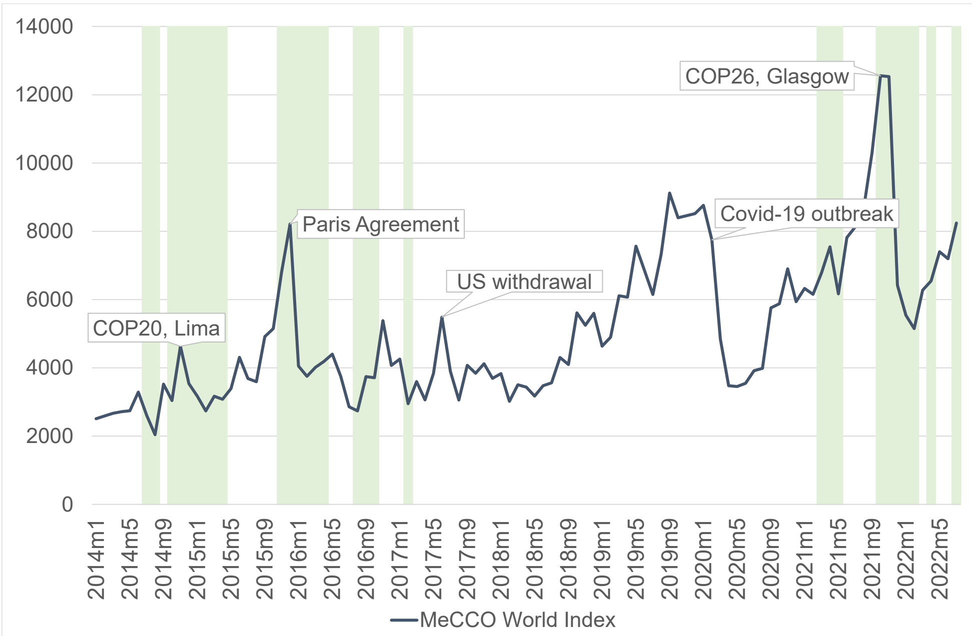
3.4.5 Heightened public attention to climate change

Building on these findings, we continue testing Hypothesis 3.5a and 3.5b, which aim to examine the relationship between periods of heightened public attention to climate change and bonds of green issuers. These hypotheses are motivated by the belief that heightened public attention to climate change may lead to greater demand for green investments. In order to test this, we utilise the MeCCO World Index[11] (Boykoff et al., 2020) as a proxy for the level of public attention to climate change in a given month. MeCCO stands for Media and Climate Change Observatory, which is a research project that tracks media coverage of climate change around the world. The MeCCO World Index is a monthly index that summarises the volume and themes of climate change coverage in 45 countries and regions around the world. The index is calculated based on data collected from a range of sources, including newspapers, television, radio, and online news outlets. The MeCCO World Index is used by researchers, policymakers, and journalists to analyse trends in climate change coverage and public perceptions of climate change around the world (e.g., Romanello et al., 2022; Watts et al., 2021). As displayed in Figure 3.4, this index captures global media coverage of climate change and can help gauge the extent to which climate change is receiving public attention. To address the mismatch in the frequency of our independent variable (the monthly MeCCO Index) and our dependent variable (daily yield spreads), we average daily spreads to obtain a monthly average. This approach ensures

[11] Source: MeCCO.

that each observation of the dependent variable corresponds appropriately in time to our key independent variable, avoiding the potential forward-looking bias that could arise from using daily data in conjunction with a monthly index.

Figure 3.4. Media coverage related to climate risk and greenium. This figure displays the Media and Climate Change Observatory (MeCCO) World Index over time, measuring the amount of media coverage related to climate change in major newspapers. The light green shaded background highlights the months during which the greenium is statistically significant at the 10% level. Sample period: January 2014 to July 2022.



Moreover, given the global coverage of MeCCO Index, employing monthly fixed effects in our regression analysis would result in the complete absorption of this key variable. To be able to capture the impact of the MeCCO Index, we opted for quarterly fixed effects. By examining the relationship between the MeCCO World Index and the issuance of green bonds, we can test whether increased public attention to climate change translates into greater demand for green investments.

The regression results, presented in Table 3.10, demonstrate that both conventional and green bonds benefit from increased attention to climate change, as measured by the climate news index. This heightened attention leads to a reduction in their yield spreads. Specifically, in column (1) the negative coefficient of the index (-10.03) indicates the news effect on conventional bonds, while the lack of significance of the coefficient of the interaction between the index and the Green Bond dummy suggests that the news effect remains unchanged for green bonds. However, the statistical significance of the interaction between the climate news index and the Certified dummy at -19.71 provides evidence that certified green bonds outperform both conventional bonds and non-certified green bonds during periods of heightened public attention to climate change.

In column (2), we corroborate the findings using the Innovations on MeCCO index[12] in place of the percentage change on the same index. This result is consistent with green bond signalling theory Flammer (2021): by issuing a green bond, firms credibly signal a sustained commitment to environmental sustainability. This signal creates a *halo effect*, extending beyond the financed project to the issuer's overall strategy and to all its outstanding debt. In line with the carbon premium literature (Bolton & Kacperczyk, 2021b; Sangiorgi & Schopohl, 2021), such signalling can lower investors' assessment of transition risk, so the issuer is seen as less exposed to shocks such as new climate regulations. As public attention to climate change intensifies, investors may therefore value all of the issuer's bonds more highly, not only its green bonds, which lowers yield spreads across the issuer's debt.

The negative coefficient for the interaction between the MeCCO World Index and the Certified status indicates that certification's impact on reducing yield spreads intensifies during periods of heightened public attention to climate change. To understand the

[12] A variable representing the innovations on the MeCCO World index, derived from the residuals of an AR1 model on the index.

Table 3.10. Climate change news. This table reports panel regressions of daily corporate bond yield spreads on the Media and Climate Change Observatory (MeCCO) World Index, a news-based indicator of climate change awareness. The explanatory variables include the Δ% MeCCO index which is the percentage change in the MeCCO World index (1); Innovations on the MeCCO index (2) which are the innovations of the MeCCO index derived from the residuals of an AR1 model applied to the index; a Green Bond dummy, which equals 1 if a bond is green; a Certified dummy, which equals 1 for certified bonds; the bid-ask spread; years to maturity; the natural logarithm of the issue amount and coupon rate. Differently from the previous regression models, this analysis utilises monthly average yield spreads for each bond. Consequently, the refined sample consists of 21,016 observations. Due to the MeCCO Index being a monthly global measure, fixed effects are set at the quarterly level to prevent the complete absorption of the MeCCO Index in our regression model. Sample period: January 2014 to July 2022. Standard errors clustered at the quarter-issuer level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread (monthly avg)	**(1)**	**(2)**
Green bond	-1.7449***	-1.7472***
	(0.6182)	(0.6197)
Certified	-5.7329***	-5.7915***
	(1.0426)	(1.0422)
Δ% MeCCO index	-10.0321***	
	(1.7399)	
*Green bond*Δ% MeCCO index*	2.2257	
	(1.8238)	
*Certified*Δ% MeCCO index*	-19.7077***	
	(6.4365)	
Innovations on MeCCO index		-0.0012***
		(0.0003)
*Green bond*Innovations on MeCCO index*		0.0003
		(0.0003)
*Certified*Innovations on MeCCO index*		-0.0022**
		(0.0009)
Rating FE	YES	YES
Currency FE	YES	YES
Issuer FE	YES	YES
Quarter FE	YES	YES
R-squared	0.6197	0.6029
Bonds	688	688
Observations	21,016	21,016

economic significance of these coefficients, we consider the standard deviation of the $\Delta\%$ MeCCO Index, which is 0.21, as reported in Table 3.2. A standard deviation increase in the $\Delta\%$ MeCCO Index corresponds to a yield spread reduction of approximately 2.1 bps for conventional and non-certified green bonds.[13] For certified green bonds, the reduction is more pronounced at 6.25 bps.[14] This translates to 2.77% and 8.23%, respectively, of the average bond yield spreads in our sample. In specification (2), a standard deviation increase in the Innovations on the MeCCO Index leads to a yield spread reduction of approximately 1.35 bps for conventional and non-certified green bonds.[15] Certified green bonds see a larger decrease of 3.82 bps.[16]

3.4.6 Robustness tests

This section presents a series of robustness tests designed to assess the impact of varying fixed effects, the exclusion of specific time periods, and the consideration of different time windows post-disaster events, among other factors. Below, we detail each of these robustness checks and their implications for our analysis.

Robustness with issuer×time fixed effects. Building on our comprehensive matching strategy, we applied more granular fixed effects by incorporating quarter × issuer and month × issuer fixed effects, as detailed in Table 3.A.12. These refined models were designed to control for any residual unobserved heterogeneity at the issuer level. This approach did not alter the primary conclusions, further demonstrating the robustness of our findings to variations in the control for unobservable factors.

[13] Calculated as 0.21×10.03.
[14] Calculated as $0.21 \times (19.71 + 10.03)$.
[15] Calculated as 1124.23×0.0012.
[16] Calculated as $1124.23 \times (0.0012 + 0.0022)$.

Exclusion of negative yield spread observations. As seen from the minimum value of the yield spread in Table 3.2, we observe instances where bonds exhibit a negative yield spread compared to government bonds. Negative yield spreads can indicate illiquidity, which may influence our results. To indirectly account for this, we include bid-ask spreads in our analysis, serving as a measure of liquidity risk. In addition, we have also conducted a test excluding all pair-day observations for which at least one bond in the pair had negative yield spreads. This led to a reduction in our sample size from 346,418 to 335,394 observations. This robustness test, reported in Table 3.A.3 of the appendix, supports our initial findings, reinforcing that the observed lower spread for green bonds holds true even when instances of negative yield spreads are excluded.

Exclusion of the Paris Agreement period. Recognising the potential impact of the Paris Agreement on the greenium, we conducted a robustness test by excluding the 12-month period following the COP21 (November 2015 to October 2016). The analysis, shown in Table 3.A.4, demonstrates that the greenium persists across all specifications, albeit with a slight reduction of about one-tenth of a basis point. This suggests that the presence of the greenium in the market is robust beyond this significant environmental policy event.

Controlling for ESG Scores. To account for the potential influence of corporate governance and firm-specific ESG performance on bond spreads, we incorporate time-varying ESG score grades from Refinitiv in our robustness tests, as presented in Table 3.A.5. The results confirm that the inclusion of ESG scores does not materially affect the relationship between green bond certification and bond spreads, further supporting the robustness of our baseline findings across different model specifications.[17]

[17] It is important to note that the ESG scores provided by Refinitiv may be subject to backfilling, as highlighted by Berg et al. (2021). This means that the historical scores available today may differ from the ratings investors had access to in real-time during the sample period. While this limitation should be considered when interpreting

Alternative liquidity measures. To investigate the impact of alternative liquidity measures on the greenium, we employ three distinct illiquidity proxies, as presented in Table 3.A.6, and Table 3.A.7. In Table 3.A.6, Columns (1) and (4) use *Market illiquidity*, measured as the weighted average bid-ask spread across bonds in the market by outstanding amount. Columns (2) and (5) control for *Issuer illiquidity*, defined as the daily average bid-ask spread of each issuer.In Columns (3) and (6), we include γ *illiquidity*, based on the measure proposed by Bao et al. (2011). This last illiquidity measure is defined as:

$$\gamma = -\text{Cov}(\Delta p_t, \Delta p_{t+1})$$

where p_t represents the natural logarithm of the bond's clean price. We further assess the effects of liquidity shocks, measured with our alternative indicators, during disaster events. Results are reported in Table 3.A.7 and confirm our previous conclusions. In addition, we test the interactions of the Green Bond and Certified dummies with the bid-ask spread in Table 3.A.8. The interaction terms are not statistically significant in any of these specifications.

Linearity assumption and quantile regression test. While much of the literature has focused on linear models to analyse the determinants of bond yield spreads (e.g., Caramichael & Rapp, 2024; Fatica & Panzica, 2021; Gianfrate & Peri, 2019; Hachenberg & Schiereck, 2018; Karpf & Mandel, 2018; Pietsch & Salakhova, 2022; Zerbib, 2019), we extend our analysis using quantile regression to explore whether the impact of green bond status varies across different points of the conditional distribution of yield spreads. Quantile regression allows us to capture potential heterogeneity in the effects of covariates, which may be missed by a linear model that only examines the average effect. Our results, presented

the results, the robustness tests incorporating ESG ratings still offer useful insights into the role of firm-level ESG performance in bond pricing.

in Table 3.A.9, demonstrate that the greenium is consistently negative and statistically significant across different quantiles (10th, 25th, 50th, 75th, and 90th). This suggests that the greenium is not only present on average but is also robust across the conditional distribution of yield spreads, indicating that investors value green bonds similarly across bonds with both lower and higher yield spreads. These findings highlight the robustness of the greenium beyond linear models, supporting its relevance in different market conditions.

Green certification with issuer-time fixed effects. The effect of green certification on bond spreads was further examined under different issuer-time fixed effects, as reported in Table 3.A.12. This analysis reaffirms the influence of green certification, supporting the robustness of our baseline findings under various model specifications.

Extreme weather events. The robustness of our findings concerning the impact of extreme weather events on bond spreads was tested over different time windows (3-day and 7-day post-disaster dummies). Tables 3.A.10 and 3.A.11 present these analyses, underscoring the consistent effect of extreme weather events and the certification of green bonds on yield spreads. Furthermore, we tested the robustness of the original models including the *5 days post-disaster* and the *Log(Damages in $m)* under more granular fixed effects. The tests are displayed in Tables 3.A.13 and 3.A.14, which confirm the relationship between extreme weather events and yield spreads.

Climate Change News Impact. Finally, we tested the robustness of the relationship between climate change news coverage, as captured by the MeCCO World Index, and corporate bond yield spreads. The analyses, utilising quarter×issuer fixed effects and presented in Table 3.A.15, confirm the significance of climate change awareness on financial markets, reinforcing our primary analyses under alternative specifications.

Taken together, these robustness tests strengthen our findings. The consistency of results across these tests underscores the robust nature of the greenium and its determinants in the corporate bond market.

3.5 Conclusion

In our study, we have undertaken an in-depth analysis of the secondary market for corporate green bonds and its underlying dynamics. Our results corroborate the existence of a greenium in the secondary bond market, demonstrating that green bonds generally trade at a premium in comparison to their conventional counterparts. Further, we have identified dynamic fluctuations in the greenium over time, which correspond to major climate change-related events and policy decisions. A striking example of this was the increased greenium around the time of the 2015 Paris Agreement. This result points to the substantial influence that environmental policy changes and climate events can exert on the market sentiment towards green bonds. We also confirm the importance of the external review process in the green bond market. Bonds that have been externally reviewed exhibit an (up to five time) larger greenium than non-certified bonds. This highlights the significance of third-party certification and verification mechanisms in promoting investor trust, incentivising issuers to adhere to high environmental standards and preventing greenwashing practices. Our results show that in environmentally material industries, certified green bonds benefit from an even larger greenium, whereas non-certified green bonds in these industries may face scepticism and, in some cases, even a discount due to concerns over greenwashing. These findings suggest a potential path for governments to shape green bond regulations by advancing rigorous certification requirements or incentivising certification for green bonds, particularly in high-impact industries. Such regulatory approaches could enhance transparency in the green bond market, reduce greenwashing risk, and increase the credibility of climate-focused finance. Aligning green bond market practices with established certification standards may further encourage capital flow towards sustainable projects, thereby supporting climate goals.

Furthermore, this study brings to light the complex nature of the elements influencing green bonds' performance, particularly focusing on the effects of natural disasters and climate change news on bond spreads. The effect of natural disasters in the bond market is complex. Generally, disasters result in increased bond spreads due to various factors like amplified market uncertainty and risk, potential indirect impacts on the issuer through disruptions in supply chains or other economic consequences, leading to diminished demand for bonds from the affected countries. Yet, certified green bonds can also garner a "green premium" during these events, with the scale of this premium directly being influenced by the extent of disaster damages. These findings underscore the importance in evaluating disaster risk and the potential benefits that certified green bond holders can gain from hedging against such risks. Therefore, these aspects of our study can offer valuable information for entities considering the issuance of green bonds, investors looking for hedging strategies, and policymakers working towards sustainable finance and disaster resilience.

Considering the role of climate change news, we show that a rise in the MeCCO World index (a proxy for global media attention to climate change) is linked to a positive shift in market sentiment towards environmentally responsible investments, shaping public perception and awareness. As investors become more informed about the environmental risks and opportunities associated with their investments, they start to favour companies that are taking proactive steps to mitigate climate change impacts, in part because the green bond signal generates a *halo effect* that extends beyond the financed projects to the issuer's overall strategy and all outstanding debt, and because perceived transition risk is lower for such issuers. This increased demand for environmentally responsible investments translates into lower spreads across the issuer's debt, affecting both green and conventional bonds issued by companies that are actively working to address climate change issues, such as the green issuers in our sample. The effect is even stronger for certified green bonds. Thus, investors can benefit by increasing their holdings in certified green bonds, which typically experience a widening of the greenium and offer opportunities for capital appreciation.

Finally, environmental awareness and concern positively impact investor demand for certified green bonds, which in turn could encourage issuers to prioritise environmental sustainability in their business practices. Corporations may also leverage these insights by strategically timing their green bond issuances to periods of heightened climate awareness, such as around key policy announcements, when investor demand and greenium premiums tend to be more favourable. Such timing could allow companies to secure lower financing costs.

Appendices to Chapter 3

Table 3.A.1. Conversion of S&P ratings to numerical values. This table displays the conversion of Standard and Poor's (S&P) credit ratings into numerical values.

S&P Rating	Value
AAA	26
AA+	25
AA	24
AA-	23
A+	22
A	21
A-	20
BBB+	19
BBB	18
BBB-	17
BB+	16
BB	15
BB-	14
B+	13
B	12
B-	11
CCC+	10
CCC	9
CCC-	8
CC	7
C	6

Table 3.A.2. Greenium across environmental impact industries. This table reports the greenium for certified and green bonds compared to conventional bonds, based on industries' environmental impact (SASB classifications). The greenium is calculated for Environmental Impact (SASB > 0), No Impact industries (SASB $= 0$), High Impact (SASB ≥ 3), and Low Impact industries (SASB < 3). The results in Panel A correspond to specification (1) with quarter-year fixed effects from Table 3.7, and those in Panel B correspond to specification (2) with month-year fixed effects from Table 3.7. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Comparison	**No Impact (SASB = 0)**	**Impact (SASB > 0)**	**Low Impact (SASB < 3)**	**High Impact (SASB ≥ 3)**
Panel A: Quarter-Year Fixed Effects				
Certified vs Conventional	-8.45***	-9.01***	-8.05***	-15.49***
	(1.18)	(1.63)	(0.96)	(5.47)
Green vs Conventional	-2.22***	-0.28	-2.13***	3.01
	(0.61)	(1.42)	(0.66)	(2.09)
Panel B: Month-Year Fixed Effects				
Certified vs Conventional	-8.42***	-8.82***	-7.99***	-15.26***
	(0.75)	(1.01)	(0.61)	(3.33)
Green vs Conventional	-2.10***	-0.18	-2.03***	3.17**
	(0.38)	(0.87)	(0.41)	(1.30)

Table 3.A.3. Determinants of the yield spread (robustness test excluding negative yield spreads). This table presents the results of our robustness test, adjusting the baseline panel regression model (Equation 3.1) by excluding pair-day observations where either the green bond or its matched conventional conventional bond displayed a negative yield spread. The refined sample, with the exclusion, consists of 335,394 observations, down from the initial 346,418. The analysis employs a Green Bond dummy and a Certified dummy. Each set of columns tests the relationship under different time fixed effects: quarterly (Column 1), monthly (Column 2), and daily (Column 3), with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, coupon rate, alongside rating, issuer, and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.48**	-1.35***	-1.30***
	(0.58)	(0.36)	(0.08)
Certified	-6.21***	-6.26***	-6.27***
	(1.00)	(0.64)	(0.16)
Bid ask spread	0.27***	0.23***	0.21***
	(0.05)	(0.03)	(0.01)
Time to maturity	2.73***	2.89***	2.95***
	(0.19)	(0.12)	(0.03)
Log(Issue amount)	-2.83***	-2.90***	-2.93***
	(0.62)	(0.38)	(0.09)
Coupon rate	2.53***	2.58***	2.60***
	(0.85)	(0.52)	(0.13)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6605	0.6798	0.6869
Bonds	688	688	688
Observations	335,394	335,394	335,394

Table 3.A.4. Determinants of the yield spread (robustness test excluding the Paris Agreement period). This table presents the results of our robustness test, adjusting the baseline panel regression model (Equation 3.1) by excluding the Paris Agreement time span from November 2015 to October 2016. The refined sample, with the exclusion, consists of 339,370 observations, down from the initial 346,418. Each set of columns tests the relationship under different time fixed effects: quarterly (Column 1), monthly (Column 2), and daily (Column 3), with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, coupon rate, alongside rating, issuer, and currency fixed effects. The period of analysis extends from January 2014 to July 2022, except for the period from November 2015 to October 2016. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.35**	-1.24***	-1.20***
	(0.67)	(0.41)	(0.10)
Certified	-7.19***	-7.23***	-7.23***
	(1.10)	(0.69)	(0.18)
Bid ask spread	0.45***	0.40***	0.38***
	(0.06)	(0.04)	(0.01)
Time to maturity	2.72***	2.87***	2.93***
	(0.21)	(0.14)	(0.03)
Log(Issue amount)	-1.53**	-1.60***	-1.62***
	(0.73)	(0.45)	(0.11)
Coupon rate	-0.36	-0.30	-0.28
	(1.19)	(0.72)	(0.18)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6023	0.6175	0.6231
Bonds	688	688	688
Observations	339,370	339,370	339,370

Table 3.A.5. Determinants of the yield spread (robustness test with ESG score control). This table presents the results of our robustness test, adjusting the baseline panel regression model (Equation 3.1) by incorporating time-varying ESG scores from Refinitiv to control for corporate governance and firm-specific characteristics. ESG scores are categorised into four categories from A to D, where "A" (baseline category) is the highest score and "D the lowest." The sample consists of 346,418 observations. Each set of columns tests the relationship under different time fixed effects: quarterly (Column 1), monthly (Column 2), and daily (Column 3), with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating, issuer, and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.48**	-1.37***	-1.32***
	(0.65)	(0.40)	(0.09)
Certified	-6.69***	-6.73***	-6.74***
	(1.11)	(0.70)	(0.18)
ESG Score: A (baseline)	—	—	—
ESG Score: B	0.99	0.95	0.90*
	(2.88)	(1.82)	(0.44)
ESG Score: C	17.71*	17.88***	17.83***
	(10.33)	(6.33)	(1.44)
ESG Score: D	28.50***	29.08***	29.01***
	(10.40)	(6.42)	(1.49)
ESG Score: Not Rated	17.59**	17.60***	17.60***
	(8.54)	(5.26)	(1.22)
Bid ask spread	0.43***	0.38***	0.37***
	(0.05)	(0.03)	(0.01)
Time to maturity	2.83***	2.98***	3.03***
	(0.21)	(0.13)	(0.03)
Log(Issue amount)	-1.59**	-1.66***	-1.68***
	(0.71)	(0.44)	(0.11)
Coupon rate	-0.03	0.01	0.03
	(1.15)	(0.70)	(0.17)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6032	0.6186	0.6240
Bonds	688	688	688
Observations	346,418	346,418	346,418

Table 3.A.6. The impact of alternative illiquidity measures on green bond premium. This table presents the results of a panel regression model examining the determinants of daily yield spread using three alternative illiquidity measures, with and without bid-ask spread as a control variable. Columns (1)–(3) show results without bid-ask spread, while Columns (4)–(6) include it. Column (1) and (4) include Market Illiquidity (measured as the weighted average bid-ask spread of bonds in the market by outstanding amount), Columns (2) and (5) include Issuer Illiquidity (the daily average bid-ask spread of each issuer), and Columns (3) and (6) include γ illiquidity, based on the measure proposed by Bao et al. (2011). Explanatory variables include the Green Bond dummy, Certified dummy, time to maturity in years, the natural logarithm of the issue amount, and the coupon rate, alongside rating, currency, and issuer fixed effects. Standard errors clustered at both the month-issuer levels are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Green bond	-1.04***	-0.37	-0.47	-1.63***	-0.85**	-1.41***
	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.41)
Certified	-8.17***	-7.87***	-7.59***	-7.83***	-7.58***	-7.17***
	(0.72)	(0.69)	(0.69)	(0.71)	(0.68)	(0.69)
Bid ask spread				0.27***	0.19***	0.39***
				(0.03)	(0.02)	(0.04)
Market illiquidity	1.99***			1.82***		
	(0.11)			(0.11)		
Issuer illiquidity		0.70***			0.54***	
		(0.07)			(0.07)	
γ *illiquidity*			0.16**			0.14*
			(0.08)			(0.08)
Time to maturity	4.15***	3.68***	4.03***	3.32***	3.19***	2.85***
	(0.11)	(0.12)	(0.15)	(0.12)	(0.12)	(0.15)
Log(Issue amount)	-2.26***	-1.76***	-2.48***	-1.84***	-1.60***	-1.86***
	(0.44)	(0.45)	(0.45)	(0.43)	(0.45)	(0.44)
Coupon rate	-0.83	0.45	0.29	-1.02	0.20	-0.13
	(0.71)	(0.68)	(0.70)	(0.70)	(0.68)	(0.70)
Rating FE	YES	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
R-squared	0.6280	0.6199	0.6110	0.6309	0.6210	0.6172
Observations	346,418	346,418	344,310	346,418	346,418	344,310

Table 3.A.7. Extreme weather events, illiquidity, and bond spreads. This table presents panel regressions examining the impact of green bond issuance, disaster events, certification, and alternative illiquidity measures on bond yield spreads. Columns (1)–(3) exclude bid-ask spread as a control, while Columns (4)–(6) include it. Illiquidity measures tested include Market Illiquidity (weighted average bid-ask spread of bonds in the market), Issuer Illiquidity (daily average bid-ask spread per issuer), and γ illiquidity based on the measure proposed by Bao et al. (2011). Control variables include the Green Bond dummy, a Certified dummy, time to maturity, natural logarithm of the issue amount, and coupon rate, alongside rating, issuer, and currency fixed effects. Standard errors clustered at both the month-issuer levels are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Green bond	-0.96**	-0.33	-0.42	-1.59***	-0.82**	-1.40***
	(0.40)	(0.40)	(0.41)	(0.41)	(0.40)	(0.42)
Certified	-7.82***	-7.47***	-7.16***	-7.47***	-7.18***	-6.74***
	(0.72)	(0.69)	(0.69)	(0.71)	(0.68)	(0.69)
5 days post-disaster	5.09***	4.78***	5.69***	4.47***	4.50***	4.73***
	(1.09)	(1.12)	(1.15)	(1.08)	(1.12)	(1.14)
Green bond × 5 days post-disaster	-1.98**	-1.08	-1.23	-1.05	-0.51	0.03
	(0.89)	(0.85)	(0.87)	(0.87)	(0.84)	(0.84)
Certified × 5 days post-disaster	-11.82***	-12.95***	-14.28***	-11.97***	-13.15***	-14.22***
	(2.62)	(2.60)	(2.60)	(2.56)	(2.56)	(2.52)
Market illiquidity	1.98***			1.81***		
	(0.11)			(0.11)		
Issuer illiquidity		0.70***			0.54***	
		(0.07)			(0.07)	
γ illiquidity			0.16**			0.14*
			(0.08)			(0.08)
Bid ask spread				0.27***	0.19***	0.39***
				(0.03)	(0.02)	(0.04)
Time to maturity	4.15***	3.68***	4.03***	3.32***	3.19***	2.85***
	(0.11)	(0.12)	(0.15)	(0.12)	(0.12)	(0.15)
Log(Issue amount)	-2.24***	-1.76***	-2.47***	-1.83***	-1.60***	-1.86***
	(0.44)	(0.45)	(0.45)	(0.43)	(0.44)	(0.44)
Coupon rate	-0.84	0.42	0.26	-1.04	0.18	-0.15
	(0.71)	(0.68)	(0.70)	(0.70)	(0.68)	(0.70)
Rating FE	YES	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
R-squared	0.6282	0.6201	0.6113	0.6311	0.6212	0.6175
Observations	346,418	346,418	346,418	346,418	346,418	346,418

Table 3.A.8. Sensitivity of the greenium to bid-ask spread. This table presents the results of a panel regression model examining the impact of liquidity and certification on the greenium. The explanatory variables include a Green Bond dummy, a Certified dummy, the bid-ask spread, time to maturity in years, the natural logarithm of the issue amount, and the coupon rate, alongside rating, issuer and currency fixed effects. Each column controls for different fixed effects to account for time variation: Column (1) uses Quarter FE; Column (2) uses Month FE; and Column (3) uses Daily FE, with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. The interaction term assesses whether green and certified bonds display differential sensitivity to liquidity changes. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-2.09**	-2.16**	-2.24**
	(0.88)	(0.88)	(0.88)
Green bond × *Bid ask spread*	0.03	0.03	0.04
	(0.03)	(0.03)	(0.03)
Certified	-7.63***	-7.31***	-7.10***
	(1.64)	(1.61)	(1.62)
Certified × *Bid ask spread*	0.02	0.01	-0.00
	(0.05)	(0.05)	(0.05)
Bid ask spread	0.41***	0.36***	0.34***
	(0.05)	(0.05)	(0.05)
Time to maturity	2.84***	2.98***	3.04***
	(0.14)	(0.14)	(0.14)
Log(Issue amount)	-1.79***	-1.86***	-1.89***
	(0.45)	(0.45)	(0.45)
Coupon rate	-0.13	-0.07	-0.04
	(0.71)	(0.70)	(0.70)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Daily FE	NO	NO	YES
R-squared	0.6019	0.6172	0.6230
Observations	346,418	346,418	346,418

Table 3.A.9. Determinants of the yield spread (quantile regression at different percentiles). This table presents the quantile regression analysis examining the impact of the green bond label and certification on corporate bond yield spreads across different quantiles (10th, 25th, 50th, 75th, and 90th percentiles). The Green Bond dummy variable equals 1 for green bonds, and the Certified dummy variable equals 1 for certified bonds. Control variables include bid-ask spread, time to maturity, natural logarithm of issue amount, and coupon rate. The sample period spans from January 2014 to July 2022. Standard errors clustered at the month-issuer level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
Green bond	-1.08***	-0.93***	-1.28***	-1.35***	-1.30***
	(0.22)	(0.22)	(0.23)	(0.23)	(0.28)
Certified	-4.30***	-4.08***	-3.58***	-3.63***	-2.52***
	(0.60)	(0.61)	(0.54)	(0.70)	(0.81)
Bid ask spread	0.24***	0.25***	0.25***	0.26***	0.23***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Time to maturity	3.51***	3.18***	3.11***	2.75***	2.72***
	(0.13)	(0.13)	(0.12)	(0.11)	(0.14)
Log(Issue amount)	-3.09***	-2.70***	-2.45***	-2.36***	-2.31***
	(0.33)	(0.35)	(0.40)	(0.49)	(0.77)
Coupon rate	-0.78	-0.46	-0.19	1.13*	1.99**
	(0.50)	(0.53)	(0.49)	(0.59)	(0.93)
Rating FE	YES	YES	YES	YES	YES
Currency FE	YES	YES	YES	YES	YES
Issuer FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
R-squared	0.394	0.580	0.586	0.550	0.530
Observations	346,418	346,418	346,418	346,418	346,418

Table 3.A.10. Extreme weather events and bond spreads (3-day robustness check). This table presents panel regressions examining the impact of green bond issuance, disaster events, and certification on bond yield spreads. The analysis employs a Green Bond dummy (1 for green bonds), a Certified dummy (1 for certified bonds with external verification), the dummy "3 days post-disaster" that equals 1 in the three days following extreme weather events as reported in EM-DAT. Each column tests the relationship under different time fixed effect: quarterly (Column 1), monthly (Column 2) and daily (Column 3), with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating, issuer and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.47**	-1.36***	-1.31***
	(0.66)	(0.41)	(0.41)
Certified	-6.76***	-6.81***	-6.81***
	(1.09)	(0.69)	(0.69)
3 days post-disaster	4.45***	4.95***	5.73***
	(1.59)	(1.23)	(1.40)
*Green bond*3 days post-disaster*	0.48	0.29	0.26
	(1.13)	(0.87)	(0.87)
*Certified*3 days post-disaster*	-15.60***	-15.08***	-15.37***
	(3.47)	(2.77)	(2.86)
Bid ask spread	0.43***	0.39***	0.37***
	(0.05)	(0.03)	(0.04)
Time to maturity	2.82***	2.96***	3.02***
	(0.21)	(0.13)	(0.13)
Log(Issue amount)	-1.73**	-1.80***	-1.82***
	(0.71)	(0.44)	(0.44)
Coupon rate	-0.20	-0.16	-0.14
	(1.14)	(0.69)	(0.69)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6022	0.6175	0.6232
Bonds	688	688	688
Observations	346,418	346,418	346,418

Table 3.A.11. Extreme weather events and bond spreads (7-day robustness check). This table presents panel regressions examining the impact of green bond issuance, disaster events, and certification on bond yield spreads. The analysis employs a Green Bond dummy (1 for green bonds), a Certified dummy (1 for certified bonds with external verification), the dummy "7 days post-disaster" that equals 1 in the seven days following extreme weather events as reported in EM-DAT. Each column tests the relationship under different time fixed effect: quarterly (Column 1), monthly (Column 2) and daily (Column 3), with corresponding standard errors clustered at both the quarter-issuer, month-issuer, and day-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating, issuer and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**	**(3)**
Green bond	-1.47**	-1.34***	-1.30***
	(0.67)	(0.41)	(0.41)
Certified	-6.47***	-6.54***	-6.53***
	(1.08)	(0.69)	(0.69)
7 days post-disaster	4.25***	4.65***	5.23***
	(1.54)	(1.16)	(1.28)
*Green bond*7 days post-disaster*	0.20	0.00	-0.04
	(1.07)	(0.83)	(0.83)
*Certified*7 days post-disaster*	-13.46***	-12.94***	-13.19***
	(3.05)	(2.44)	(2.49)
Bid ask spread	0.43***	0.39***	0.37***
	(0.05)	(0.03)	(0.04)
Time to maturity	2.82***	2.96***	3.02***
	(0.20)	(0.13)	(0.13)
Log(Issue amount)	-1.73**	-1.80***	-1.82***
	(0.71)	(0.44)	(0.44)
Coupon rate	-0.22	-0.17	-0.15
	(1.14)	(0.69)	(0.69)
Rating FE	YES	YES	YES
Currency FE	YES	YES	YES
Issuer FE	YES	YES	YES
Quarter FE	YES	NO	NO
Month FE	NO	YES	NO
Day FE	NO	NO	YES
R-squared	0.6022	0.6175	0.6232
Bonds	688	688	688
Observations	346,418	346,418	346,418

Table 3.A.12. Green certification and bond spreads (robustness with issuer-time FE). This table presents the regression analysis examining the impact of green bond label on corporate bond yield spreads. The analysis employs a Green Bond dummy, which equals 1 for green bonds, and a Certified dummy, which equals 1 for certified green bonds. Each column tests the relationship under different FE: quarter×issuer (Column 1) and month×issuer (Column 2), with corresponding standard errors clustered at the quarter-issuer and month-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**
Green bond	-1.08***	-1.04***
	(0.40)	(0.40)
Certified	-6.28***	-6.33***
	(0.62)	(0.62)
Bid ask spread	0.24***	0.22***
	(0.02)	(0.02)
Time to maturity	3.15***	3.19***
	(0.11)	(0.11)
Log(Issue amount)	-1.73***	-1.76***
	(0.42)	(0.42)
Coupon rate	0.60	0.65
	(0.65)	(0.65)
Rating FE	YES	YES
Currency FE	YES	YES
Quarter × Issuer FE	YES	NO
Month × Issuer FE	NO	YES
R-squared	0.8457	0.8719
Bonds	688	688
Observations	346,418	346,418

Table 3.A.13. Extreme weather events and bond spreads (robustness with issuer-time FE). This table presents panel regressions examining the impact of green bond issuance, disaster events, and certification on bond yield spreads. The analysis employs a Green Bond dummy (1 for green bonds), a Certified dummy (1 for certified bonds with external verification), the dummy "5 days post-disaster" that equals 1 in the five days following extreme weather events as reported in EM-DAT. Each column tests the relationship under different FE: quarter×issuer (Column 1) and month×issuer (Column 2), with corresponding standard errors clustered at the quarter-issuer and month-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**
Green bond	-1.05***	-1.01**
	(0.40)	(0.40)
Certified	-6.07***	-6.13***
	(0.61)	(0.61)
5 days post-disaster	1.02**	0.90**
	(0.46)	(0.43)
*Green bond*5 days post-disaster*	-0.82	-0.86
	(0.81)	(0.81)
*Certified*5 days post-disaster*	-6.57***	-6.31***
	(1.56)	(1.53)
Bid ask spread	0.24***	0.22***
	(0.02)	(0.02)
Time to maturity	3.16***	3.19***
	(0.11)	(0.11)
Log(Issue amount)	-1.72***	-1.75***
	(0.42)	(0.42)
Coupon rate	0.59	0.63
	(0.65)	(0.65)
Rating FE	YES	YES
Currency FE	YES	YES
Quarter × Issuer FE	YES	NO
Month × Issuer FE	NO	YES
R-squared	0.8457	0.8720
Bonds	688	688
Observations	346,418	346,418

Table 3.A.14. Intensity of weather events and bond spreads (robustness with issuer-time FE). This table presents panel regressions examining the impact of green bond issuance, disaster events, and certification on bond yield spreads. The analysis employs a Green Bond dummy (1 for green bonds), a Certified dummy (1 for certified bonds with external verification), *Log(Damages in $m)*, which represents the natural logarithm of damages in million dollars caused by disasters, calculated for the 5-day period immediately following each disaster event and set to zero otherwise. Each column tests the relationship under different FE: quarter×issuer (Column 1) and month×issuer (Column 2), with corresponding standard errors clustered at the quarter-issuer and month-issuer levels. Control variables include bid-ask spread, years to maturity, natural logarithm of issue amount, and coupon rate, alongside rating and currency fixed effects. The period of analysis extends from January 2014 to July 2022. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread	**(1)**	**(2)**
Green bond	-1.04***	-1.00**
	(0.40)	(0.40)
Certified	-6.06***	-6.13***
	(0.61)	(0.61)
Log(Damages in $m)	0.19***	0.16**
	(0.07)	(0.07)
*Green bond*Log(Damages in $m)*	-0.15	-0.16
	(0.13)	(0.13)
*Certified*Log(Damages in $m)*	-1.09***	-1.02***
	(0.24)	(0.24)
Bid ask spread	0.24***	0.22***
	(0.02)	(0.02)
Time to maturity	3.16***	3.19***
	(0.11)	(0.11)
Log(Issue amount)	-1.72***	-1.75***
	(0.42)	(0.42)
Coupon rate	0.58	0.63
	(0.65)	(0.65)
Rating FE	YES	YES
Currency FE	YES	YES
Quarter × Issuer FE	YES	NO
Month × Issuer FE	NO	YES
R-squared	0.8457	0.872
Bonds	688	688
Observations	346,418	346,418

Table 3.A.15. Climate change news (robustness with issuer-time FE). This table reports panel regressions of daily corporate bond yield spreads on the Media and Climate Change Observatory (MeCCO) World Index, a news-based indicator of climate change awareness. The explanatory variables include the Δ% MeCCO index which is the percentage change in the MeCCO World index (1); Innovations on the MeCCO index (2) which are the innovations of the MeCCO index derived from the residuals of an AR1 model applied to the index; a Green Bond dummy, which equals 1 if a bond is green; a Certified dummy, which equals 1 for certified bonds; the bid-ask spread; years to maturity; the natural logarithm of the issue amount and coupon rate. Differently from the previous regression models, this analysis utilises monthly average yield spreads for each bond. Consequently, the refined sample consists of 21,016 observations. Due to the MeCCO Index being a monthly global measure, fixed effects are set at the quarter×issuer level to prevent the complete absorption of the MeCCO Index in our regression model. Sample period: January 2014 to July 2022. Standard errors clustered at the quarter-issuer level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Dep. variable: Yield Spread (monthly avg)	**(1)**	**(2)**
Green bond	-1.3496**	-1.3565**
	(0.6443)	(0.6457)
Certified	-5.4934***	-5.5142***
	(0.9850)	(0.9873)
Δ% MeCCO index	-10.0073***	
	(1.8081)	
*Green bond*Δ% MeCCO index*	0.9347	
	(1.8540)	
*Certified*Δ% MeCCO index*	-10.4397**	
	(4.2528)	
Innovations on MeCCO index		-0.0012***
		(0.0003)
*Green bond*Innovations on MeCCO index*		0.0001
		(0.0003)
*Certified*Innovations on MeCCO index*		-0.0012**
		(0.0006)
Rating FE	YES	YES
Currency FE	YES	YES
Quarter x Issuer FE	YES	YES
R-squared	0.8487	0.8486
Bonds	688	688
Observations	21,016	21,016

Chapter 4

Energy Efficient Securitisation and Tranche Resilience in Mortgage-Backed Securities

4.1 Introduction

Climate change and the intensifying geopolitical challenges stemming from energy import represent critical issues for the European Union (EU). In response, the EU has prioritised energy efficiency as a pivotal tool not only for reducing greenhouse gas emissions but also for enhancing the EU's energy security by lowering its dependence on imported fuels. Moreover, by diminishing overall energy demand, the adoption of energy-efficient measures contributes to stabilising energy prices, indirectly benefitting the economy at large. The importance of these measures has been heightened by recent energy price volatility and supply chain disruptions, exacerbated by events such as the Russian-Ukrainian conflict and OPEC's supply restrictions. By promoting the adoption of energy-efficient practices, particularly in the residential sector, the EU seeks to mitigate environmental impacts while securing a stable and sustainable energy future. In this study, we combine loan-level and tranche-level data to examine whether green-labelled RMBS differ in credit risk, structure, and resilience.

Using more than 7.7 million loan-quarter observations from the European DataWarehouse (2021–2024), covering 139 RMBS deals and over 3.2 million mortgages, we construct a panel capturing borrowers, loan terms, property characteristics and macroeconomic conditions. We estimate panel logit models on a sample restricted to originators that issued both Green and Non-Green RMBS, allowing within-originator comparisons and reducing confounding from cross-institution heterogeneity. We complement the loan-level analysis with tranche-level evidence by matching RMBS structures and credit ratings from Refinitiv Eikon and estimating ordered-logit models on rating bands. Finally, we simulate expected losses under alternative stress scenarios to assess differences in credit enhancement and structural resilience. We contribute to the literature in the following ways. We are the first to provide evidence on the performance of Green RMBS securitisations. Our findings show that loans in Green RMBS deals exhibit significantly lower delinquency risks, with reductions of 29.6 basis points, representing approximately a 47.6% improvement over the mean default rate. We then show that these performance differences are reflected in the securitisation structure itself. Green RMBS tranches are more likely to be investment grade and display significantly lower expected losses under stress scenarios, with senior and mezzanine tranches remaining fully protected even at extreme default and LGD levels.

In the subsequent sections of this paper, we provide an overview of the current regulatory background on energy efficiency and review existing studies (Section 4.2), and develop testable hypotheses (Section 4.2). We then describe our data and methodology (Section 4.3) and present our results (Section 4.4). Finally, we conclude the paper by summarising the main findings (Section 4.5).

4.2 Energy efficiency: background and motivation

Policy context and targets. The EU has strategically prioritised energy efficiency to address the dual challenges of climate change and energy security. Directive (EU) 2023/1791 highlights energy efficiency as a cornerstone of its efforts to reduce greenhouse gas (GHG) emissions, lower energy costs, and reduce the EU's dependency on energy imports. By improving the energy performance of buildings, the directive aims to tackle energy poverty, enhance air quality, and stimulate economic activity across member states (The EU Parliament and Council, 2023a). The EU has set ambitious targets. These include achieving a minimum 55% reduction in GHG emissions by 2030 (compared to 1990 levels), fully decarbonising the building stock by 2050 and achieving a 32.5% energy efficiency improvement by 2030 (relative to the 2007 reference scenario) (European Commission, 2020a, 2020b).[1] Furthermore, all new constructions from 2021 are required to meet nearly-zero energy building (nZEB) standards, aligning with the commitments of the Paris Agreement. To support these objectives, cumulative end-use energy savings targets demand annual reductions of 1.9% of final energy consumption by 2030. Buildings play a central role in these efforts, as around 75% of them do not meet energy efficiency standards, account for 40% of total energy use and contribute over one-third to the EU's GHG emissions (The EU Parliament and Council, 2023a). These efforts necessitate significant financial investment. Meeting the EU's 2030 energy efficiency and building renovation targets will require over €300 billion in annual investment, with an estimated investment gap of €165 billion per year (European Investment Bank, 2023). Although public funding for energy efficiency has

[1] The earlier 2020 targets, including a 20% reduction in GHG emissions compared to 1990 levels and a 20% improvement in energy efficiency, were overachieved (European Commission, 2022; European Environment Agency et al., 2021).

expanded considerably under the 2021–2027 financial framework, most of these investments will need to come from private sector contributions (European Commission, n.d.).

Energy efficiency and mortgage-backed securities. Integrating energy efficiency into financial instruments is vital for addressing the funding gap to meet the EU's 2030 targets. By mobilising private capital, products such as energy-efficient mortgages can accelerate the adoption of sustainable practices in the housing market (Liaw, 2024). Green RMBS, in particular, have become key instruments in this context, aligning the credit sector with environmental goals by freeing up lenders' balance sheets for reinvestment in green lending (FitchRatings, 2022b). Regulatory developments, including the European Green Bond (EuGB) Regulation approved on 5 October 2023, extend green bond provisions to securitisations and clarify the application of green standards (The EU Parliament and Council, 2023b). Structured finance products like securitisations are inherently more complex than traditional green bonds. In a securitisation, a financial institution (the originator) transfers a pool of loans to a securitisation special-purpose entity (SSPE), which issues securities to investors and uses the proceeds to pay the originator. This multi-entity structure created uncertainty about whether the *use-of-proceeds requirement*—mandating that funds finance or refinance projects with environmental benefits—applied to the originator or the issuer (SSPE). The EuGB Regulation resolves this by applying the requirement at the originator level, allowing green securitisations to meet sustainability goals even if the asset pool is not entirely green. This flexibility addresses the limited supply of green assets and allows proceeds to support environmentally beneficial projects. The alignment with sustainability objectives not only meets growing demand for green investments but also reflects broader market and regulatory shifts favouring environmental sustainability. Regulation has further supported Green RMBS adoption by mandating transparency to promote investor scrutiny and hinder greenwashing practices. The EU Securitisation Regulation, under Article 22, encourages disclosure of environmental impact data for securitised assets, enabling more informed investment decisions and supporting ESG integration in financial markets (The EU Parliament and Council, 2017). Green RMBS thus offer a dual benefit: they provide a scalable mechanism for private investment in energy-efficient housing and support the EU's climate and energy security goals. Thus, they exemplify how financial innovation can align capital markets with sustainability and drive the transition to a greener economy.

The relationship between energy efficiency and mortgage performance has become increasingly relevant in recent years, as households have faced substantial volatility in energy prices and tightening environmental performance standards. An emerging body of evidence documents that energy-efficient properties are associated with lower arrears and default probabilities, even after conditioning on borrower income, employment and loan characteristics (see (Billio et al., 2021; Guin & Korhonen, 2020; Kaza et al., 2014)). The mechanism typically highlighted in this literature is a collateral-based energy-cost channel: households living in inefficient dwellings face higher and more volatile energy bills, are more exposed to energy-cost shocks, and therefore experience tighter liquidity constraints—particularly during periods of elevated inflation or macroeconomic stress. Conversely, mortgages collateralised by more energy-efficient homes tend to exhibit greater resilience.

In the securitisation setting, these considerations translate into testable implications for the performance of Green RMBS. Borrowers do not observe whether their loan is securitised, nor whether it is included in a green-labelled deal, so the mechanism cannot operate through borrower behaviour. Instead, the Green RMBS label functions as a portfolio-level signal of collateral composition. Even though the EuGB Regulation allows Green RMBS to securitise non-efficient properties during the current transitional phase, originators may already be allocating comparatively more energy-efficient loans to green-labelled deals. This may occur because (i) energy-efficient collateral is more resilient to energy-cost shocks and transition risks; (ii) green-labelled transactions face higher scrutiny and transparency expectations; and (iii) anticipation of future regulatory tightening creates incentives for originators to include higher-quality collateral in these pools. Consistent with this interpretation, Chapter 5 shows that Green RMBS pools contain a significantly higher share of energy-efficient properties, measured through EPC ratings.

Under this collateral-selection channel, Green RMBS pools should exhibit lower delinquency risk than otherwise comparable non-green pools. This reasoning leads to the following hypothesis:

Hypothesis 4.1 *Loans securitised in Green RMBS deals have a lower probability of becoming delinquent within the next 12 months than otherwise comparable loans securitised in non-green RMBS from the same originator.*

The implications extend naturally to the tranche level. If Green RMBS pools contain more resilient collateral, and if this translates into lower expected losses, then the structure and credit quality of the notes issued from these pools should reflect this risk differential. Tranches backed by better-performing collateral should, on average, have higher levels of credit protection and a higher likelihood of receiving investment-grade ratings. This leads to our second hypothesis:

Hypothesis 4.2 *Tranches issued in Green RMBS deals exhibit higher credit quality ratings than tranches issued in non-green RMBS deals.*

Additionally, the resilience of securitised portfolios also depends on how risk is allocated across tranches. Even when backed by high-performing assets, a securitisation deal with a thin subordinated layer or weak structural protections may still expose senior investors to unexpected losses under stress. For this reason, we examine whether Green RMBS are not only composed of better loans, but also feature more resilient structural characteristics. Specifically, we test whether Green-labelled RMBS tranches experience lower expected losses than their Non-Green counterparts when subject to adverse default and LGD scenarios, thereby offering greater resilience under stress.

Hypothesis 4.3 *Green RMBS tranches exhibit greater resilience under stress, with lower expected losses across the capital structure compared to Non-Green RMBS.*

4.3 Data and methodology

Our dataset is retrieved from the European DataWarehouse (EDW), the repository designated by the ESMA for collecting and validating standardised loan-level data on securitised assets in Europe. The dataset complies with the updated ESMA reporting templates, introduced in 2021 and replacing the former ECB templates, which require loan-level data to be provided quarterly for asset-backed securities eligible for repurchase agreements with the European Central Bank (ECB). These templates include both mandatory and optional fields, covering detailed information on loan, borrower, and property characteristics, as well as performance indicators. For each loan, more than 150 variables can be reported by the originators of the securitisation, but only a subset of these is mandatory. These categories include borrowers' information, loan characteristics, information on the mortgaged property, and performance indicators. Notably, at the time we retrieved the data for our analyses, EPC rating is one of the optional fields.

4.3.1 Sample overview

The full dataset comprises 28,060,021 quarterly observations spanning from 2021-Q1 to 2024-Q1. The sample period begins in 2021-Q1, when EPC ratings became available in the EDW database. As shown in Table 4.A.1, the whole dataset includes 139 RMBS deals, 3,208,747 unique loans, and 3,529,410 associated properties from various countries. Most deals originate from France, Spain, and the Netherlands, reflecting dominant issuance trends in the European RMBS market during the sample period. To focus on the research objectives, we apply a series of exclusions and variable treatments. Loans are tracked until the end of the sample period unless they reach a terminal event (e.g., default, write-off, redemption); loans that default are excluded from the analysis thereafter. Additionally, loans associated with a *release equity* purpose are excluded, as such transactions, typically involving cash-out refinancing, differ significantly from standard mortgages. To address potential issues with extreme values, key numeric variables are binned into categorical quantiles. These refinements ensure that the dataset is tailored to investigate the risk factors underlying mortgage delinquency. Our analysis focuses on four delinquency indicators assessed over a 12-month horizon. These include two default variables and two arrears variables, the latter reflecting the hypothesis that energy efficiency affects mortgage performance by influencing borrowers' utility costs:

- **Default:** A dummy equal to 1 if the loan is two consecutive quarters in arrears within the next four quarters.
- **Material Default:** A dummy equal to 1 if the loan is two consecutive quarters in arrears within the next four quarters and the arrears balance exceeds 1% of the current loan balance.

- **Arrears:** A dummy equal to 1 if the loan is one quarter in arrears within the next four quarters.
- **Material Arrears:** A dummy equal to 1 if the loan is one quarter in arrears within the next four quarters and the arrears balance exceeds 1% of the current loan balance.

These indicators are particularly relevant in the context of credit risk staging under IFRS 9, where loans move from Stage 1 to Stage 2 as their credit risk increases, even before default occurs. Identifying early signs of distress (such as arrears) can improve risk differentiation and provisioning accuracy.

For each loan, we retrieve a comprehensive set of control variables capturing borrower, loan, property, and macroeconomic characteristics that may influence mortgage delinquency. Macroeconomic indicators, including unemployment rates and house price indices, are sourced from the OECD. Inflation rates and energy price indices are obtained from Eurostat.[2] Table 4.1 provides an overview and description of the variables employed in our analysis. The dataset includes 46 distinct originators, with multiple originators operating within each country. Each originator is associated with a single jurisdiction, as RMBS issuance is country-specific.

For this chapter we focus our analyses on the *Green RMBS Originator Sample*, which restricts the data to loan-quarter observations from institutions that have issued at least one green RMBS, enabling within-originator comparisons of loans securitised in green versus non-green deals and reducing confounding from cross-bank heterogeneity. This yields 7,704,340 observations. Table 4.2 and Table 4.3 report the summary statistics

[2] Eurostat ceased reporting certain series for the United Kingdom following Brexit. To ensure continuity, these were supplemented with equivalent data from the UK's Office for National Statistics (ONS). For overall inflation, we use Eurostat series `prc_hicp_manr - CP00`, complemented by ONS Series ID `D7G7 (00)` for the UK. For energy inflation, we rely on Eurostat `prc_hicp_manr - 045`, integrated with ONS Series ID `D7GT (04.5)`.

separately for categorical and continuous variables. Delinquency patterns are further illustrated in Figure 4.1 and Figure 4.2, which show the cumulative arrears and default rates for loans securitised in Green and Non-Green RMBS. As shown, loans in Green RMBS consistently exhibit lower cumulative delinquency rates than their Non-Green counterparts. To complement the loan-level data, we construct a tranche-level dataset using deal identifiers and bond issuance information from Refinitiv Eikon. This includes tranche issue amounts, seniority (senior, mezzanine, subordinated), credit ratings over time, and EU Taxonomy Green Label status. We track each tranche's most recent credit rating quarterly, along with rating history, enabling dynamic comparisons between green and non-green deals.

Table 4.1. 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 within the next 12 months, and 0 otherwise.
Material Arrears	Dummy	A variable that takes the value of 1 if the loan is one quarter in arrears within the next 12 months 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 within the next 12 months, and 0 otherwise.
Material Default	Dummy	A variable that takes the value of 1 if the loan is two consecutive quarters in arrears within the next 12 months and the arrears balance is greater than or equal to 1% of the current loan balance, and 0 otherwise.
Energy Efficiency		
Green Flag	Dummy	A binary variable indicating whether the loan is securitised in a green/energy efficiency RMBS deal, with 1 representing loans in such deals and 0 otherwise.
Loan Characteristics		
Loan Purpose	Categorical	The purpose of the loan, categorised into Purchase, Construction, Remortgage, Renovation, or Other.
Interest Type	Categorical	The type of interest rate applied to the loan, which can be Fixed, Floating, or Other.
Interest rate	Continuous	The interest rate of the loan at the time of the first reporting date.
Loan-to-Value (LTV)	Continuous	The loan-to-value ratio at the time of 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.
Property 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 (%)	Continuous	The inflation rate over the previous 12 months.

Table 4.2. Summary statistics for categorical variables. This table reports, for each categorical variable, the frequency of observations in each category and the corresponding number of observations within the Green RMBS Originator Sample, which includes only institutions that have issued at least one green RMBS.

Variable	Green RMBS Originator Sample
	Frequency; N
Sample Size	
Observations	100% (N = 7,704,340)
Delinquency	
Arrears	0.723% (N = 55,676)
Material Arrears	0.312% (N = 24,030)
Default	0.296% (N = 22,779)
Material Default	0.127% (N = 9,771)
Energy Efficiency	
Green Flag	4.792% (N = 369,192)
EE Tier: High Efficiency	13.770% (N = 1,060,888)
EE Tier: Medium Efficiency	17.900% (N = 1,379,077)
EE Tier: Low Efficiency	4.370% (N = 336,680)
EE Tier: Missing	63.960% (N = 4,927,696)
Loan Characteristics	
Loan Purpose: Purchase	70.249% (N = 5,412,222)
Loan Purpose: Construction	8.058% (N = 620,816)
Loan Purpose: Remortgage	17.855% (N = 1,375,610)
Loan Purpose: Renovation	3.715% (N = 286,216)
Loan Purpose: Other	0.123% (N = 9,476)
Int. Type: Fixed	86.830% (N = 6,689,678)
Int. Type: Floating	3.718% (N = 286,447)
Int. Type: Other	9.452% (N = 728,214)
Borrower Characteristics	
Employment: Employed - private sector	53.467% (N = 4,119,279)
Employment: Employed - public sector	20.396% (N = 1,571,377)
Employment: Employed - unknown	9.052% (N = 697,397)
Employment: Pensioner	4.912% (N = 378,437)
Employment: Self-employed	10.074% (N = 776,135)
Employment: Unemployed	1.876% (N = 144,533)
Employment: Other	0.222% (N = 17,104)
Property Characteristics	
Occupancy Type: Owner Occupied	86.271% (N = 6,646,611)
Occupancy Type: Buy to Let	11.951% (N = 920,746)
Occupancy Type: Holiday	1.777% (N = 136,906)
Occupancy Type: Other	0.001% (N = 77)
Property Type: Residential Flat	14.667% (N = 1,129,996)
Property Type: Residential House	69.217% (N = 5,332,713)
Property Type: Residential Terrace	0.758% (N = 58,399)
Property Type: Other	15.359% (N = 1,183,310)

Table 4.3. Summary statistics for continuous variables. The table reports the sample averages and corresponding standard deviations, minimums, and maximums for continuous variables in the Green RMBS Originator Sample.

Variable	Mean	St. Deviation	Min.	Max.
Green RMBS Originator Sample				
Arrears balance (€)	3.61	117.67	0.00	9789.28
↪ Arrears balance (€), if positive	1128.99	1749.42	0.01	9789.28
LTV at first reporting date	0.61	0.25	0.04	1.10
Time to maturity (quarters)	48.72	29.27	2.00	148.00
Interest rate (%)	2.24	0.86	0.00	5.70
Income (€)	49,621.81	29,533.80	0.00	235,741.00
Property value (€)	148,007.10	102,713.40	11,716.88	876,000.00
House price index change (%)	4.73	4.48	-4.10	19.00
Unemployment rate change (%)	7.04	1.25	3.40	8.10
Inflation (%)	4.88	2.49	-0.07	14.13
Energy inflation (%)	17.58	24.55	-47.67	152.97

Figure 4.1. Cumulative arrears rate by Green RMBS label. This figure presents the cumulative arrears rate over time, comparing loans securitised in Green RMBS versus Non-Green RMBS. The data is based on RMBS originators with at least one Green and one Non-Green RMBS. Only 11 quarters are shown due to missing data for the 12th quarter in Green RMBS.

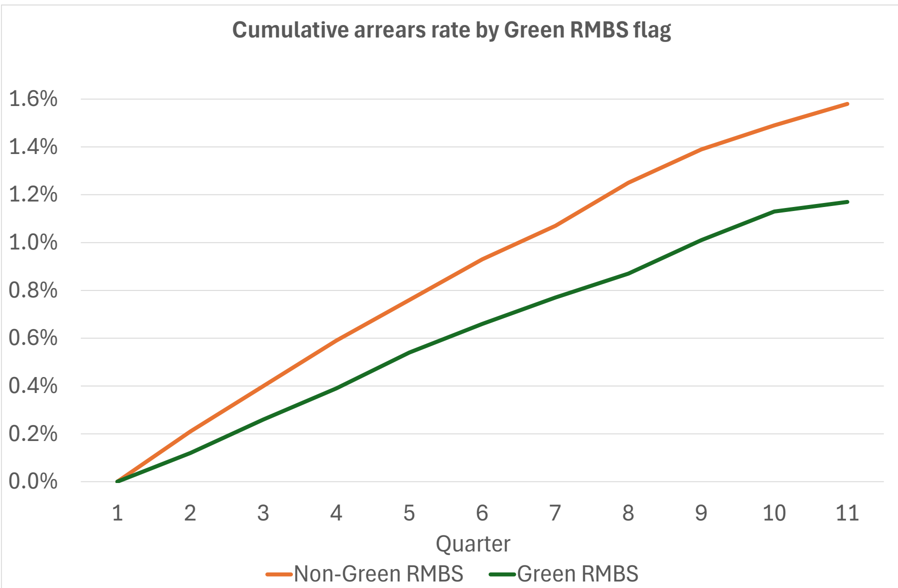
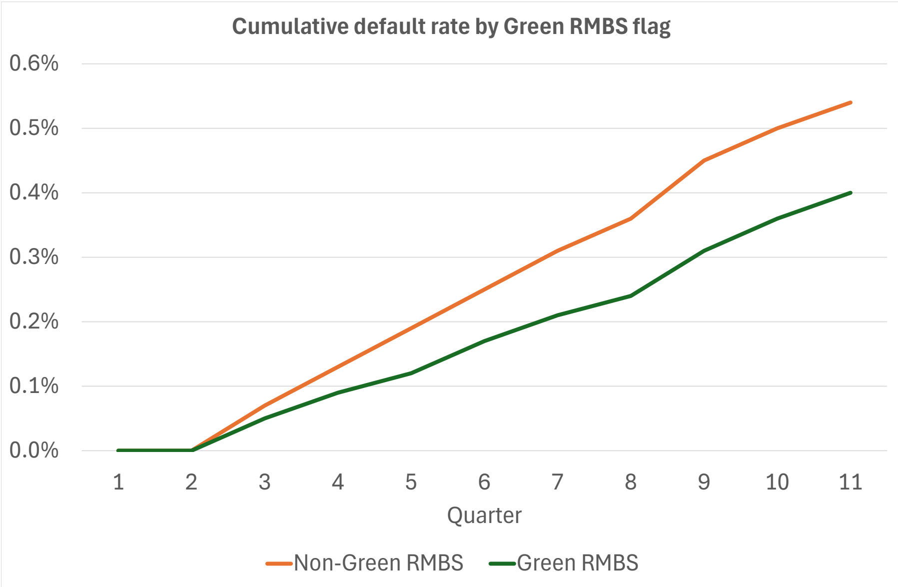


Figure 4.2. Cumulative default rate by Green RMBS label. This figure presents the cumulative default rate over time, comparing loans securitised in Green RMBS versus Non-Green RMBS. Only 11 quarters are shown due to missing data for the 12th quarter in Green RMBS.



The analysis is restricted to RMBS with mapped ISINs and available credit ratings. The final tranche-level sample includes 479 tranches and supports the analysis of structural features, expected loss simulations, and rating regressions in subsection 4.4.2.

4.3.2 Methodology

To examine the relationship between energy efficiency, Green RMBS securitisations, and mortgage delinquency, we implement a panel logit model. This approach, widely used in credit risk and securitisation literature (see, for instance Campbell et al., 2008; Chava & Jarrow, 2004; Crook, 2002; Elul et al., 2010), estimates the likelihood of mortgage delinquency under varying energy efficiency and green securitisation scenarios. This analysis relies on a subsample, i.e., the Green RMBS Originator Sample, which includes only loans from institutions that have issued both green and non-green RMBS. This sample design allows us to isolate the effect of the Green RMBS label while mitigating concerns about selection bias. The rationale is that institutions opting into green securitisation may differ systematically from those that never do, potentially leading to biased estimates if unobserved characteristics (size, governance quality, sustainability orientation, etc.) are correlated with both the likelihood of issuing a green-labelled deal and loan performance. Our approach mirrors identification strategies recommended in related empirical settings, where researchers have emphasised the importance of restricting comparisons to entities that participate in both treated and untreated groups. For example, Larcker and Watts (2020) highlight the limitations of pooled fixed-effects regressions across fundamentally different issuers, noting that observed effects may still reflect structural differences rather than the label itself. Flammer (2021) similarly stresses that limiting the sample to repeat issuers of both types of instruments helps control for issuer-level heterogeneity. By applying this logic to the RMBS context, our Green RMBS Originator Sample reduces the risk that differences in delinquency rates are driven by institutional characteristics unrelated to the Green RMBS flag.

Using the Green RMBS Originator Sample, we assess whether loans securitised in Green RMBS deals are less likely to be delinquent. For each loan i observed at time t, we estimate the probability of entering a delinquent state within the next four quarters. We adopt a logistic regression model with quarterly data, where the dependent variable captures the log-odds of delinquency as a function of loan, borrower, property, and macroeconomic characteristics. The baseline specification is:

$$
\begin{aligned}
\textit{Loan Delinquency}_{i,t} = \; & \alpha + \beta_1 \textit{Green RMBS}_i \\
& + \gamma \textit{Loan Characteristics}_i + \delta \textit{Borrower Characteristics}_i \\
& + \phi \textit{Property Characteristics}_{i,t} + \theta \textit{Macro Variables}_{i,t} \\
& + \textit{Originator FE} + \textit{Quarter FE} + \varepsilon_{i,t}
\end{aligned}
\tag{4.1}
$$

where $\textit{Loan Delinquency}_{i,t}$ is a binary variable equal to 1 if the loan becomes delinquent between time t and the next four quarters (performance window). This forward-looking specification enables the estimation of annualised delinquency using quarterly data, while preserving intra-year variation (Campbell et al., 2008; Siddiqi, 2012; Singer & Willett, 2003). Results are robust to alternative specifications using annual observations only.[3] The key explanatory variable is $\textit{Green RMBS}_i$, which indicates whether loan i is included in a green-labelled RMBS transaction. For the controls, we include variables following the existing literature. Loan characteristics include loan-to-value (LTV) ratios, interest rate at the first reporting date, interest rate type, and purpose (Ertan et al., 2017). Borrower characteristics comprise employment status and income level. Macro variables include country-specific changes in unemployment rates and house price indices, and inflation levels over the previous 12 months (Gerardi et al., 2018). Moreover, we include property characteristics such as property type, occupancy type, and property value. Including originator fixed effects[4] controls for structural features of specific RMBS deals and originator-level credit practices (and, indirectly, for country FE, as originator FE is more granular than country), while quarter fixed effects account for temporal shifts in market conditions. Standard errors are clustered at the 3-letter postcode level, following the most conservative specifications of previous papers on the topic (Billio et al., 2021; Guin & Korhonen, 2020).

[3] Results available upon request.

[4] Ideally, we would control for Deal FE, but as the variable of interest, Green Flag, is at the deal level, this would prevent us from observing its coefficient. Thus, we resort to control for Originator FE and quarter FE, and in an additional robustness tests in the Appendix we control for the interaction Originator × Quarter FE.

In addition to the loan-level analysis, we investigate whether the structural features and credit risk of RMBS tranches differ between Green and Non-Green deals. We match tranche-level data from Refinitiv Eikon, including tranche size, seniority, and credit ratings, to the corresponding RMBS deals. To quantify credit quality, we rely on the most recent tranche rating each quarter, constructing a panel with time-varying ratings. We estimate an ordered logistic regression model, where the dependent variable is the tranche rating band, categorised into three ordered outcomes: Investment Grade (AAA–A3), Speculative Grade (BAA1–BAA3), and Distressed (BA1–C/D). This model assumes a latent, continuous credit quality variable underlies the observed rating categories, with transitions determined by estimated thresholds:

$$\begin{aligned} Rating^*_{i,t} = \ & \alpha + \beta_1 \, Green\ RMBS_i \\ & + \gamma \, Tranche\ Characteristics_i \\ & + \theta \, Quarter\ FE + \varepsilon_{i,t} \end{aligned} \tag{4.2}$$

where $Rating^*_{i,t}$ is the unobserved creditworthiness of tranche i in quarter t. The observed ordinal rating band is determined as:

$$Rating^*{}_{i,t} = \begin{cases} \text{Distressed (BA1–C/D)} & \text{if } Rating^*_{i,t} \leq \tau_1 \\ \text{Speculative (BAA1–BAA3)} & \text{if } \tau_1 < Rating^*_{i,t} \leq \tau_2 \\ \text{Investment Grade (AAA–A3)} & \text{if } Rating^*_{i,t} > \tau_2 \end{cases}$$

where τ_1 and τ_2 are cut-off thresholds estimated by the model. To address potential concerns over stale credit ratings, we apply a weighting scheme based on *rating recency*. Specifically, for tranche i in quarter t, the weight is defined as:

$$\text{Rating Recency}_{i,t} = \frac{1}{1 + d_{i,t}}$$

where $d_{i,t}$ denotes the number of days since the last rating update. This gives greater weight to more recent observations. We also estimate a generalised ordered logit specification as a robustness check. Finally, we simulate expected losses across the capital structure (senior, mezzanine, subordinated) under various LGD assumptions, using the balance-weighted average default rate of each deal. This approach enables us to capture how tranche erosion varies with deal performance and credit enhancement. The structural results are discussed in detail in subsection 4.4.2.

4.4 Results

4.4.1 Green flags and mortgage delinquencies

The results from the panel logit regressions examining the effect of the Green Flag on mortgage delinquency are reported in Table 4.4. The analysis considers four dependent variables capturing different definitions of delinquency: arrears, material arrears, default, and material default. The Green Flag indicates whether a loan is part of a green-labelled RMBS deal. Across all four specifications, the Green Flag is negatively and significantly associated with delinquency risk, with all estimates statistically significant at the 1% level. The marginal effects indicate that securitised loans in green deals are associated with a reduction in the probability of arrears by 28.53 basis points, material arrears by 15.71 basis points, default by 14.06 basis points, and material default by 5.46 basis points. These effects are economically meaningful: they represent a 39.5% reduction in arrears relative to the sample mean of 72.2 basis points; a 50.4% reduction in material arrears (mean: 31.2 basis points); a 47.6% reduction in default (mean: 29.6 basis points); and a 43.1% reduction in material default (mean: 12.7 basis points).

Table 4.4. The impact of the Green Flag label on mortgage delinquency. 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 *Green Flag*. Other control variables include loan, borrower and property 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 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Green Flag	-28.533***	-15.708***	-14.064***	-5.460***
	(6.692)	(2.731)	(3.047)	(1.346)
LTV:				
1st quintile (baseline)	-	-	-	-
2nd quintile	12.477***	3.860***	8.003***	2.995***
	(2.178)	(1.073)	(1.416)	(0.674)
3rd quintile	30.656***	13.033***	16.965***	6.296***
	(4.614)	(2.335)	(1.959)	(1.165)
4th quintile	45.973***	19.503***	11.987***	4.093***
	(7.217)	(3.246)	(2.337)	(0.960)
5th quintile	90.105***	41.993***	21.720***	10.353***
	(15.986)	(7.081)	(3.542)	(2.157)
Time to Maturity (quarters)	-0.537**	-0.356***	-0.560***	-0.239***
	(0.242)	(0.104)	(0.077)	(0.041)
Loan purpose:				
Purchase (baseline)	-	-	-	-
Construction	-14.328***	-8.255***	-10.051***	-4.356***
	(3.891)	(2.098)	(2.053)	(1.008)
Other	-47.052***	-20.013***	-20.013***	-7.565***
	(6.762)	(3.408)	(3.747)	(1.954)
Remortgage	-9.747*	-3.477	-6.311***	-1.817**
	(5.230)	(2.220)	(2.049)	(0.836)
Renovation	-17.345***	-10.836***	-7.102***	-5.041***
	(4.316)	(2.976)	(1.966)	(1.336)
Interest rate:				
1st quintile (baseline)	-	-	-	-
2nd quintile	-14.975*	-3.983	-9.622***	-1.070
	(8.590)	(3.343)	(3.406)	(1.774)
3rd quintile	-2.930	0.665	-6.100*	-0.712
	(8.956)	(3.430)	(3.350)	(1.760)
4th quintile	9.820	8.799**	1.539	3.206*
	(8.756)	(3.731)	(3.168)	(1.694)
5th quintile	58.522***	31.599***	28.744***	14.742***
	(11.978)	(5.235)	(4.365)	(2.422)
Interest type:				
Fixed (baseline)	-	-	-	-
Floating	75.876***	26.534***	49.851***	14.106***
	(23.650)	(8.821)	(6.834)	(3.321)
Other	342.409**	99.336**	168.915***	35.279***
	(164.217)	(40.341)	(45.233)	(12.103)

Table 4.4 continued from previous page

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Employment:				
Employed - private sector (baseline)	-	-	-	-
Employed - public sector	-23.829***	-7.634***	-10.847***	-2.227***
	(2.306)	(1.300)	(1.285)	(0.629)
Employed - unknown	30.592***	17.439***	19.596***	9.515***
	(8.071)	(2.934)	(3.182)	(1.880)
Other	21.964*	-9.286	-1.693	-3.472
	(11.800)	(7.025)	(11.742)	(4.932)
Pensioner	-10.048***	-2.626*	-4.317**	0.311
	(3.746)	(1.564)	(2.094)	(1.066)
Self-employed	57.573***	24.976***	28.668***	13.882***
	(5.098)	(3.051)	(3.295)	(2.229)
Unemployed	54.981***	29.342***	26.295***	12.503***
	(5.174)	(4.809)	(4.846)	(2.542)
Income:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-30.718***	-12.228***	-11.511***	-3.287***
	(3.794)	(2.116)	(1.754)	(0.979)
3rd tertile	-46.478***	-19.576***	-16.948***	-5.476***
	(5.647)	(2.824)	(1.965)	(1.233)
Occupancy type:				
Owner occupied (baseline)	-	-	-	-
Buy to Let	-6.173	-6.805*	-0.482	-2.591
	(7.620)	(3.737)	(2.760)	(1.697)
Holiday	-18.011**	-12.196**	-7.564**	-4.242
	(7.916)	(5.118)	(3.665)	(2.723)
Property type:				
Residential flat (baseline)	-	-	-	-
Other	-2.261	-1.283	-0.937	-0.275
	(3.010)	(1.504)	(1.058)	(0.985)
Residential house	4.487	1.527	2.407*	0.806
	(2.947)	(1.442)	(1.279)	(0.892)
Residential terrace	-7.707*	-2.028	-2.278	-0.556
	(4.091)	(2.055)	(1.800)	(0.860)
Property value:				
1st tertile (baseline)	-	-	-	-
2nd tertile	8.334***	3.794**	-1.393	-0.439
	(2.599)	(1.485)	(1.175)	(0.651)
3rd tertile	7.864**	3.842**	-2.112	-0.741
	(4.011)	(1.555)	(1.556)	(1.164)
Macro variables	Yes	Yes	Yes	Yes
House price index	2.121**	0.555	-0.421	-0.528
	(1.022)	(0.516)	(0.583)	(0.327)
Unemployment	10.309*	11.932**	5.387	6.012***
	(5.838)	(5.988)	(4.439)	(1.871)
Inflation	7.271**	7.212***	9.146***	4.368***
	(3.516)	(2.362)	(2.276)	(1.001)
Quarter FE	Yes	Yes	Yes	Yes
Originator FE	Yes	Yes	Yes	Yes
Pseudo R2	0.089	0.139	0.132	0.195
Observations	7,658,281	7,692,664	7,689,861	7,700,345

These results suggest that loans securitised in green RMBS deals are significantly less likely to become delinquent, regardless of the severity of the outcome considered.[5] Other risk drivers behave as expected. Higher loan-to-value ratios are associated with a higher probability of default, with marginal effects increasing across quintiles—for example, from around 3.9 basis points in the second quintile to 42 basis points in the fifth for material arrears. Loans with floating or hybrid interest rates are substantially riskier than fixed-rate loans, with increases of 26.5 and 99.3 basis points, respectively. Borrower employment and income characteristics are also important: public sector workers face significantly lower default risk compared to private sector employees, while unemployed and self-employed borrowers face much higher risks. Finally, default risk decreases monotonically with borrower income, with those in the top income tertile significantly less likely to default than those in the bottom tertile.

We further test the robustness of our findings by adopting a more conservative fixed effects structure, introducing interaction terms between Quarter and Originator fixed effects. As shown in Table 4.A.4, the Green Flag remains negatively and significantly associated with all four measures of mortgage delinquency. The marginal effect on arrears is –30.12 basis points, corresponding to a 41.7% reduction relative to the mean of 72.23 basis points. For material arrears, the estimated reduction is 16.48 basis points, or 52.8% of the mean value of 31.19 basis points. The estimated effect on default is 14.67 basis points, equivalent

[5] It is important to clarify the interpretation of the Green RMBS indicator in this setting. Borrowers neither observe nor respond to the securitisation status of their mortgages, and they are unlikely to know whether their loan has been included in a green-labelled deal. Accordingly, the analysis in this chapter does not treat inclusion in a Green RMBS as a behavioural "treatment" at the household level. Instead, the Green RMBS label is used as a portfolio-level proxy for originators' collateral selection: it captures systematic differences between the loans and properties that banks choose to securitise in green versus non-green deals. The empirical strategy focuses on the Green RMBS Originator Sample and estimates Equation (4.1) within institutions that issue both types of deals, conditioning on detailed borrower, loan, property and macroeconomic characteristics, as well as originator and quarter fixed effects. Under this design, the coefficient on the Green RMBS indicator measures a conditional performance difference between loans placed into green and non-green RMBS, rather than a structural causal effect of securitisation. The underlying mechanism is explored more directly in 5, where I document that Green RMBS pools contain a higher share of energy-efficient properties and that EPC ratings have incremental predictive power for mortgage delinquency.

to a 49.6% reduction relative to the mean of 29.57 basis points. Finally, the marginal effect on material default is 5.85 basis points, which translates to a 46.1% reduction from its mean of 12.68 basis points. These results confirm that loans included in green securitisations are more resilient, even under stricter fixed effects.

Notably, this is observed notwithstanding the EuGB Regulation applying the *use-of-proceeds requirement* to the originator (as in traditional green bonds) rather than the issuer (SSPE). This means that green-labelled securitisations are not prohibited from including energy-inefficient loans. However, as it will be shown in the next chapter, Green RMBS do tend to contain more efficient properties, which may be driven by two factors:

- **Regulatory transition phase:** The EuGB Regulation takes a pragmatic approach by applying the use-of-proceeds requirement at the originator level, addressing the limited supply of taxonomy-aligned green assets. This approach may evolve as more green assets become available. Originators may already be adjusting by prioritising energy-efficient collateral to anticipate future regulatory tightening.
- **Increased scrutiny of green securitisations:** Green RMBS face stricter transparency and disclosure rules. Issuers must report the proportion of taxonomy-aligned exposures in the prospectus, incentivising a higher share of energy-efficient loans and reinforcing investor confidence in the environmental credibility of green securitisations.

Given these dynamics, securitising energy-efficient loans serves a dual role in risk management. Like other Asset-Backed Securities (ABS), RMBS distribute credit risk across a wide investor base, reducing exposure for individual institutions (Shin, 2009). Green RMBS, however, offer an additional layer of resilience due to the energy-efficient nature of their underlying collateral. These properties are less exposed to systematic energy price risk, which can erode disposable income and impair mortgage performance—risks that are difficult to diversify in traditional RMBS. Moreover, Green RMBS are better positioned to manage transition risks linked to tightening environmental regulation, such as the phased introduction of minimum energy performance standards. In contrast, RMBS backed by inefficient properties face higher exposure to these risks: properties may lose value, require costly retrofits, or risk becoming *stranded*. By including more energy-efficient collateral, Green RMBS align more closely with evolving policy standards, offering enhanced durability and sustainability for investors. By spreading risk, reducing exposure to energy cost volatility, and mitigating transition risk, Green RMBS represent a robust and forward-looking financial instrument. In doing so, they support the EU's climate targets by narrowing the green investment gap. As such, Green RMBS are well positioned to play a central role in the transition to a greener economy.

4.4.2 Tranche composition and risk transfer

While previous sections show that Green RMBS are associated with better-performing collateral, (through lower default rates and stronger borrower resilience) an important question remains: "how does the green label affect the securitisation structure itself?" We examine whether differences in collateral performance are reflected at the tranche level, and whether Green RMBS exhibit distinct structural features such as credit enhancement, rating quality, and expected loss distribution. This is key from both credit risk and sustainable finance perspectives: superior loan performance does not automatically ensure investor protection if tranche structures are less resilient. For instance, thinner subordinated tranches could reduce credit enhancement, increasing tail risk for senior investors. Conversely, a greater share of investment-grade tranches may reflect more effective risk transfer aligned with better asset quality. We begin by comparing average tranche structures in Green vs. Non-Green RMBS deals. As shown in Table 4.5, deal-level differences are not statistically significant. However, Green RMBS show a higher share of senior tranches (94.3% vs. 91.7%) and a lower share of mezzanine (1.1% vs. 2.0%) and subordinated tranches (4.6% vs. 6.3%). Differences in credit quality are more pronounced: Green tranches have better average ratings (1.2 notches higher, $p < 0.01$), a higher share of investment-grade tranches (87.5% vs. 78.9%, $p < 0.01$), and fewer speculative-grade (12.5% vs. 17.9%, $p < 0.05$) and distressed tranches (0.0% vs. 3.2%, $p < 0.01$). Figure 4.3 shows that Green tranches are concentrated in the AAA bucket, while Non-Green tranches are more dispersed across lower rating bands.

Table 4.5. Deal-level and Tranche-level statistics for Green vs. Non-Green RMBS. This table compares the securitisation structure and rating characteristics of Green and Non-Green RMBS deals. Panel A reports deal-level statistics, including the natural logarithm of the total deal balance in €, the number of tranches per deal, and the balance-weighted share of senior, mezzanine, and subordinated tranches within the average deal. Panel B focuses on tranche-level characteristics: the natural logarithm of the tranche issue amount, the coupon rate, and the average rating rank (where 1 indicates the highest possible credit rating and 21 the lowest). Tranches are classified as *investment-grade* if their ratings fall between AAA and A3, *speculative-grade* if rated between Baa1 and Baa3, and *distressed* if rated between Ba1 and C/D. The final column shows the p-value from a two-tailed t-test on the difference in means between Green and Non-Green RMBS. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable description	Non-Green	Green	Difference	p-value
Panel A: Deal-Level Averages				
Log(Deal Balance in €)	20.64	20.21	0.42	0.373
Number of tranches	2.18	2.00	0.18	0.759
Senior tranches (%)	91.72	94.28	2.56	0.594
Mezzanine tranches (%)	1.98	1.08	–0.90	0.794
Subordinated tranches (%)	6.29	4.64	–1.65	0.647
Panel B: Tranche-Level Averages				
Log(Issue Amount)	18.10	18.01	–0.09	0.873
Coupon (%)	4.34	5.37	1.03	0.244
Average rating rank	4.54	3.36	–1.18	0.000***
Investment grade (%)	78.90	87.50	8.56	0.001***
Speculative grade (%)	17.90	12.50	–5.36	0.027**
Distressed (%)	3.20	0.00	–3.20	0.004***

To formally assess this relationship, we estimate an ordered logistic regression where the dependent variable is the tranche rating band (AAA–A3, BAA1–BAA3, BA1–C). Results in Table 4.6 confirm that the Green Flag is significantly associated with a higher likelihood of investment-grade ratings, even after controlling for issuance quarter, tranche size, and seniority. In our most conservative model (Column 4), Green RMBS tranches are 24.3% more likely to receive investment-grade ratings ($p < 0.01$) and 18.6% less likely to fall into the speculative-grade band ($p < 0.01$). These findings hold under alternative specifications, including a generalised ordered logit (Table 4.A.5) and an unweighted model (Table 4.A.6). The performance gap also extends to expected loss outcomes under stress. Table 4.7 presents simulated tranche-level losses based on observed differences in default rates between Green and Non-Green RMBS. Panel A assumes an LGD of 75.15%, derived from the European Banking Authority (2020) by averaging the 25th percentile net recovery rates for residential real estate loans across the countries in our sample.

Table 4.6. Green label and tranche ratings. This table presents the marginal effects of an ordered logistic regressions assessing the impact of the Green label on tranches. The dependent variable is the quarterly reported ordinal credit rating band of each tranche in the time period 2021–2024. Four specifications are shown. Robust standard errors are in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

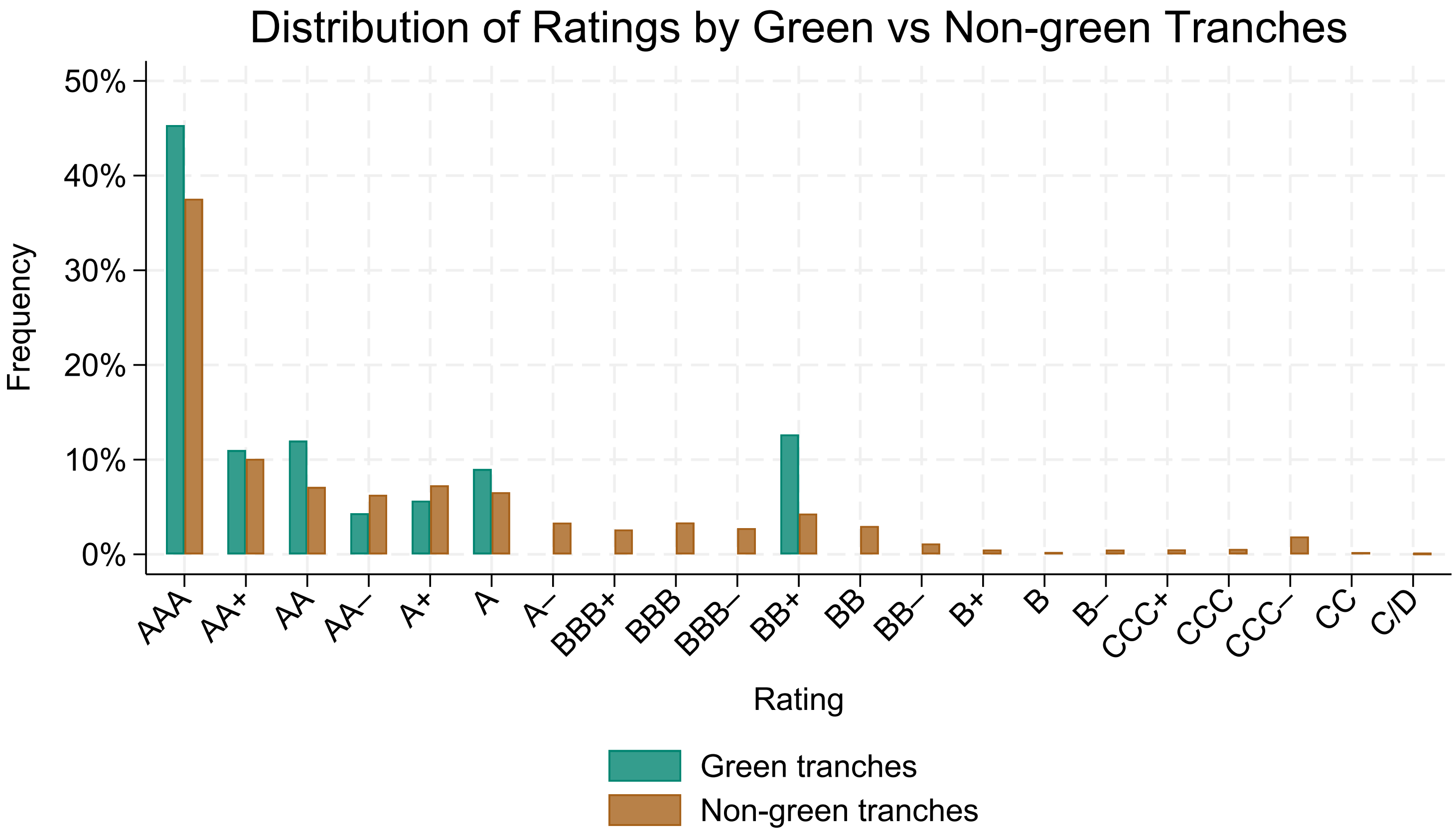
Ordered Logit				
	Marginal effect of Green Label			
Rating band	(1)	(2)	(3)	(4)
AAA – A3 (Investment Grade)	0.284**	0.248*	0.215***	0.243***
	(0.128)	(0.131)	(0.082)	(0.091)
BAA1 – BAA3 (Speculative)	-0.230**	-0.199*	-0.166***	-0.186***
	(0.103)	(0.105)	(0.064)	(0.071)
BA1 – C (Distressed)	-0.054*	-0.049	-0.049**	-0.057**
	(0.028)	(0.029)	(0.022)	(0.024)
Quarter FE	No	Yes	Yes	Yes
Issue Amount	No	No	Yes	Yes
Seniority	No	No	No	Yes
Pseudo-R^2	0.008	0.052	0.211	0.225
Observations	6,790	6,790	6,790	6,790

Table 4.7. Expected loss by tranche under different default rate scenarios and LGD assumptions. This table reports the expected loss borne by investors in senior, mezzanine, and subordinated tranches for loans securitised in Green and Non-Green RMBS. Losses are computed under two LGD assumptions: 75.15% and 100%. For each group, we show expected losses at the average default rate and at the 50th, 75th, and 99th percentiles of the observed default rate distribution. Losses are expressed as a percentage of the respective tranche's notional balance. The LGD of 75.15% corresponds to the 25th percentile net recovery rate for residential real estate loans across the countries in our sample (European Banking Authority, 2020).

Panel A: *LGD = 75.15%*			**Expected Loss to Investors (%)**		
Green Flag	**Percentile**	**Default Rate**	**Senior**	**Mezzanine**	**Subordinated**
Non-Green	*Average*	1.92%	0.00	0.00	22.91
Green	*Average*	0.42%	0.00	0.00	6.80
Non-Green	*50th pct*	0.40%	0.00	0.00	4.74
Green	*50th pct*	0.05%	0.00	0.00	0.76
Non-Green	*75th pct*	1.25%	0.00	0.00	14.96
Green	*75th pct*	0.29%	0.00	0.00	4.66
Non-Green	*99th pct*	19.60%	7.04	100.00	100.00
Green	*99th pct*	2.43%	0.00	0.00	39.31

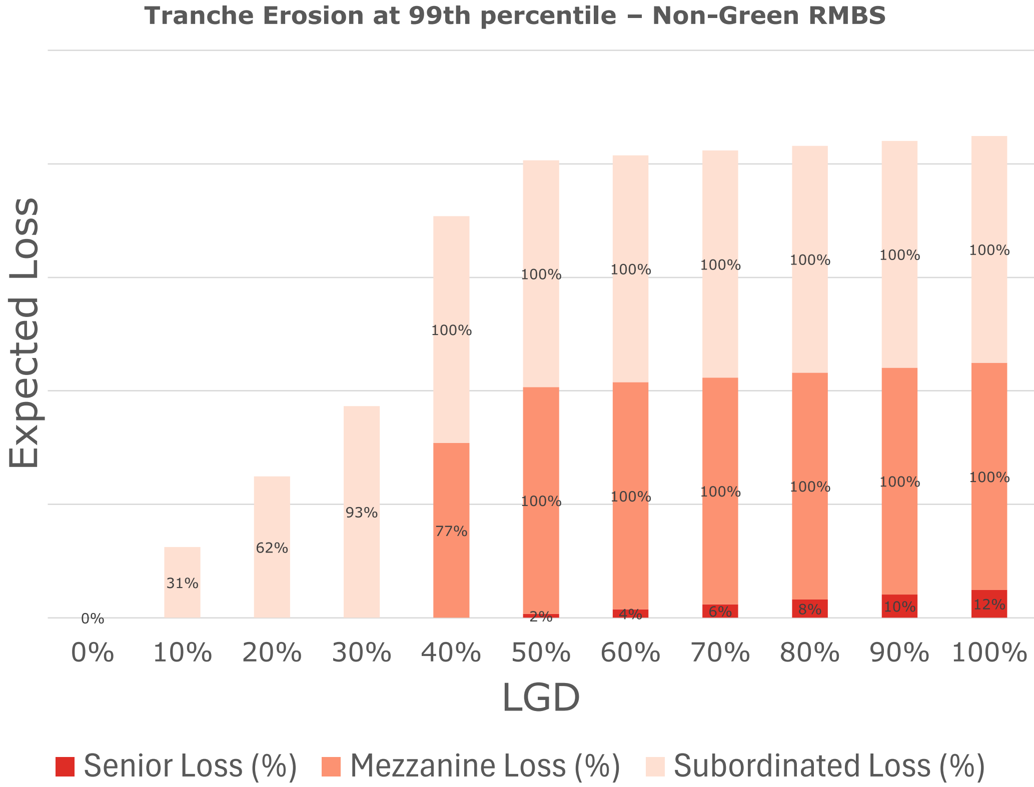
Panel B: *LGD = 100%*			**Expected Loss to Investors (%)**		
Green Flag	**Percentile**	**Default Rate**	**Senior**	**Mezzanine**	**Subordinated**
Non-Green	*Average*	1.92%	0.00	0.00	30.49
Green	*Average*	0.42%	0.00	0.00	9.05
Non-Green	*50th pct*	0.40%	0.00	0.00	6.30
Green	*50th pct*	0.05%	0.00	0.00	1.01
Non-Green	*75th pct*	1.25%	0.00	0.00	19.91
Green	*75th pct*	0.29%	0.00	0.00	6.20
Non-Green	*99th pct*	19.60%	12.35	100.00	100.00
Green	*99th pct*	2.43%	0.00	0.00	52.31

Figure 4.3. Distribution of ratings by Green vs Non-Green RMBS tranches. This figure displays the frequency distribution of tranche-level credit ratings for green and non-green residential mortgage-backed securities.



Panel B reports a worst-case scenario assuming LGD = 100%. Under moderate stress (50th percentile default rates), expected losses on subordinated tranches are just 0.76% in Green RMBS versus 4.74% in Non-Green (Panel A). The pattern holds under full loss (LGD = 100%), where Green subordinated tranches face losses of 1.01% compared to 6.30% in Non-Green. Under extreme stress (99th percentile), expected losses on Green subordinated tranches rise to 39.31%, but Non-Green subordinated tranches are fully wiped out (100%). Mezzanine tranches in Non-Green RMBS also suffer total losses, while those in Green RMBS remain fully protected. In Panel B, even senior tranches in Non-Green RMBS experience losses of 12.35%, while Green RMBS mezzanine and senior tranches remain unaffected. Figure 4.4 visualises loss absorption across the capital structure under these scenarios. Together, these results show that Green RMBS not only securitise better-performing assets but also translate that quality into stronger structural resilience. Green deals are more efficiently designed, offering better credit quality and lower expected losses, while maintaining protection for senior tranches. Although the slightly thinner subordinated tranches in Green RMBS may suggest weaker credit enhancement, our simulations show this is offset by higher-quality collateral, limiting tail risk. These findings reinforce the case for Green RMBS as a robust, climate-aligned securitisation vehicle.

Figure 4.4. Tranche erosion at the 99th percentile default scenario. The figure shows the expected loss experienced by investors in Green and Non-Green RMBS tranches across increasing levels of LGD, assuming a 99th percentile default scenario. The stacked bars represent the proportion of each tranche type (Subordinated, Mezzanine, and Senior) eroded by credit losses.



4.5 Conclusion

This study provides new evidence on the role of Green RMBS in mitigating credit risk and advancing sustainability goals in the European mortgage market. We show that loans securitised within green-labelled RMBS deals have significantly lower delinquency risk and that green deals are structured with stronger credit quality. Green tranches are more likely to receive investment-grade ratings and they display greater resilience under stress scenarios, with senior and mezzanine notes remaining protected even in extreme conditions. The loan-level estimates and respective marginal effects imply reductions of 28.53 basis points for arrears, 15.71 basis points for material arrears, 14.06 basis points for default, and 5.46 basis points for material default. Relative to the corresponding means, these are large effects: 39.5%, 50.4%, 47.6%, and 43.1% respectively. The results remain robust under a more conservative fixed-effects structure with Originator $\times$ Quarter interactions (Table 4.A.4). This pattern arises even though the EuGB use-of-proceeds requirement applies at the originator rather than the SSPE level, which does not force pools to be fully green. A plausible interpretation is that originators anticipate tighter standards and face stronger scrutiny on disclosure, so they select collateral with better energy performance, which in turn supports loan outcomes. These loan-level differences translate into structure and ratings. Ordered-logit estimates show that green-labelled tranches are significantly more likely to be investment grade and less likely to be speculative, after controlling for issuance timing, tranche size and seniority (Table 4.6, with robustness in Table 4.A.5 and Table 4.A.6). Stress tests based on observed default differentials confirm stronger resilience. Under moderate stress, expected losses on subordinated tranches are 0.76% in Green RMBS versus 4.74% in Non-Green. Under a full-loss assumption, subordinated losses are 1.01% in Green versus 6.30% in Non-Green, and at the 99th percentile of default rates Non-Green mezzanine tranches are wiped out while Green mezzanine and senior tranches remain protected. Taken together, the evidence supports a dual reading. First, the green label is informative for investors because it coincides with lower realised delinquency and stronger tranche outcomes. Second, part of the advantage reflects collateral composition, as green deals contain a higher share of energy-efficient properties. The next chapter examines that collateral channel directly by quantifying the incremental predictive power of EPC information in rating-style PD models and by tracing the implications for pool expected loss and securitisation resilience.

Appendices to Chapter 4

Table 4.A.1. Overview of RMBS data by country. This table summarises the number of deals, loans, properties, and observations across various countries in the RMBS dataset. Sample period: 2021Q1—2024Q1.

Country	**N. of deals**	**N. of loans**	**N. of properties**	**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

Table 4.A.2. Summary statistics for categorical variables conditional on delinquency status. The table reports the share of loans within each category when the target variable is active (i.e., equals 1). Statistics are reported for the Green RMBS Originator Sample, across four delinquency definitions: Arrears, Material Arrears, Default, and Material Default.

Variable	Arrears = 1	Material Arrears = 1	Default = 1	Material Default = 1
Energy Efficiency				
Green Flag	3.93%	2.74%	3.60%	3.84%
Loan Characteristics				
Loan Purpose: Purchase	73.48%	69.72%	70.37%	64.67%
Loan Purpose: Construction	5.37%	4.83%	4.22%	3.68%
Loan Purpose: Remortgage	18.26%	21.21%	22.78%	28.23%
Loan Purpose: Renovation	2.49%	3.61%	1.99%	2.34%
Loan Purpose: Other	0.39%	0.63%	0.64%	1.09%
Int. Type: Fixed	75.91%	72.66%	66.73%	56.06%
Int. Type: Floating	17.86%	25.29%	30.18%	41.60%
Int. Type: Other	6.23%	2.04%	3.09%	2.34%
Borrower Characteristics				
Employment: Employed - private sector	48.39%	42.70%	40.75%	29.72%
Employment: Employed - public sector	9.87%	9.03%	8.94%	7.93%
Employment: Employed - unknown	13.76%	13.88%	18.23%	22.93%
Employment: Pensioner	3.02%	4.12%	2.88%	3.63%
Employment: Self-employed	21.09%	25.92%	25.14%	31.93%
Employment: Unemployed	3.66%	4.25%	3.97%	3.77%
Employment: Other	0.22%	0.10%	0.09%	0.07%
Property Characteristics				
Occupancy Type: Owner Occupied	84.62%	81.34%	85.15%	83.79%
Occupancy Type: Buy to Let	14.35%	17.28%	14.06%	15.19%
Occupancy Type: Holiday	1.04%	1.38%	0.79%	1.01%
Occupancy Type: Other	0.00%	0.00%	0.00%	0.00%
Property Type: Residential Flat	11.29%	13.89%	12.63%	14.97%
Property Type: Residential House	70.56%	64.78%	65.70%	59.38%
Property Type: Residential Terrace	5.39%	7.85%	9.82%	13.88%
Property Type: Other	12.76%	13.49%	11.85%	11.76%

Table 4.A.3. Summary statistics for continuous variables conditional on delinquency status. This table reports means, standard deviations, minimums, and maximums for continuous variables, conditional on the target variable being equal to 1. Results are shown for four delinquency definitions: Arrears, Material Arrears, Default, and Material Default for the Green RMBS Originator Sample.

Variable	Mean	St. Deviation	Min.	Max.
Green RMBS Originator Sample – when Arrears = 1				
Arrears balance (€)	137.66	424.53	0.00	9789.28
LTV at reporting	0.66	0.24	0.04	1.10
Time to maturity (quarters)	52.68	28.91	2.00	148.00
Interest rate (%)	2.90	1.20	0.00	5.70
Income (€)	46,600.63	31,194.56	0.00	235,740.96
Property value (€)	149,963.50	102,579.53	11,716.88	876,000.00
Green RMBS Originator Sample – when Material Arrears = 1				
Arrears balance (€)	332.44	785.12	0.00	9789.28
LTV at reporting	0.55	0.25	0.04	1.10
Time to maturity (quarters)	38.86	27.67	2.00	148.00
Interest rate (%)	3.23	1.26	0.00	5.70
Income (€)	46,655.35	32,768.83	0.00	235,740.96
Property value (€)	142,167.84	102,228.72	11,716.88	876,000.00
Green RMBS Originator Sample – when Default = 1				
Arrears balance (€)	409.97	907.47	0.00	9789.28
LTV at reporting	0.65	0.25	0.04	1.10
Time to maturity (quarters)	49.99	29.87	2.00	148.00
Interest rate (%)	3.21	1.26	0.00	5.70
Income (€)	45,644.27	31,031.37	0.00	235,740.96
Property value (€)	154,989.97	103,885.78	11,716.88	876,000.00
Green RMBS Originator Sample – when Material Default = 1				
Arrears balance (€)	870.94	1501.13	0.00	9789.28
LTV at reporting	0.57	0.26	0.04	1.10
Time to maturity (quarters)	39.89	30.12	2.00	148.00
Interest rate (%)	3.56	1.26	0.00	5.70
Income (€)	46,073.06	31,628.92	0.00	228,744.00
Property value (€)	152,675.57	104,016.76	11,716.88	876,000.00

Table 4.A.4. The impact of the Green Flag label on mortgage delinquency, with interaction of quarter and originator 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 interaction of Quarter and Originator Fixed Effects (Quarter × Originator FE) is used for robustness. The main explanatory variable is the *Green Flag*. Other control variables include loan, borrower and property characteristics. Macroeconomic variables are omitted as they are captured by the Quarter × Originator FE. Robust standard errors are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Green Flag	-30.121***	-16.480***	-14.669***	-5.853***
	(6.789)	(2.743)	(3.041)	(1.406)
LTV:				
1st quintile (baseline)	-	-	-	-
2nd quintile	12.656***	3.998***	8.116***	3.162***
	(2.149)	(1.071)	(1.411)	(0.698)
3rd quintile	30.980***	13.246***	17.079***	6.534***
	(4.626)	(2.377)	(1.949)	(1.181)
4th quintile	46.235***	19.685***	12.004***	4.233***
	(7.181)	(3.244)	(2.289)	(0.958)
5th quintile	89.850***	41.760***	21.351***	10.392***
	(15.858)	(7.098)	(3.522)	(2.258)
Time to Maturity (quarters)	-0.525**	-0.344***	-0.548***	-0.235***
	(0.238)	(0.103)	(0.076)	(0.040)
Loan purpose:				
Purchase (baseline)	-	-	-	-
Construction	-14.186***	-8.212***	-10.038***	-4.415***
	(3.906)	(2.100)	(2.052)	(1.026)
Other	-45.892***	-19.425***	-19.412***	-7.351***
	(6.935)	(3.484)	(3.865)	(2.040)
Remortgage	-9.274*	-3.274	-6.156***	-1.793**
	(5.332)	(2.254)	(2.079)	(0.850)
Renovation	-16.911***	-10.614***	-6.974***	-5.055***
	(4.304)	(2.966)	(1.967)	(1.349)
Interest rate:				
1st quintile (baseline)	-	-	-	-
2nd quintile	-14.518*	-3.646	-9.293***	-0.964
	(8.512)	(3.263)	(3.355)	(1.783)
3rd quintile	-2.869	0.849	-5.873*	-0.653
	(8.922)	(3.403)	(3.304)	(1.772)
4th quintile	9.660	8.834**	1.694	3.274*
	(8.733)	(3.722)	(3.161)	(1.717)
5th quintile	58.200***	31.593***	28.866***	14.965***
	(12.008)	(5.288)	(4.396)	(2.424)
Interest type:				
Fixed (baseline)	-	-	-	-
Floating	79.308***	29.643***	52.802***	15.563***
	(24.073)	(8.962)	(7.254)	(3.668)
Other	317.380**	99.953**	167.180***	37.055***
	(152.769)	(39.334)	(44.790)	(12.630)

Table 4.A.4 continued from previous page

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Employment:				
Employed - private sector (baseline)	-	-	-	-
Employed - public sector	-23.825***	-7.624***	-10.844***	-2.258***
	(2.303)	(1.297)	(1.283)	(0.638)
Employed - unknown	30.428***	17.417***	19.562***	9.705***
	(7.945)	(2.946)	(3.151)	(1.917)
Other	23.664**	-8.873	-0.997	-3.350
	(12.017)	(7.233)	(12.080)	(5.170)
Pensioner	-9.802***	-2.439	-4.182**	0.413
	(3.724)	(1.577)	(2.092)	(1.092)
Self-employed	57.669***	25.012***	28.665***	14.101***
	(5.104)	(3.062)	(3.294)	(2.283)
Unemployed	54.788***	29.220***	26.216***	12.663***
	(5.148)	(4.791)	(4.839)	(2.566)
Income:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-30.566***	-12.081***	-11.416***	-3.289***
	(3.745)	(2.098)	(1.755)	(0.988)
3rd tertile	-46.293***	-19.377***	-16.793***	-5.475***
	(5.572)	(2.792)	(1.960)	(1.244)
Occupancy type:				
Owner occupied (baseline)	-	-	-	-
Buy to Let	-5.899	-6.523*	-0.311	-2.508
	(7.419)	(3.661)	(2.696)	(1.702)
Holiday	-17.878**	-12.100**	-7.511**	-4.286
	(7.896)	(5.103)	(3.662)	(2.763)
Property type:				
Residential flat (baseline)	-	-	-	-
Other	-2.987	-1.647	-1.192	-0.413
	(3.015)	(1.479)	(1.092)	(0.995)
Residential house	4.505	1.576	2.442*	0.854
	(2.929)	(1.435)	(1.275)	(0.900)
Residential terrace	-7.515*	-2.036	-2.227	-0.565
	(4.057)	(2.051)	(1.804)	(0.866)
Property value:				
1st tertile (baseline)	-	-	-	-
2nd tertile	8.340***	3.788**	-1.416	-0.442
	(2.586)	(1.479)	(1.169)	(0.658)
3rd tertile	7.810**	3.819**	-2.130	-0.736
	(3.981)	(1.549)	(1.550)	(1.184)
Quarter $\times$ Originator FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0914	0.1420	0.1340	0.1970
Observations	7,658,281	7,692,664	7,689,861	7,575,997

Table 4.A.5. Green label and tranche ratings. This table presents the marginal effects of a generalised ordered logistic regressions assessing the impact of the Green label on tranche-level credit ratings. The dependent variable is the quarterly reported ordinal credit rating band of each tranche in the time period 2021–2024. Four specifications are shown. Robust standard errors are in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Generalised Ordered Logit				
	Marginal effect of Green Label			
Rating band	(1)	(2)	(3)	(4)
AAA – A3 (Investment Grade)	0.283**	0.247*	0.216**	0.251***
	(0.128)	(0.131)	(0.085)	(0.095)
BAA1 – BAA3 (Speculative)	0.078	0.092	0.142	0.147
	(0.174)	(0.154)	(0.108)	(0.124)
BA1 – C (Distressed)	-0.362**	-0.339***	-0.358***	-0.398***
	(0.149)	(0.112)	(0.103)	(0.102)
Quarter FE	No	Yes	Yes	Yes
Issue Amount	No	No	Yes	Yes
Seniority	No	No	No	Yes
Pseudo-R^2	0.009	0.061	0.222	0.252
Observations	6,790	6,790	6,790	6,790

Table 4.A.6. Green label and tranche ratings (unweighted specification). This table presents the marginal effects of ordered logistic regressions assessing the impact of the Green label on tranche-level credit ratings. Unlike the baseline model, these specifications do not apply the *rating recency* weight. The dependent variable is the quarterly reported ordinal credit rating band of each tranche in the time period 2021–2024. Four specifications are shown. Robust standard errors are in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Ordered Logit — Unweighted Specification				
	Marginal effect of Green Label			
Rating band	(1)	(2)	(3)	(4)
AAA – A3 (Investment Grade)	0.106***	0.106***	0.118***	0.094***
	(0.031)	(0.031)	(0.024)	(0.023)
BAA1 – BAA3 (Speculative)	-0.087***	-0.087***	-0.092***	-0.073***
	(0.025)	(0.025)	(0.018)	(0.017)
BA1 – C (Distressed)	-0.019***	-0.019***	-0.026***	-0.021***
	(0.006)	(0.006)	(0.005)	(0.005)
Quarter FE	No	Yes	Yes	Yes
Issue Amount	No	No	Yes	Yes
Seniority	No	No	No	Yes
Pseudo-R^2	0.002	0.008	0.182	0.211
Observations	6,790	6,790	6,790	6,790

Chapter 5

EPC Ratings and Delinquency Risk under Energy Inflation and Income Vulnerability

5.1 Introduction

Recent geopolitical tensions and energy price volatility have sharpened the policy focus on household energy use in Europe. Residential buildings account for a large share of final energy consumption and emissions, so improving their efficiency is a central lever in EU strategy (The EU Parliament and Council, 2023a). Energy efficiency matters for credit risk through two intuitive channels. First, it affects borrowers' cash flows: inefficient dwellings require more energy to heat and cool, which raises utility bills and tightens the household budget constraint. Second, it affects collateral value through operating-cost differences and exposure to future retrofit needs in a tightening regulatory environment (Lorenz & Lützkendorf, 2008; Popescu et al., 2012). Empirical work from individual markets suggests that more efficient homes are associated with lower arrears or default risk (Billio et al., 2021; Guin & Korhonen, 2020; Kaza et al., 2014). At the same time, lenders have not consistently priced such transition-related risks in mortgage rates, indicating room for better integration of energy information into risk assessment (Bell et al., 2023). This chapter studies the collateral channel directly, independently of any labelling choices. We investigate three issues. Do loans secured by energy-efficient properties exhibit lower delinquency risk once standard drivers are controlled for? Is the efficiency effect stronger for financially constrained borrowers? Does energy price inflation amplify the relationship between efficiency and delinquency? To answer these questions we exploit the European DataWarehouse (EDW) loan-level RMBS data and the enhanced ESMA reporting template, which makes Energy Performance Certificate (EPC) fields available at property level from 2021Q1 onward. We contribute to the existing literature in three main ways. First, we harmonise national EPC labels into a common EU-wide consumption metric to run the largest scale study showing that lower energy efficiency is associated with higher delinquency. Second, we find that this effect is economically larger for below-median income borrowers, consistent with an affordability channel through utility costs. Third, we find that periods of elevated energy inflation strengthen the link between low efficiency and delinquency; the amplification is robust to benchmark-rate controls and to a fixed-rate pre-tightening subsample. We also show that arrears balances are higher for inefficient properties and rise with energy inflation.

The rest of the chapter proceeds as follows. Section 5.2 summarises the policy context and the role of EPCs. Section 5.3 presents the hypotheses explored in this chapter. Section 5.4 describes data, harmonisation and empirical design. Section 5.5 presents results on main effects, income heterogeneity, and the inflation amplifier, with robustness checks and arrears-balance intensity. Section 5.6 concludes with implications for mortgage risk management and, by aggregation, for portfolio and pool expected loss.

5.2 Energy Performance Certificates: background and motivation

Energy use in the housing stock sits at the centre of the EU strategy to cut emissions, improve energy security and shield households from volatile energy costs. Recent legislation places efficiency gains among the primary instruments to reach these aims, with targets for 2030 and 2050 that envisage a substantial upgrade of residential buildings (European Commission, 2020a, 2020b; The EU Parliament and Council, 2023a). Meeting those targets requires large, sustained investment. Estimates point to annual needs in excess of €300 billion and a sizeable financing gap that public budgets cannot fill alone, which underscores the role of private intermediation (European Investment Bank, 2023). In this policy setting, household-level energy efficiency has macro relevance because it affects both emissions trajectories and the distribution of energy-budget risk across borrowers.

Energy Performance Certificates (EPCs) operationalise building efficiency in a way that lenders and investors can use. EPCs summarise expected energy consumption for a dwelling, so they speak to two drivers of mortgage risk. First, they map into running costs: inefficient homes require more energy for heating and cooling, lifting utility bills and tightening borrower cash flows, especially when energy prices rise (Bell et al., 2023). Second, they map into collateral value through differences in operating costs and potential retrofit needs as standards tighten over time (Lorenz & Lützkendorf, 2008; Popescu et al., 2012). Evidence from property markets shows that better environmental or efficiency attributes are associated with stronger fundamentals, such as higher rents, lower turnover and price premia (Devine & McCollum, 2022; Sanderford et al., 2015). Supervisory and market commentary also recognises EPCs as relevant inputs for risk assessment and product design in mortgage markets (FitchRatings, 2023).

Data availability is improving. Member States are upgrading EPC registers and moving toward more consistent templates and interoperability, including provisions to facilitate access for financial institutions and to support EU-wide monitoring (The EU Parliament and Council, 2024). In parallel, the ESMA loan-level template for RMBS has made EPC fields available at property level. This allows us to construct a harmonised, comparable measure of energy use for each loan and to study how energy efficiency correlates with mortgage performance in a multi-country setting. The next section details the data, the harmonisation from national labels to a common kWh/m^2/year metric, and the empirical design used in this chapter.

5.3 Hypotheses development

Energy efficiency influences the financial resilience of households through its impact on essential living costs. More efficient homes require less energy for heating, cooling and basic consumption, resulting in lower and more predictable utility bills. Because energy expenditure is non-discretionary, borrowers in inefficient homes face tighter liquidity constraints and are more likely to miss mortgage payments. Building on this and leveraging harmonised, EU-level data on residential buildings' EPC ratings as retrieved from the new ESMA template, we hypothesise that high EPC ratings are associated with lower risk of mortgage delinquency.

Hypothesis 5.1 *Loans backed by properties with higher EPC ratings exhibit a lower probability of delinquency.*

This hypothesis is consistent with emerging evidence from different mortgage markets. Empirical research from various markets supports the notion that energy-efficient properties contribute to better loan performance. Kaza et al. (2014) examine ENERGY STAR-certified homes in the United States and find that these properties are associated with significantly lower default and prepayment risks. They attribute this effect to reduced energy costs or potentially better financial standing of borrowers residing in energy-efficient homes. However, they note that further research is needed to explore the exact mechanisms underlying this relationship. Similarly, Guin and Korhonen (2020) provide evidence from the UK, showing that mortgages secured by energy-efficient properties are less likely to experience payment arrears, even after accounting for borrower income. Their study also calls for additional research to better understand the channels through which energy efficiency influences loan performance. In the Netherlands, Billio et al. (2021) use provisional data derived from cadastral and housing survey information to infer the energy efficiency of residential building. They report that loans backed by properties with higher estimated energy efficiency are associated with lower probabilities of default, and underscore the importance of integrating reliable EPC data into analyses of mortgage performance. Building on these findings and leveraging harmonised, EU-level data on residential buildings' EPC ratings as retrieved from the new ESMA template, we hypothesise that high EPC ratings are associated with lower risk of mortgage delinquency. If the channel through which low EPC ratings affect delinquency and default probability is the one of higher running costs influencing household disposable income, we would expect this effect to be stronger for low-income households. For low-income borrowers, energy costs represent a substantial portion of household expenses. Poor energy efficiency exacerbates financial strain for these borrowers, increasing the likelihood of mortgage delinquency. Conversely, higher-income borrowers are better equipped to absorb energy-related expenses, mitigating this effect. Therefore, we propose the following hypothesis:

Hypothesis 5.2 *The adverse impact of poor energy efficiency on mortgage delinquency is amplified for lower-income households.*

Moreover, the recent developments in the energy markets, provide us with an exceptional circumstance to further test the channel of energy costs affecting delinquency. We hypothesise that recent events, such as the 2021–2023 energy crisis, highlight the importance of external factors in shaping the relationship between energy efficiency and loan performance. Fluctuations in energy prices can amplify the effects of energy efficiency on loan performance. Rising energy costs disproportionately impact households with less energy-efficient properties, further straining their ability to meet mortgage obligations. During periods of high energy inflation, these dynamics become particularly pronounced, motivating our fourth hypothesis:

Hypothesis 5.3 *The adverse impact of poor energy efficiency on mortgage delinquency is amplified during periods of high energy inflation.*

5.4 Data and methodology

5.4.1 Sample overview

For this chapter we focus on the *EPC sample*, which retains only loan-quarter observations where the property-level EPC field is populated for at least one linked property. This yields 4,503,026 observations. We exclude loans after terminal events such as default, write-off or full redemption, and loans with a *release equity* purpose to maintain comparability. Numeric variables with extreme values are binned into categorical quantiles where appropriate, consistent with the merged specification. Macroeconomic covariates include country-level unemployment changes, house price indices and inflation; energy inflation is based on the energy sub-index. For the United Kingdom, missing Eurostat series are supplemented with Office for National Statistics releases to ensure continuity.[1]

EPC ratings are the key focus of this chapter. To assess their impact on mortgage performance, we construct a continuous variable representing the average energy consumption of the properties linked to each loan, expressed in kWh/m^2/year. EPC ratings from the EDW database[2] serve as the basis. Since EPC schemes vary across countries, we harmonise them by converting each rating into a numeric value corresponding to the midpoint of its country-specific consumption range. This mapping, summarised in Table 5.1, aligns national EPC scales to a unified framework. For example, in France, EPC A spans 1–50 kWh/m^2/year, EPC B spans 51–95, and so on. The midpoint of each range is used as the numeric value. Each loan's average EPC kWh/m^2/year is then computed as a weighted average of the numeric EPC values across its associated properties, with weights based on original property values to give greater influence to higher-value assets.

[1]For overall inflation, Eurostat `prc_hicp_manr - CP00` and ONS Series ID `D7G7 (00)`; for energy inflation, Eurostat `prc_hicp_manr - 045` and ONS Series ID `D7GT (04.5)`.

[2]The EPC rating variable is at the property level and coded as "RREC10" in the ESMA template.

Table 5.1. Conversion of EPC ratings 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. We gratefully adopt the green–to–magenta colour-blind–safe palette from ColorBrewer2 developed by Harrower and Brewer (2003).

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	A
0-5											
5-10											
10-15											
15-20											
20-25											
25-30											
30-35											(≤32)
35-40										(≤36)	B
40-45										B	
45-50	B										
50-55				B	B				B		
55-60											
60-65										(≤63)	
65-70										C	C
70-75											
75-80					C	B			B-		
80-85											
85-90			B								
90-95				C							
95-100	C									(≤103)	
100-110		B			D		B		C	D	D
110-120											
120-130							C				
130-140					E						(≤135)
140-150											E
150-160	D			D		C	D		D		
160-170					F			B		(≤161)	
170-180			C							E	F
180-190											
190-200								C			
200-210		C			G		E		E		G
210-220	E										
220-230						(≤175)					
230-240				E		D					
240-250											
250-260			(≤255)					D	F		
260-270			D				F				
270-280	(≤275)										
280-290	F									(≤291)	
290-300								E		F	
300-310		D				E					
310-320											
320-330											
330-340				F				(≤335)			
340-350	(≤345)		E					F			
350-360	G						G				
360-370										(≤367)	
370-380										G	
380-390						F		G			
400-425		E									
425-450			F								
450-500 +				G		G					

Specifically, for loan l in quarter q, the weighted average is calculated as:

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

where n_l is the number of properties linked to loan l in quarter q, w_{iq} denotes the original value of property i, and EPC_{iq} is the numeric EPC value of property i.

The resulting EPC values are categorised into three energy efficiency tiers: loans in the bottom third of the EPC range (0–167 kWh/m^2/year, lower consumption) are classified as *high efficiency*; the middle third (167–333) as *medium efficiency*; and the top third (above 333, higher consumption) as *low efficiency*. This classification is based on the full EPC consumption range of 0–500 kWh/m^2/year. We study delinquency over a forward one-year window using quarterly data. For each loan i at time t, the dependent variable equals one if the event occurs between t and $t + 4$ quarters. We consider four outcomes:

- **Arrears**: one quarter in arrears within the next four quarters.
- **Material Arrears**: arrears within the next four quarters with arrears balance >1% of current balance.
- **Default**: two consecutive quarters in arrears within the next four quarters.
- **Material Default**: default with arrears balance >1% of current balance.

To capture intensity conditional on delinquency we also analyse **Arrears Balance** as a continuous outcome. Controls follow the merged specification: loan-to-value (LTV) quintiles, interest rate at first reporting, interest rate type (fixed, floating, hybrid), loan purpose, property value and characteristics, borrower employment status and income tertiles, plus macro variables (country unemployment change, house price index change, inflation).

Table 5.2 provides an overview and description of the variables employed in our analysis. Table 5.3 and Table 5.4 report the summary statistics for the full sample and the Green RMBS Originator Sample separately for categorical and continuous variables. To summarise simple pairwise associations relevant for interpretation, Table 5.5 reports Pearson correlations between EE Tier indicators and income and Property Value tertiles, and between EPC kWh/m^2/year and the corresponding continuous measures; coefficients are small throughout, indicating weak alignment. Table 5.6 presents the distribution of energy efficiency tiers and EPC ratings across loans securitised in Green versus Non-Green RMBS deals. Table 5.A.1 shows that loans with a High-Efficiency collateral are more likely to be securitised in Green RMBS. Figure 5.1 and Figure 5.2 present cumulative arrears and default rates by EE Tiers, with loans backed by higher-efficiency properties demonstrating lower delinquency rates over time.

Table 5.2. 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 within the next 12 months, and 0 otherwise.
Material Arrears	Dummy	A variable that takes the value of 1 if the loan is one quarter in arrears within the next 12 months 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 within the next 12 months, and 0 otherwise.
Material Default	Dummy	A variable that takes the value of 1 if the loan is two consecutive quarters in arrears within the next 12 months and the arrears balance is greater than or equal to 1% of the current loan balance, and 0 otherwise.
Arrears balance (€)	Continuous	The arrears balance for loans in arrears.
Energy Efficiency		
EE Tier	Categorical	Categorises the Energy Efficiency Tier of the loan based on the average kWh consumption per m^2 per year across all the properties. 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 kWh/m^2/year	Numerical	Average kWh consumption per m^2 per year across all the properties.
EPC rating	Categorical	Categorises properties based on their EPC rating. Categories include EPC A/B (high), EPC C/D/E (medium), and EPC F/G (low).
Loan Characteristics		
Loan Purpose	Categorical	The purpose of the loan, categorised into Purchase, Construction, Remortgage, Renovation, or Other.
Interest Type	Categorical	The type of interest rate applied to the loan, which can be Fixed, Floating, or Other.
Interest rate	Continuous	The interest rate of the loan at the time of the first reporting date.
Loan-to-Value (LTV)	Continuous	The loan-to-value ratio at the time of 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.
Property 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		
HPI change (%)	Continuous	The percentage change in the house price index over the previous 12 months.
Unemp. rate change (%)	Continuous	The percentage change in the unemployment rate over the previous 12 months.
Inflation (%)	Continuous	The inflation rate over the previous 12 months.
Energy inflation (%)	Continuous	The energy inflation over the previous 12 months.

Table 5.3. Summary statistics for categorical variables. This table reports the sample averages at the observation level for categorical variables within the EPC populated sample, which excludes observations without populated EPC data.

Variable	EPC Sample
Sample Size	
Observations	4,503,026
Delinquency	
Arrears (bps)	49.571
Material Arrears (bps)	12.576
Default (bps)	16.766
Material Default (bps)	4.404
Energy Efficiency	
Green Flag	5.779%
EE Tier: High Efficiency	32.318%
EE Tier: Medium Efficiency	50.942%
EE Tier: Low Efficiency	16.740%
EE Tier: Missing	0.000%
Loan Characteristics	
Loan Purpose: Purchase	78.499%
Loan Purpose: Construction	8.611%
Loan Purpose: Remortgage	9.958%
Loan Purpose: Renovation	2.762%
Loan Purpose: Other	0.169%
Int. Type: Fixed	59.989%
Int. Type: Floating	3.328%
Int. Type: Other	36.683%
Borrower Characteristics	
Employment: Employed - private sector	38.494%
Employment: Employed - public sector	13.876%
Employment: Employed - unknown	33.349%
Employment: Pensioner	4.299%
Employment: Self-employed	8.037%
Employment: Unemployed	0.912%
Employment: Other	1.033%
Property Characteristics	
Occupancy Type: Owner Occupied	90.052%
Occupancy Type: Buy to Let	8.125%
Occupancy Type: Holiday	1.805%
Occupancy Type: Other	0.018%
Property Type: Residential Flat	27.950%
Property Type: Residential House	69.231%
Property Type: Residential Terrace	0.376%
Property Type: Other	2.443%

Table 5.4. Summary statistics for continuous variables. The table reports the sample averages and corresponding standard deviations, minimums, and maximums for continuous variables in the EPC populated sample.

Variable	Mean	St. Deviation	Min.	Max.
EPC Sample				
Arrears balance (€)	1.34	49.96	0.00	9789.28
↪ Arrears balance (€), if positive	670.94	895.61	0.01	9789.28
LTV at first reporting date	0.68	0.24	0.04	1.10
Time to maturity (quarters)	72.41	31.67	2.00	148.00
Interest rate (%)	2.10	0.95	0.00	5.70
Income (€)	48,668.29	31,881.81	0.00	235,741.00
Property value (€)	159,370.00	116,525.60	11,716.88	876,000.00
House price index change (%)	6.14	6.43	-4.10	19.00
Unemployment rate change (%)	6.22	2.14	3.40	15.40
Inflation (%)	5.97	3.42	-0.07	14.13
Energy inflation (%)	30.66	47.05	-47.67	152.97

Table 5.5. Correlations between Energy Efficiency and income/property value. This table assesses whether energy-efficiency tiers overlap materially with borrower income or property value. We report Pearson correlation coefficients. *Panel A* shows correlations between indicator variables for EE Tier (High $\leq$ 167 kWh/m^2/year; Medium 167–333; Low > 333) and borrower income tertiles. *Panel B* shows correlations between EE Tier indicators and property value tertiles. *Panel C* reports correlations using continuous measures: EPC consumption (kWh/m^2/year) with total income and with property value.

Panel A: EE Tier × Income tertiles (Pearson correlations between dummies)

EE Tier	**Income low (1)**	**Income medium (2)**	**Income high (3)**
EE Tier: High	-0.0909	-0.0500	0.1187
EE Tier: Medium	0.0061	0.0488	-0.0527
EE Tier: Low	0.1056	-0.0027	-0.0780

Panel B: EE Tier × Property value tertiles (Pearson correlations between dummies)

EE Tier	**Property value low (1)**	**Property value medium (2)**	**Property value high (3)**
EE Tier: High	-0.1130	0.0351	0.0902
EE Tier: Medium	0.0769	-0.0220	-0.0634
EE Tier: Low	0.0385	-0.0144	-0.0281

Panel C: Correlations between continuous variables

Corr(EPC kWh/m^2/year, Total income)	-0.1589
Corr(EPC kWh/m^2/year, Property value)	-0.0772

Notes: Dummy–dummy entries are Pearson correlations computed on binary indicators (EE Tier cells vs tertile indicators). *Correlations between continuous variables* use EPC consumption in kWh/m^2/year. By construction, *EE Tier: High* corresponds to *low* kWh/m^2/year energy consumption; so, for example, a positive association between higher income and *EE Tier: High* (Panel A) naturally coincides with a *negative* correlation between continuous EPC consumption and income (Panel C).

Table 5.6. Energy efficiency distribution in Green and Non-Green RMBS deals. This table presents the distribution of energy efficiency tiers (Panel A) and EPC ratings (Panel B) across loans securitised in Green versus Non-Green RMBS deals. Frequencies are shown both including and excluding loans with missing EPC information. In Panel A, energy efficiency tiers are based on annual energy consumption in kWh/m^2: *High Efficiency* tier: ≤ 167 kWh/m^2/year, *Medium Efficiency* tier: $167 - 333$ kWh/m^2/year, *Low Efficiency* tier: > 333 kWh/m^2/year. The classification is based on the standard EPC consumption range from 0 to 500 kWh/m^2 per year. In Panel B, efficiency categories are based on EPC labels: A/B (High), C/D/E (Medium), F/G (Low).

Panel A: EE Tier composition

EE Tier	**Freq. including missing**		**Freq. excluding missing**	
	Non-Green RMBS	**Green RMBS**	**Non-Green RMBS**	**Green RMBS**
High Efficiency	11.58%	57.17%	33.76%	81.12%
Medium Efficiency	18.20%	12.01%	53.04%	17.04%
Low Efficiency	4.53%	1.30%	13.20%	1.84%
Missing	65.69%	29.52%	–	–

Panel B: EPC rating composition

EPC Rating	**Freq. including missing**		**Freq. excluding missing**	
	Non-Green RMBS	**Green RMBS**	**Non-Green RMBS**	**Green RMBS**
A/B (High)	9.71%	53.73%	28.31%	76.23%
C/D/E (Medium)	20.07%	15.46%	58.50%	21.93%
F/G (Low)	4.53%	1.30%	13.20%	1.84%
Missing	65.69%	29.52%	–	–

Figure 5.1. Cumulative arrears rate by EE Tier. This figure shows the cumulative arrears rate (arrears as a percentage of loan balance) over 12 quarters, split by EE Tier (high, medium, and low energy efficiency). The sample includes loans with EPC ratings populated at the reporting date, based on RMBS data.

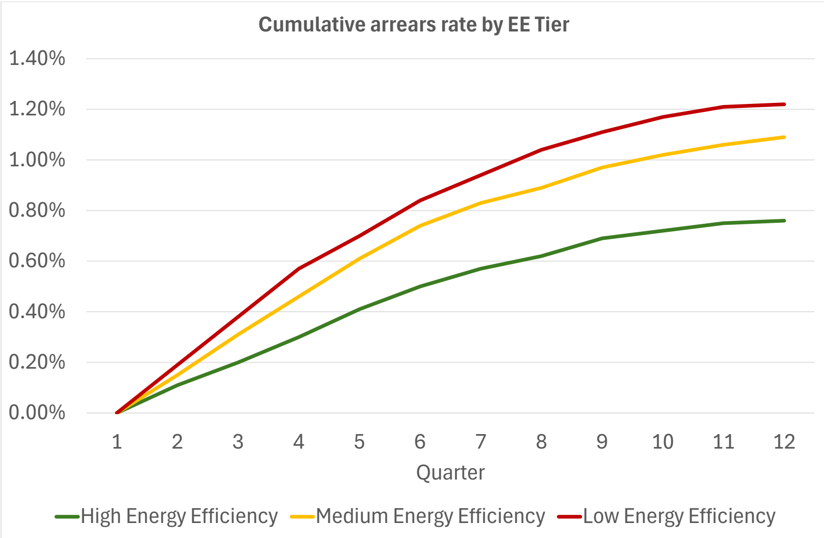
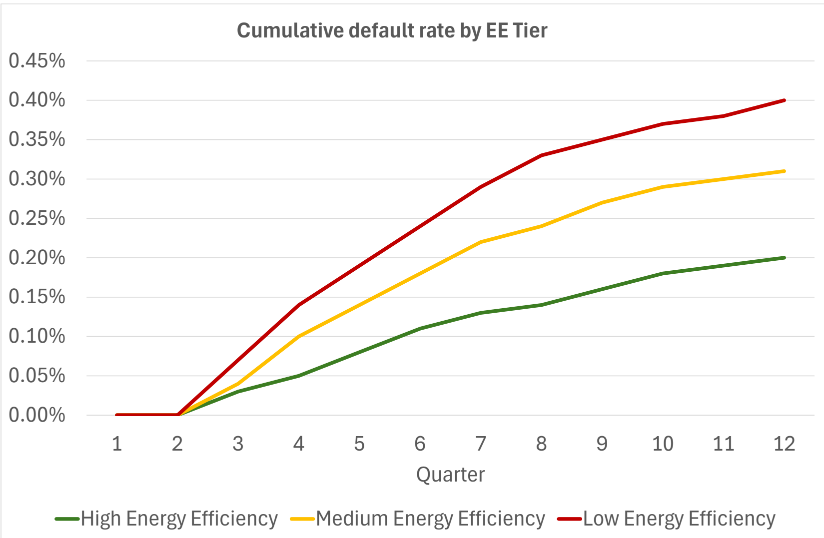


Figure 5.2. Cumulative default rate by EE Tier. This figure shows the cumulative default rate (defined as two consecutive quarters in arrears) over 12 quarters, split by EE Tier (high, medium, and low energy efficiency). The sample includes loans with EPC ratings populated at the reporting date, based on RMBS data.



5.4.2 Methodology

We estimate forward-looking logistic models with deal and quarter fixed effects and cluster standard errors at the 3-letter postcode level:

$$\begin{aligned} \mathit{Delinquency}_{i,t} &= \alpha + \beta_1\, \mathit{EE\ Tier}_{i,t} + \gamma\, \mathit{Loan}_i + \delta\, \mathit{Borrower}_i \\ &\quad + \phi\, \mathit{Property}_{i,t} + \theta\, \mathit{Macro}_{i,t} + \mathit{Deal\ FE} + \mathit{Quarter\ FE} + \varepsilon_{i,t}. \end{aligned} \tag{5.1}$$

$\mathit{EE\ Tier}_{i,t}$ is a categorical variable with High as the omitted category and indicators for Medium and Low efficiency.

To test whether affordability constraints amplify the efficiency–delinquency link, we interact efficiency tiers with a binary indicator for borrower income below the sample median:

$$\begin{aligned} \mathit{Delinquency}_{i,t} &= \alpha + \beta_1\, \mathit{EE\ Tier}_{i,t} + \eta\, (\mathit{EE\ Tier}_{i,t} \times \mathit{Low\ Income}_i) + \kappa\, \mathit{Low\ Income}_i \\ &\quad + \gamma\, \mathit{Loan}_i + \delta\, \mathit{Borrower}_i + \phi\, \mathit{Property}_{i,t} + \theta\, \mathit{Macro}_{i,t} \\ &\quad + \mathit{Deal\ FE} + \mathit{Quarter\ FE} + \varepsilon_{i,t}. \end{aligned} \tag{5.2}$$

This specification yields separate marginal effects for below- and above-median income groups for each outcome.

We examine whether energy price inflation strengthens the impact of low efficiency in two ways. First, we interact efficiency tiers with an indicator for energy inflation above the sample median:

$$\begin{aligned} \mathit{Delinquency}_{i,t} &= \alpha + \beta_1\, \mathit{EE\ Tier}_{i,t} + \pi\, (\mathit{EE\ Tier}_{i,t} \times \mathit{High\ Inflation}_{c,t}) + \xi\, \mathit{High\ Inflation}_{c,t} \\ &\quad + \gamma\, \mathit{Loan}_i + \delta\, \mathit{Borrower}_i + \phi\, \mathit{Property}_{i,t} + \theta\, \mathit{Macro}_{i,t} \\ &\quad + \mathit{Deal\ FE} + \mathit{Quarter\ FE} + \varepsilon_{i,t}. \end{aligned} \tag{5.3}$$

To study the monetary extent of distress we model *Arrears Balance* using OLS and a Tobit specification censored at zero:

$$\begin{aligned} \textit{Arrears Balance}_{i,t} = \alpha + \beta_1\, \textit{EE Tier}_{i,t} + \rho\,(\textit{EE Tier}_{i,t} \times \textit{Energy Infl.}_{c,t}) + \lambda\, \textit{Energy Infl.}_{c,t} \\ + \gamma\, \textit{Loan}_i + \delta\, \textit{Borrower}_i + \phi\, \textit{Property}_{i,t} + \theta\, \textit{Macro}_{i,t} \\ + \textit{Deal FE} + \textit{Quarter FE} + \varepsilon_{i,t}. \end{aligned} \tag{5.4}$$

This complements the binary outcomes by showing whether inflation raises the size of arrears more for inefficient properties.

5.5 Results

5.5.1 EPC tiers on mortgage delinquency

We investigate the role of energy efficiency ratings of the collateral, *EE Tier*, based on the *EPC kWh/m^2/year* measure, in mortgage delinquency.

Table 5.7 presents the results of the panel logit regressions using *EE Tier* as the key explanatory variable. The analysis is based on the EPC-populated sample, which excludes observations with missing EPC data. The table reports four specifications corresponding to different delinquency indicators: arrears, material arrears (arrears exceeding 1% of the loan balance), default, and material default (default with arrears exceeding 1% of the loan balance). The results indicate that EPC ratings significantly affect mortgage delinquency. In all four specifications, loans in the Low Efficiency tier are associated with a significantly higher risk of delinquency relative to the High Efficiency baseline. For arrears (column 1), the marginal effect of Low Efficiency is 13.65 basis points, representing a 27.53% increase over the mean arrears rate of 49.57 bps. For material arrears (column

2), the effect is 7.06 bps, corresponding to a 56.14% increase over the mean of 12.58 bps. For default (column 3), the effect is 5.97 bps, a 35.61% increase over the mean of 16.77 bps. Finally, the effect on material default (column 4) is 3.96 bps, representing an 89.94% increase over the mean of 4.40 bps. Loans in the Medium Efficiency tier also show elevated delinquency risk compared to the High Efficiency group. For arrears, the marginal effect is 8.17 bps, a 16.48% increase over the mean. For material arrears, the effect is 2.86 bps, or a 22.73% increase. The corresponding increase in default risk is 1.91 bps (11.39%), while the increase for material default is 1.00 bps, equivalent to a 22.72% rise over the mean. These findings remain robust after controlling for a comprehensive set of loan, borrower, and property characteristics, along with macroeconomic conditions. Quarterly and deal fixed effects are included to account for time-varying and deal-specific heterogeneity. The LTV ratio consistently emerges as a significant predictor of delinquency, with higher-LTV loans associated with increased risk across all specifications. Specifically, loans in the fifth LTV quintile show a delinquency increase of approximately 39 bps in arrears and 13.5 bps in material arrears, confirming the critical role of LTV in mortgage performance. Other control variables perform as expected. Floating-rate loans continue to exhibit higher delinquency risk. Borrowers who are self-employed or unemployed also face significantly elevated delinquency rates. In terms of income, loans in the lowest income tertile (baseline) display the highest risk, while borrowers in the second and third tertiles show progressively lower delinquency probabilities. The third tertile, in particular, is associated with a reduction of approximately 22.71 bps in arrears and 8.24 bps in material arrears, reinforcing the link between borrower income and loan performance.

To further assess robustness, we conduct two additional tests. First, we include an interaction term between Deal and Quarter Fixed Effects (Deal $\times$ Quarter FE), capturing deal-specific time-varying effects. As reported in Table 5.A.3, all previously observed results remain intact, confirming the stability of the energy efficiency–delinquency relationship. Second, we replace the EE Tier variable with the raw EPC rating, foregoing cross-country harmonisation. This test enables a simpler yet meaningful comparison based on label categories. As shown in Table 5.A.2, the medium efficiency tier (C/D/E labels) is not statistically significant, but the low efficiency tier (F/G labels) remains significant relative to the high efficiency baseline (A/B labels).

Table 5.7. The impact of energy efficiency labels on mortgage delinquency. 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 *EE Tier*, categorised as high, medium, or low efficiency. Other control variables include loan, borrower and property 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 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
EE Tier:				
High efficiency (baseline)	-	-	-	-
Medium efficiency	8.1734***	1.9054***	2.8572**	1.0043**
	(2.6220)	(0.6651)	(1.2106)	(0.4360)
Low efficiency	13.6520***	5.9719***	7.0612***	3.9646***
	(3.4682)	(1.3833)	(1.5068)	(0.9072)
LTV:				
1st quintile (baseline)	-	-	-	-
2nd quintile	3.6021	0.9332	1.0030	1.5323
	(2.8307)	(1.5883)	(1.7668)	(1.1776)
3rd quintile	12.1736***	5.4499**	4.0975*	1.5521
	(4.0713)	(2.4331)	(2.3371)	(1.3272)
4th quintile	24.9191***	4.2865	8.8826***	1.8264
	(4.0744)	(2.9911)	(2.3314)	(1.5820)
5th quintile	39.1576***	5.8844**	13.5089***	2.0618
	(5.4026)	(2.6311)	(2.6486)	(1.4911)
Time to Maturity (quarters)	0.2409***	-0.1089**	0.1003***	-0.0352
	(0.0549)	(0.0470)	(0.0246)	(0.0267)
Loan purpose:				
Purchase (baseline)	-	-	-	-
Construction	0.4127	1.0396	-0.8234	1.2547
	(4.4470)	(1.4386)	(2.3495)	(1.1538)
Remortgage	-1.4674	-0.9881	-1.4106	-2.6575***
	(2.9843)	(2.4347)	(2.4854)	(0.5180)
Renovation	-14.7241***	-1.8081	-6.5339***	-2.5669**
	(3.8279)	(2.4243)	(2.3416)	(1.0205)
Other	-4.2868	-4.2331	-4.7208	3.0111
	(4.2419)	(2.9445)	(4.6842)	(5.2724)
Interest rate:				
1st quintile (baseline)	-	-	-	-
2nd quintile	-1.8478	-4.7013***	-0.1195	0.8884
	(4.7097)	(1.6527)	(1.4162)	(0.7098)
3rd quintile	-1.8036	-4.2570**	0.1071	0.9211
	(5.1347)	(1.9730)	(1.3657)	(0.7111)
4th quintile	12.8930*	0.4272	7.6185***	3.1699***
	(6.7805)	(2.1064)	(2.4266)	(1.0511)
5th quintile	29.7007**	6.9427**	15.1475***	5.7459***
	(12.2376)	(3.3831)	(4.9515)	(1.7785)

Table 5.7 continued from previous page

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Interest type:				
Fixed (baseline)	-	-	-	-
Floating	2.8149	7.2156**	3.9442	1.7096
	(8.8305)	(3.0277)	(2.7990)	(1.2101)
Other	-11.9801	-7.4064**	-5.7168	-4.6169***
	(12.7278)	(3.6915)	(5.1761)	(1.6679)
Employment:				
Employed - private sector (baseline)	-	-	-	-
Employed - public sector	-19.8456***	-5.6885***	-6.1548***	-1.5226***
	(1.8758)	(0.9296)	(0.9756)	(0.5804)
Employed - unknown	-2.2475	-1.3726	-0.4808	-0.7763
	(3.0977)	(1.5341)	(4.7794)	(1.1741)
Pensioner	-6.1357	-0.2664	-2.7686	0.4088
	(4.6482)	(1.6490)	(1.8750)	(1.1859)
Self-employed	36.0157***	14.3081***	11.2418***	5.4086***
	(4.4757)	(1.9531)	(2.3083)	(1.0703)
Unemployed	48.1748***	18.6433***	20.5157***	4.2362
	(12.3727)	(4.7493)	(6.9055)	(2.8639)
Other	24.0275*	12.4234*	11.0729	12.8976
	(13.4727)	(7.3728)	(7.9888)	(8.6865)
Income:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-10.2983***	-3.5999**	-3.9397**	-1.4740*
	(3.4233)	(1.5495)	(1.7473)	(0.8441)
3rd tertile	-22.7108***	-7.4994***	-8.2465***	-3.2949***
	(3.2235)	(1.9670)	(1.6632)	(1.0911)
Occupancy type:				
Owner occupied (baseline)	-	-	-	-
Buy to Let	4.6882*	0.6742	4.0718**	0.3889
	(2.4979)	(1.1724)	(1.7198)	(0.9641)
Holiday	-6.2320	-1.6186	-2.4788	-1.1687
	(7.7599)	(2.6465)	(4.5560)	(1.4125)
Property type:				
Residential flat (baseline)	-	-	-	-
Residential house	1.3169	-0.6362	1.9412	-1.1124
	(3.3134)	(1.6279)	(1.5199)	(1.0929)
Residential terrace	7.1287	8.0903**	1.0007	2.8236
	(7.0760)	(3.4212)	(1.9525)	(2.3502)
Other	7.3415	-0.9631	4.4824	1.4321
	(9.5858)	(3.0067)	(5.1645)	(2.5773)
Property value:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-3.7934**	-2.9894**	-1.9275*	-1.2655**
	(1.7433)	(1.3227)	(1.1477)	(0.5916)
3rd tertile	-2.0548	-2.7984*	-0.9274	-1.6746**
	(3.2227)	(1.4605)	(1.6444)	(0.7054)
Macro variables	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0564	0.0597	0.0680	0.0606
Observations	4,471,096	4,300,723	4,412,604	4,064,874

5.5.2 Energy price inflation and borrower income

Having established that the energy efficiency of properties affects the probability of default in securitised mortgages, we now investigate the channel through which this effect arises. Specifically, we examine whether the relationship is driven by higher utility bills from poor energy efficiency, which reduce disposable income available for mortgage repayments. To explore this hypothesis, we conduct two sets of analyses. First, we analyse the interaction between income and energy efficiency (subsubsection 5.5.2.1), under the expectation that financially constrained households are more affected by energy inefficiency. Second, we test whether energy prices moderate the relationship between energy efficiency and delinquency risk (subsubsection 5.5.2.2).

5.5.2.1 Borrower income

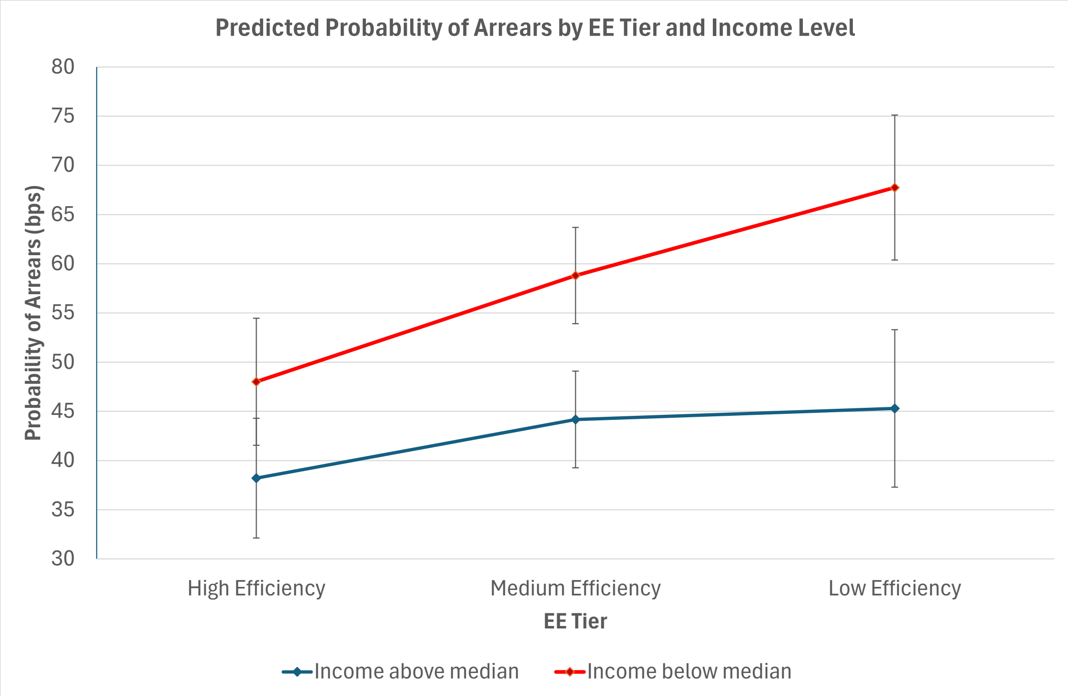
We begin by examining the interaction between energy efficiency and borrower income. Table 5.8 presents the results, with income split into two groups: above or below the median. The dependent variables are arrears (column 1), material arrears (column 2), default (column 3), and material default (column 4). Income is modelled as a binary variable indicating whether it is above or below the median. All other controls are retained, including LTV, interest rates, borrower and property characteristics, macroeconomic variables, and fixed effects for deal and quarter. Interacting this binary income variable with the energy efficiency tiers allows us to estimate separate marginal effects for each income group. This setup reflects two baseline delinquency levels, corresponding to the inherent risk differences between above- and below-median income borrowers. Within each group, the marginal effects of moving from high to medium or low energy efficiency are then assessed.

Table 5.8. The impact of income and energy efficiency interactions on mortgage delinquency. This 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). We interact income bands (above or below the median) with different energy efficiency levels (high, medium, and low) to test how differently energy efficiency impacts the probability of mortgage delinquency depending on whether the household income is above or below the median. Robust standard errors are clustered at the regional level (3-digit postcode). Macroeconomic variables are included. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Income below median (standalone)	14.238***	5.011***	5.011***	1.710**
	(1.815)	(0.921)	(0.921)	(0.788)
Above Median Income × High efficiency (baseline)	-	-	-	-
Above Median Income × Medium efficiency	5.968*	0.998	-0.0435	0.564
	(3.060)	(1.114)	(1.559)	(0.464)
Above Median Income × Low efficiency	7.088	6.148***	3.619	3.398***
	(4.324)	(2.229)	(2.354)	(1.348)
Below Median Income × High efficiency (baseline)	-	-	-	-
Below Median Income × Medium efficiency	10.796***	2.842***	5.848***	1.471*
	(3.094)	(0.967)	(1.630)	(0.788)
Below Median Income × Low efficiency	19.742***	6.678***	10.448***	4.756***
	(4.789)	(1.643)	(1.826)	(1.194)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes
Macro variables	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0563	0.0675	0.0597	0.0596
Observations	4,471,096	4,300,723	4,412,604	4,064,874

The results show that energy efficiency has a stronger impact on delinquency among below-median income borrowers. For this group, moving from high to low energy efficiency increases arrears by 19.74 basis points, a 39.8% rise over the mean arrears rate of 49.57 bps. The marginal effects for material arrears, default, and material default are 6.68 bps, 10.45 bps, and 4.76 bps, corresponding to increases of 53.12%, 62.29%, and 108.19% relative to their respective sample means. In contrast, among above-median income borrowers, the effect of energy efficiency is smaller and, in some cases, not statistically significant. For instance, moving from high to low energy efficiency increases arrears by 7.09 bps and default by 3.62 bps, though both estimates are insignificant. The corresponding effects for material arrears and material default are 6.15 bps and 3.40 bps. To aid interpretation, Figure 5.3 shows marginal effects by energy efficiency tier for each income group. Borrowers below the median exhibit a higher baseline delinquency rate even for high-efficiency properties, as shown by the vertical difference in intercepts between the red and blue lines. More importantly, the slope of the red line is steeper, indicating that the increase in delinquency from high to low energy efficiency is more pronounced. For example, the change from high to low efficiency on the red line reflects the 19.74 bps increase in arrears, while the same transition on the blue line corresponds to a 7.09 bps increase. These results suggest that income plays a key role in shaping how energy efficiency affects mortgage performance. Lower-income households appear more vulnerable to liquidity constraints arising from high utility bills, leaving them less able to meet mortgage obligations. By contrast, higher-income borrowers are better positioned to absorb such costs. These findings support the hypothesis that the energy efficiency–delinquency relationship operates, at least in part, through an income channel.

Figure 5.3. Marginal effects of arrears probability by income group and energy efficiency tier. This figure illustrates the marginal effects for arrears probability across three energy efficiency tiers (high, medium, and low), separately for borrowers with above-median and below-median income. The results are derived from the regression presented in Table 5.8, column 1. Confidence intervals are shown at the 90% level.



5.5.2.2 Energy price inflation

This section investigates whether the impact of energy efficiency on mortgage delinquency is moderated by fluctuations in energy prices. Specifically, we test whether higher energy inflation amplifies the adverse effects of poor energy efficiency, as rising energy costs reduce borrowers' disposable income for mortgage payments. Using the same econometric approach as in the income interaction analysis, we estimate the additional marginal effects of moving from high to low efficiency under two conditions: above- and below-median energy inflation.

This enables us to quantify how the relationship between energy efficiency and delinquency risk varies with inflationary pressure.

Table 5.9 presents results from panel logit regressions, where we interact energy inflation levels (above or below the median of 18.4%) with energy efficiency tiers (high, medium, low). The findings show that low-efficiency properties are significantly more likely to become delinquent across all four indicators (arrears, material arrears, default, and material default) regardless of energy inflation levels. However, the effects are substantially stronger when energy inflation is above the median. Under high energy inflation, low-efficiency properties exhibit increases of 16.40 bps in arrears, 6.59 bps in material arrears, 8.06 bps in default, and 4.24 bps in material default. These represent increases of 33.09%, 52.41%, 48.06%, and 96.27% over the corresponding sample means. For medium-efficiency properties, the effects under high inflation are smaller but still significant: arrears increase by 8.54 bps (17.23%), material arrears by 2.37 bps (18.84%), default by 3.60 bps (21.47%), and material default by 1.33 bps (30.23%). Under low energy inflation, the adverse effects of energy inefficiency persist but are attenuated.

Low-efficiency properties show increases of 8.70 bps in arrears (17.55%), 4.87 bps in material arrears (38.71%), 5.32 bps in default (31.74%), and 3.45 bps in material default (78.41%). For medium-efficiency properties, the marginal effects under low inflation are smaller and mostly insignificant, except for arrears (7.53 bps, 15.19%). All specifications control for loan, borrower, and property characteristics, as well as macroeconomic conditions. As a robustness, we re-estimate the same specification without quarter fixed effects and report the corresponding marginal effects, including the standalone effect of the high-inflation dummy, in Table 5.A.4 in the Appendix. Periods with above-median energy inflation are associated with statistically significant increases in arrears and default probabilities (i.e., 7.2 bps for arrears, 2.1 bps for material arrears, 2.8 bps for default and 0.8 bps for material default), while the interaction patterns by EPC tier remain very similar to those in the main table: the increase in delinquency from high to low efficiency is markedly stronger when energy inflation is above the median than when it is below. Additionally, to rule out the possibility that these results are driven by interest rate changes rather than energy inflation, we include country-level benchmark rates in Table 5.10.

Table 5.9. The impact of energy inflation and energy efficiency interactions on mortgage delinquency. This 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). We interact energy inflation bands (below or above the median of 18.4%) with different energy efficiency levels (high, medium, and low) to test how energy inflation and energy efficiency jointly affect the probability of mortgage delinquency. Robust standard errors are clustered at the regional level (3-digit postcode). Macroeconomic variables are included. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

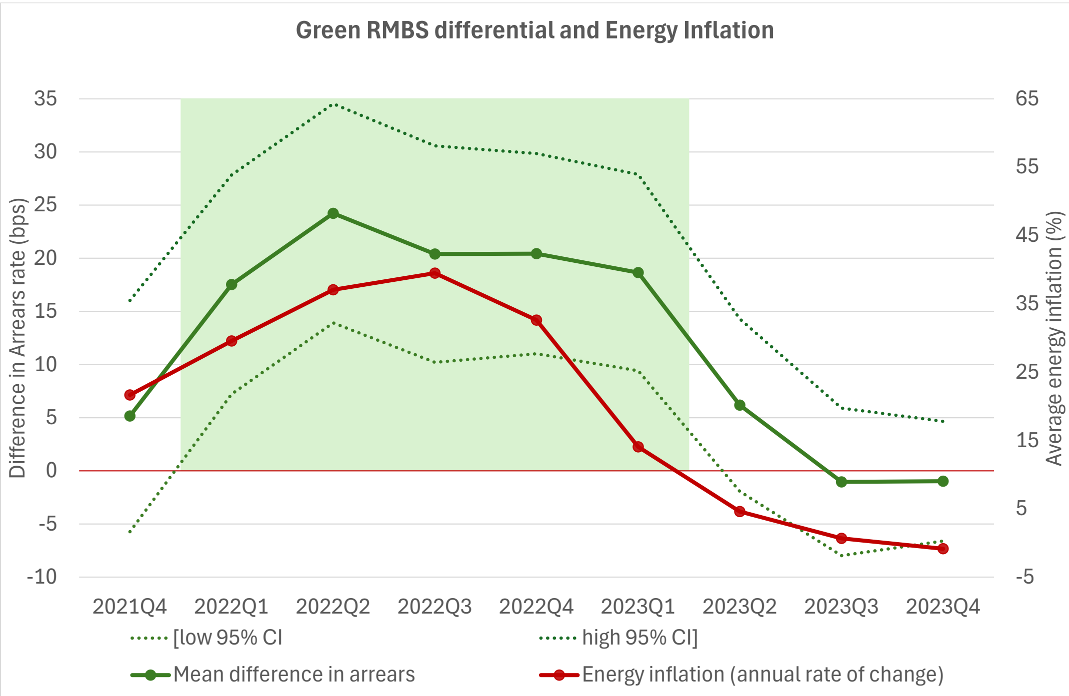
Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Below Median Energy Inflation × High efficiency (baseline)	-	-	-	-
Below Median Energy Inflation × Medium efficiency	7.533***	1.125	1.666	0.454
	(2.902)	(0.954)	(1.201)	(0.474)
Below Median Energy Inflation × Low efficiency	8.703***	4.871***	5.32**	3.447***
	(2.970)	(1.553)	(2.227)	(1.196)
Above Median Energy Inflation × High efficiency (baseline)	-	-	-	-
Above Median Energy Inflation × Medium efficiency	8.541***	2.375***	3.600**	1.325***
	(2.996)	(0.751)	(1.528)	(0.517)
Above Median Energy Inflation × Low efficiency	16.398***	6.593***	8.062***	4.241***
	(4.264)	(1.633)	(1.474)	(0.972)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes
Macro variables	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0565	0.0681	0.0598	0.0596
Observations	4,471,096	4,300,723	4,412,604	4,064,874

Table 5.10. The impact of energy inflation and energy efficiency interactions on mortgage delinquency (robustness test). This 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). We interact energy inflation bands (below or above the median of 18.4%) with different energy efficiency levels (high, medium, and low) to test how energy inflation and energy efficiency jointly affect the probability of mortgage delinquency. Robust standard errors are clustered at the regional level (3-digit postcode). In this robustness test, we add controls to include the benchmark rate average (3-month Euribor for EU countries and SONIA for the UK) and its standard deviation. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Below Median Energy Inflation × High efficiency (baseline)	-	-	-	-
Below Median Energy Inflation × Medium efficiency	7.426***	1.115	1.352	3.81
	(2.819)	(0.930)	(1.140)	(4.40)
Below Median Energy Inflation × Low efficiency	8.172***	4.698***	4.703**	30.74***
	(2.954)	(1.521)	(2.139)	(10.81)
Above Median Energy Inflation × High efficiency (baseline)	-	-	-	-
Above Median Energy Inflation × Medium efficiency	8.402***	2.353***	3.676**	13.76***
	(2.974)	(0.749)	(1.558)	(5.48)
Above Median Energy Inflation × Low efficiency	16.483***	6.674***	8.344***	44.82***
	(4.290)	(1.657)	(1.530)	(10.58)
Loan, borrower, property characteristics	Yes	Yes	Yes	Yes
Benchmark Rate Average	Yes	Yes	Yes	Yes
Benchmark Rate Std. Dev.	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Quarter FE	No	No	No	No
Pseudo R2	0.0548	0.0667	0.0583	0.0593
Observations	4,471,096	4,300,723	4,412,604	4,064,874

Specifically, we control for the quarterly average and standard deviation of the 3-month Euribor (for EU countries) and SONIA (for the UK). Although other specifications use Deal × Quarter or Originator × Quarter fixed effects—which would absorb macro-level variation—they would also absorb energy inflation itself. Including benchmark rates as separate controls allows us to isolate the energy inflation channel. The results remain robust. Given the higher concentration of energy-efficient loans in Green RMBS (Table 5.6), we also explore how the delinquency differential between Green and Non-Green RMBS evolves over time. Figure 5.4 plots this differential against quarterly energy inflation.

Figure 5.4. Green RMBS differential and energy inflation. This figure presents the difference in arrears rates (in bps) between Green and non-Green RMBS over time, plotted against the average energy inflation rate (as a percentage). The left vertical axis corresponds to the difference in arrears rates, and the right vertical axis corresponds to the energy inflation rate. Quarters where the difference is statistically significant at the 5% level are highlighted in green.



From 2022Q1 to 2023Q1, during the period of highest energy inflation, the difference becomes statistically significant. Green RMBS consistently exhibit lower arrears, suggesting they are more resilient to rising energy costs. This supports the hypothesis that energy-efficient loans are less vulnerable to inflationary shocks. To further validate these results, we interact the continuous energy inflation variable with energy efficiency tiers in regressions using arrears balance as the dependent variable. Results from OLS and Tobit models are shown in Table 5.A.5. For medium-efficiency properties, the OLS coefficient is €0.133 when energy inflation is 0%, a 9.93% increase over the mean arrears balance of €1.34. For low-efficiency properties, the coefficient is €0.140 (10.45%). In the Tobit model, the medium-efficiency interaction is insignificant, while the low-efficiency interaction is significant at €1.568. Given a mean arrears balance of €523.01 among delinquent loans, this corresponds to a 0.30% increase. Table 5.A.6 reports marginal effects of energy efficiency on arrears balance across energy inflation levels from –40% to +100%. This range reflects the actual variation observed during the sample period, from the 5th to 95th percentile (–41.1% to +129.97%). At 0% inflation, medium-efficiency properties have a marginal effect of €0.133 (9.93% increase), which rises to €0.161 (12.01%) at +40%. For low-efficiency properties, the effect increases from €0.140 at 0% to €0.207 (15.45%) at +40%. In the Tobit model, the effect for low-efficiency loans reaches €183.69 at +100%, a 35.12% increase over the €523.01 mean arrears balance. These results confirm that energy inflation exacerbates the financial strain on households with energy-inefficient properties, increasing both delinquency risk and arrears balance. The vulnerability of these borrowers rises markedly as energy costs increase, underscoring the role of energy efficiency in household financial resilience during inflationary periods. These findings confirm that the interaction between energy inflation and low energy efficiency significantly affects arrears balances, with the impact becoming more pronounced as inflation rises. Borrowers with energy-inefficient properties are particularly vulnerable to energy price volatility, experiencing both higher delinquency rates and greater arrears balances under inflationary stress. This evidence reinforces the conclusion that energy efficiency strengthens household financial resilience and that its impact on mortgage performance is strongly mediated by exposure to energy costs.

5.6 Conclusion

This chapter shows that the energy performance of the collateral is a determinant of mortgage delinquency. Using a harmonised EPC measure that maps national labels to a common kWh/m^2/year scale and aggregates across linked properties at the loan level, we document a that loans secured on energy-inefficient homes are more likely to fall into arrears and default than comparable loans on efficient homes. The pattern is economically relevant and robust to an extensive set of controls, alternative fixed effects, and alternative constructions of the efficiency metric. The results hold when we replace the harmonised kWh measure with raw EPC labels and when we study arrears balances with OLS and Tobit specifications. Moreover, the efficiency–delinquency link is strongest for financially constrained borrowers and when energy prices are high, which is consistent with a disposable-income channel. Poor efficiency raises utility bills, tightens liquidity, and leaves households with less headroom to service debt. Higher-income borrowers are better able to absorb these costs, which explains the heterogeneity we observe.

These findings have direct implications for risk management. Incorporating EPC information improves PD models and sharpens risk segmentation, especially in environments with elevated energy price volatility. For lenders, EPC data help with affordability assessments, risk-based pricing, and the construction of more resilient securitisation pools. For investors, they provide a transparent, decision-useful signal that links climate-relevant housing characteristics to credit outcomes and stress-test performance. There are policy implications as well. Targeted retrofit programmes and clear disclosure standards can lower household vulnerability and enhance financial stability.

Appendices to Chapter 5

Table 5.A.1. Determinants of securitisation into Green RMBS. This table presents marginal effects (in percentage points) from four specifications of probit regressions where the dependent variable is a dummy equal to one if the loan is securitised into a Green RMBS. The sample is cross-sectional, including each loan only once at its first reporting date. Specifications (1) to (4) progressively introduce additional controls for loan characteristics, borrower characteristics, and collateral characteristics. 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.: Green Flag	**Marginal Effect (%)**			
	(1)	**(2)**	**(3)**	**(4)**
EE Tier:				
High Efficiency (baseline)	-	-	-	-
Medium efficiency	-19.14***	-15.58***	-13.22***	-13.41***
	(5.84)	(4.30)	(3.72)	(3.67)
Low efficiency	-20.44***	-16.83***	-14.27***	-14.45***
	(5.89)	(4.47)	(3.93)	(3.89)
Missing	-20.65***	-16.98***	-14.33***	-14.46***
	(5.78)	(4.46)	(3.98)	(3.93)
Loan characteristics	No	Yes	Yes	Yes
Borrower characteristics	No	No	Yes	Yes
Collateral characteristics	No	No	No	Yes
Pseudo R2	0.2668	0.3357	0.3535	0.3525
Observations	3,220,853	3,220,602	3,220,602	2,961,434

Table 5.A.2. The impact of EPC ratings on mortgage delinquency 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 rating*, categorized into three groups: A/B, C/D/E, and F/G. We run the regressions on a sample where the EPC rating field is populated to ensure a fair comparison. Other control variables include loan characteristics, borrower characteristics, and property 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 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
EPC rating:				
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
Property 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

Table 5.A.3. The impact of energy efficiency labels on mortgage delinquency 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 *EE Tier*, categorised as high, medium, or low efficiency. The interaction of Deal and Quarter Fixed Effects (Deal x Quarter FE) is used for robustness. Other control variables include loan, borrower, and property 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 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
EE Tier:				
High efficiency (baseline)	-	-	-	-
Medium efficiency	8.0990***	2.0144***	2.9235**	1.1326**
	(2.6427)	(0.6928)	(1.2493)	(0.4902)
Low efficiency	13.6373***	6.3388***	7.2669***	4.4980***
	(3.4483)	(1.4251)	(1.5190)	(0.9540)
LTV:				
1st quintile (baseline)	-	-	-	-
2nd quintile	5.0296*	1.2180	1.5126	1.8239
	(2.8737)	(1.5582)	(1.7154)	(1.2277)
3rd quintile	14.1368***	6.1760***	4.8759**	1.9440
	(4.0408)	(2.3750)	(2.2891)	(1.3375)
4th quintile	27.2403***	5.0154*	9.9530***	2.2964
	(4.0177)	(3.0285)	(2.2175)	(1.6412)
5th quintile	41.9973***	6.8681***	14.8608***	2.6203*
	(5.2870)	(2.5879)	(2.5243)	(1.4999)
Time to Maturity (quarters)	0.2381***	-0.1191**	0.1016***	-0.0415
	(0.0533)	(0.0480)	(0.0244)	(0.0290)
Loan purpose:				
Purchase (baseline)	-	-	-	-
Construction	0.2735	1.0539	-0.9263	1.3999
	(4.5407)	(1.5287)	(2.4077)	(1.3113)
Remortgage	-1.5791	-1.0453	-1.4556	-3.0214***
	(2.9562)	(2.5755)	(2.5186)	(0.5226)
Renovation	-14.2283***	-1.8737	-6.5519**	-2.9277**
	(3.9655)	(2.6136)	(2.5568)	(1.1462)
Other	-4.3776	-4.5199	-4.8932	3.4264
	(4.3144)	(3.0541)	(4.8044)	(6.0888)
Interest rate:				
1st quintile (baseline)	-	-	-	-
2nd quintile	-4.1367	-5.3336***	-0.9346	0.8776
	(3.7250)	(1.7221)	(1.5567)	(0.8357)
3rd quintile	-3.9183	-4.8130**	-0.6213	0.9268
	(4.4435)	(2.1152)	(1.4222)	(0.8197)
4th quintile	11.0111*	0.2085	7.2071***	3.5048***
	(6.2063)	(2.2425)	(2.3881)	(1.0907)
5th quintile	27.8269**	7.1558**	14.9670***	6.4248***
	(11.7598)	(3.4469)	(4.8551)	(1.7523)

Table 5.A.3 continued from previous page

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Interest type:				
Fixed (baseline)	-	-	-	-
Floating	2.6409	7.6396**	4.0212	1.9431
	(8.8310)	(3.1263)	(2.8769)	(1.3611)
Other	-11.6338	-7.8896**	-5.9813	-5.2666***
	(12.8184)	(3.8574)	(5.3256)	(1.8668)
Employment:				
Employed - private sector (baseline)	-	-	-	-
Employed - public sector	-19.953***	-6.0513***	-6.3550***	-1.7271***
	(1.8553)	(0.8870)	(0.9645)	(0.6548)
Employed - unknown	-2.0805	-1.6263	-0.4419	-0.9247
	(3.2009)	(1.5625)	(5.1199)	(1.3296)
Pensioner	-5.3390	-0.2165	-2.6480	0.5191
	(4.6227)	(1.7711)	(1.9534)	(1.3459)
Self-employed	36.2816***	15.2549***	11.6437***	6.1722***
	(4.4962)	(1.8779)	(2.3910)	(1.1944)
Unemployed	48.5189***	19.9324***	21.2791***	4.8598
	(12.3668)	(4.7490)	(7.0297)	(3.2188)
Other	24.7145*	13.1931*	11.5205	14.8942
	(13.3574)	(7.6880)	(8.1251)	(9.7560)
Income:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-10.3360***	-3.8028**	-4.0434**	-1.6569*
	(3.3936)	(1.5861)	(1.7772)	(0.9368)
3rd tertile	-22.7168***	-7.9233***	-8.4470***	-3.7139***
	(3.2459)	(1.9795)	(1.7175)	(1.1818)
Occupancy type:				
Owner occupied (baseline)	-	-	-	-
Buy to Let	4.0845	0.5944	3.9733**	0.3893
	(2.6729)	(1.2782)	(1.8657)	(1.1065)
Holiday	-6.1203	-1.6780	-2.4630	-1.3104
	(7.8284)	(2.8267)	(4.7435)	(1.6086)
Property Type:				
Residential flat (baseline)	-	-	-	-
Residential house	1.3388	-0.6683	2.0352	-1.2662
	(3.3975)	(1.7646)	(1.5874)	(1.2734)
Residential terrace	7.2899	8.6851**	1.0733	3.2404
	(7.1074)	(3.6113)	(2.0221)	(2.6720)
Other	7.4731	-1.0181	4.7079	1.6407
	(9.6680)	(3.2184)	(5.3608)	(2.9391)
Property value:				
1st tertile (baseline)	-	-	-	-
2nd tertile	-4.7130***	-3.3855**	-2.2774**	-1.5692**
	(1.5369)	(1.4479)	(1.1529)	(0.7284)
3rd tertile	-2.8379	-3.1714*	-1.2195	-2.0198**
	(3.1915)	(1.6270)	(1.6964)	(0.8773)
Macro variables	No	No	No	No
Deal x Quarter FE	Yes	Yes	Yes	Yes
Pseudo R2	0.0596	0.0649	0.0614	0.0563
Observations	4,440,249	4,037,700	4,264,802	3,568,412

Table 5.A.4. The impact of energy inflation and energy efficiency interactions on mortgage delinquency. This 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). We interact energy inflation bands (below or above the median of 18.4%) with different energy efficiency levels (high, medium, and low) to test how energy inflation and energy efficiency jointly affect the probability of mortgage delinquency. Robust standard errors are clustered at the regional level (3-digit postcode). This robustness excludes quarter FE to ensure the standalone dummy variable for energy inflation above median be explicit. Macroeconomic variables are included. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Delinquency indicator	**Marginal Effect (bps)**			
	(1 - A)	**(2 - MA)**	**(3 - D)**	**(4 - MD)**
Above median energy inflation (standalone)	7.158***	2.081***	2.800***	0.854***
	(1.953)	(0.525)	(0.936)	(0.291)
Below Median Energy Inflation × High efficiency (baseline)	-	-	-	-
Below Median Energy Inflation × Medium efficiency	7.639***	1.252	1.645*	0.393
	(2.407)	(0.774)	(0.988)	(0.391)
Below Median Energy Inflation × Low efficiency	8.205***	4.252***	4.590**	2.753***
	(2.733)	(1.358)	(1.956)	(0.977)
Above Median Energy Inflation × High efficiency (baseline)	-	-	-	-
Above Median Energy Inflation × Medium efficiency	8.564***	2.433***	3.717**	1.459**
	(3.339)	(0.833)	(1.699)	(0.583)
Above Median Energy Inflation × Low efficiency	17.585***	7.309***	8.827***	4.867***
	(4.977)	(1.862)	(1.705)	(1.134)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes
Macro variables	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Quarter FE	No	No	No	No
Pseudo R2	0.0565	0.0681	0.0598	0.0596
Observations	4,471,096	4,300,723	4,412,604	4,064,874

Table 5.A.5. The impact of energy inflation and energy efficiency on arrears balance. This table presents the coefficients (in euros) from two specifications: OLS and Tobit regressions, where the dependent variable is the arrears balance. We interact the continuous energy inflation variable with different energy efficiency levels (high, medium, and low) to investigate the effect on arrears balance. The OLS and Tobit regressions are applied to test the robustness of the findings. Robust standard errors are clustered at the regional level (3-digit postcode). Macroeconomic variables are included. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.: Arrears balance (€)	**Coefficients (€)**	
	OLS	**Tobit**
High efficiency (baseline)	-	-
Medium efficiency	0.133***	-0.177
	(0.042)	(20.892)
Low efficiency	0.140***	26.897
	(0.047)	(24.557)
Energy Inflation	0.0004	-0.155
	(0.0008)	(0.497)
High efficiency × Energy Inflation	-	-
Medium efficiency × Energy Inflation	0.0007	1.280***
	(0.0007)	(0.498)
Low efficiency × Energy Inflation	0.0017***	1.568***
	(0.0007)	(0.446)
Loan characteristics	Yes	Yes
Borrower characteristics	Yes	Yes
Property characteristics	Yes	Yes
Macro variables	Yes	Yes
Deal FE	Yes	Yes
Quarter FE	Yes	Yes
R2 / Pseudo R2	0.0562	0.0675
Observations	4,486,060	4,486,060

Table 5.A.6. Marginal effects of energy efficiency levels at different energy inflation levels on arrears balance. This table presents the marginal effects (in euros) derived from Table Table 5.A.5, where the dependent variable is the arrears balance. The marginal effects are computed for different levels of energy inflation (from -40% to +100%) for medium and low energy efficiency, with the high-efficiency category as the baseline. 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.: Arrears balance (€)	**Coefficients (€)**	
EPC	**Energy Inflation Level**	**OLS**	**Tobit**
Medium			
	-40%	0.105*	-51.373
		(0.058)	(34.570)
	-20%	0.119**	-25.775
		(0.049)	(26.766)
	0%	0.133***	-0.177
		(0.042)	(20.892)
	20%	0.147***	25.421
		(0.038)	(18.846)
	40%	0.161***	51.019**
		(0.040)	(21.739)
	60%	0.175***	76.617***
		(0.046)	(28.083)
	80%	0.189***	102.215***
		(0.055)	(36.103)
	100%	0.204***	127.813***
		(0.066)	(44.910)
Low			
	-40%	0.072	-35.818
		(0.062)	(35.794)
	-20%	0.106**	-4.460
		(0.053)	(29.371)
	0%	0.140***	26.898
		(0.047)	(24.557)
	20%	0.173***	58.256***
		(0.046)	(22.413)
	40%	0.207***	89.613***
		(0.049)	(23.676)
	60%	0.241***	120.971***
		(0.057)	(27.887)
	80%	0.275***	152.329***
		(0.068)	(33.967)
	100%	0.308***	183.687***
		(0.080)	(41.094)
Loan characteristics		Yes	Yes
Borrower characteristics		Yes	Yes
Property characteristics		Yes	Yes
Macro variables		Yes	Yes
Deal FE		Yes	Yes
Quarter FE		Yes	Yes
R2/Pseudo R2		0.0563	0.0675
Observations		4,486,060	4,486,060

Chapter 6

Conclusion

6.1 Summary and concluding remarks

This thesis examines how climate and energy-efficiency information is priced and reflected in credit risk across three segments of fixed-income markets: corporate green bonds (Chapter 3), European Green RMBS and tranche outcomes (Chapter 4), and loan-level mortgage performance using EPCs (Chapter 5). A unifying theme is evaluation under changing conditions. In the corporate bond setting, secondary-market spreads are analysed around climate-salience shocks such as transitioning policies, climate disaster events, and surges in media coverage. In securitisation, deal-level green status is linked to underlying loan performance and tranche resilience, and loan-level differences are translated into stress-loss comparisons. In mortgages, EPC-based efficiency is tested as a moderator of arrears when energy prices accelerate, using measures of energy inflation as the stress. Across these settings, credible environmental attributes and higher building efficiency are associated with lower credit risk, manifesting as narrower yield spreads, stronger tranche protection, or lower delinquency rates.

The first empirical chapter studies whether green bonds trade at a persistent discount in yield spreads, how that discount moves over time, and whether certification or salient climate events matter. The central finding is that the greenium is time-varying rather than constant. It widens around periods of elevated climate attention, such as the months surrounding the Paris Agreement, and it compresses during periods when climate salience is lower. Certification strengthens the effect. Certified issues exhibit a materially larger spread advantage than non-certified green bonds when other characteristics are held constant. The patterns are strongest where environmental issues are financially material to the issuer's industry. In high-impact sectors, certified green bonds enjoy the largest greenium, whereas non-certified green bonds can even trade at wider spreads than conventional peers, consistent with investor concerns about greenwashing. In addition, certified bonds show greater resilience in the days following climate-related disaster news mapped to the issuer's country of domicile. This pattern is consistent with investors rewarding credible and verifiable environmental signals when attention is high. Methodologically, Chapter 3 differs from much of the early literature by focusing on secondary-market spreads and allowing the green effect to vary by month, rather than estimating a single average. The design uses issuer fixed effects, controls for bid-ask, maturity, rating, size and coupon, and benchmarks spreads to sovereign curves to isolate credit pricing. It also separates the baseline green label from the incremental effect of certification. Taken together, these choices support a simple interpretation. Markets price environmental credibility, and that pricing is stronger when climate risk is more prominent.

The second empirical chapter moves from corporate bonds to securitisation. Using EDW loan-level data, we document that loans included in Green-labelled RMBS deals have materially lower probabilities of moving into arrears or default over the next four quarters compared with loans in non-green deals, after controlling for borrower, loan, property, and macro factors with originator and time fixed effects. These differences are economically meaningful and appear across multiple delinquency definitions, including restricted definitions that require arrears balances to exceed materiality thresholds. At the structure level, green deals look stronger. They have a higher share of investment-grade tranches and fewer distressed buckets. We confirm this with an ordered logit over rating bands and with a simple recency weight that gives more influence to fresh rating updates. We then translate these loan-level differences into simulated tranche outcomes using observed default rates and two recovery settings that picture moderate and severe conditions. In these simulations, subordinated tranches in green deals take smaller losses, and senior and mezzanine tranches remain protected in scenarios where non-green structures show erosion. The message is straightforward. Better underlying credit quality in green transactions is reflected in stronger structural outcomes at the tranche level. The evidence indicates that the green label in RMBS aligns with stronger underwriting and risk transfer.

The third empirical chapter investigates whether the energy efficiency of mortgaged properties helps explain delinquency outcomes in securitised EU loans. Using harmonised EPC data from 2021 to 2024, the analysis shows a consistent efficiency–risk gradient: borrowers in less efficient homes are more likely to enter arrears or default. This relationship remains stable after controlling for borrower, loan, property, and macroeconomic characteristics, and the differences are economically meaningful. Importantly, the effect is not evenly distributed. It is significantly stronger for lower-income households, where energy costs appear to place greater pressure on repayment capacity. The gradient also becomes steeper during periods of high energy inflation, which supports the interpretation of a cash-flow channel. In these settings, energy efficiency appears to act as a financial buffer, reducing the burden of volatile energy prices and helping preserve borrower liquidity.

Taken together, the three chapters provide evidence on how environmental information enters credit markets and under what conditions these effects become more pronounced. We can identify three themes connecting the chapters. First, *credibility* matters. In Chapter 3, certification strengthens the greenium and improves resilience around climate events. In Chapters 4 and 5, transparent loan-level reporting and populated EPC fields are associated with better measured outcomes. Signals that are verifiable and comparable are the ones that markets appear to price and that are visible in risk metrics. Second, *environmental attributes* are financially relevant. At the market level, credible environmental features help explain spread differences that vary over time with climate attention. At the deal level, this supports stronger tranche ratings and lower expected losses under stress. At the household level, higher efficiency is linked to lower delinquency. These links are simple in intuition. Credible labels help investors allocate capital. Better collateral mixes improve pool performance. Lower running costs improve borrower bugets. Third, *context* matters. The greenium varies with climate attention and disaster news. Policy developments that change disclosure, taxonomies, or investor mandates shift the environment in which markets form expectations. The benefits of energy efficiency are most visible when energy prices rise quickly. The results therefore favour a dynamic view. Environmental pricing is not fixed. It responds to information and to the salience of climate risk.

These findigs suggest several implications. For investors, the evidence points to three practical points. First, the pricing of green features changes over time. Timing, security selection, and hedging should account for shifts in climate attention and for the added value of certification. Second, in securitisation, deal-level green labels correlate with better loan performance and stronger structural outcomes. This supports a focus on collateral screening and disclosure quality. Third, at the loan level, EPC information can improve risk differentiation and enhance modelling. For banks and originators, the results point to the usefulness of EPC data for both underwriting and portfolio monitoring. Where efficiency information is available and reliable, it can refine probability-of-default estimates, inform affordability tests in volatile energy markets, and support the design of Green RMBS that maintain protection for senior investors under stress. For policymakers, the main message is that standardisation and coverage of environmental data matter. Clear labelling frameworks improve comparability and reduce uncertainty. Where disclosure rules have raised the quality and completeness of reporting, markets appear to respond with better pricing and risk recognition. Continued efforts to align definitions and to expand reporting coverage can therefore support both financial stability and climate objectives.

Overall, this thesis shows that environmental information is not merely a disclosure exercise. It carries content that is visible in spreads, in the resilience of securitisation structures and in loan performance. The strongest evidence appears where signals are credible and data are comparable. Certification in the bond market, RMBS labelling and populated EPCs in mortgage data help markets and institutions distinguish quality. Aligning financial decisions with measurable efficiency and clear standards advances risk management and sustainability at the same time.

6.2 Limitations of the empirical findings

6.2.1 Limitations of Chapter 3

Our findings on the greenium, certification, and market reactions to climate events are based on large secondary-market datasets and models with extensive fixed effects. Several limitations remain, which are outlined below.

Measuring climate awareness. We use the monthly MeCCO World Index as a proxy for climate attention. While useful, media coverage is only an indirect measure of investor sentiment and differs across countries and languages. Aligning daily bond spreads to monthly media values may also smooth over short-term price reactions.

Certification and selection bias. Green certification is not randomly assigned. Issuers who certify may differ in ways we cannot observe, such as in governance or transparency, which could also affect bond pricing. Although issuer fixed effects and controls help, they cannot fully eliminate this concern. Certification should be seen as a signal, bearing in mind that some of the premium may stem from issuer characteristics.

Country mapping and disaster exposure. We match climate disasters from EM-DAT to the issuer's country of domicile and examine market responses over a five-day window. This does not guarantee that the issuer's assets or operations are directly affected, especially for multinationals. As a result, our estimates likely reflect broader investor sentiment or attention rather than pure exposure to physical risk. The short window helps limit unrelated news, though some anticipatory or delayed trading effects may remain.

Defining green and certified bonds. Green labels and certifications are sourced from Bloomberg, Refinitiv, and the Climate Bonds Initiative. Coverage has improved over time, but some bonds may still be misclassified or missing. We apply consistent rules and focus on fixed-coupon, non-optionable bonds, but a degree of misclassification is possible.

Constructing yield spreads and accounting for market frictions. We analyse spreads over sovereign benchmarks. Benchmark choice, on-the-run status, and temporary liquidity distortions can introduce noise. We control for bid–ask spread, maturity, size, rating, coupon, and time, but such frictions may still affect precision. They are unlikely to be systematically related to green labels, so their main impact is to increase estimation noise.

Policy changes and overlapping shocks. Between 2014 and 2022, various policy changes occurred, including asset purchases, new disclosure rules, and evolving green taxonomies. Time fixed effects absorb many of these shifts, but we cannot fully disentangle mechanisms such as changes in investor demand from shifts in perceived transition risk. Our results should therefore be interpreted as reduced-form relationships consistent with multiple channels.

Issuance timing and market composition. Issuers may time green bond issuance to coincide with favourable sentiment, and investors may shift their portfolios toward sustainable assets at the same time. Fixed effects, placebo tests, and time interactions help address this, but they cannot entirely rule out endogenous timing. Our dynamic results are best viewed as conditional price responses to realised issuance and attention.

Multiple interactions and inference caution. We interact green status with time, disasters, certification, and sector materiality. We highlight consistent patterns and report robustness tests, but individual interaction effects should be interpreted with caution.

6.2.2 Limitations of Chapter 4

This chapter uses supervisory loan-level data from EDW, harmonised EPC information, and tranche-level deal records. The points below outline key limitations. Most of these introduce measurement noise that tends to reduce statistical power. The main results should be seen as conservative associations, not definitive causal effects.

Sample scope and generalisability. The EDW dataset covers securitisations that meet ESMA template standards and are usually eligible for ECB repo operations. This means our sample skews toward high-quality, transparent RMBS. Results may not apply to private or ineligible deals. Within this scope, however, the evidence is relevant to the part of the market most aligned with regulatory and central bank practice.

Green labelling at the deal level. The green flag is assigned at the deal level. Under the EU Green Bond Regulation, the use-of-proceeds condition applies at the originator level, not the individual loan. We use originator fixed effects and a separate EPC-based sample to help distinguish labelling from collateral quality, but we cannot claim the label itself causes better performance. The association remains robust: green-labelled deals are linked with stronger loan and tranche outcomes.

Policy transitions and evolving incentives. From 2021 to 2024, disclosure rules and market practices evolved. Some originators may have improved collateral while also choosing to label deals as green. Our fixed effects absorb stable issuer traits and time shocks but cannot fully separate selection effects from real risk differences.

Outcome definitions and staging proxies. We construct arrears and default measures using quarter-ahead transitions and thresholds consistent with IFRS 9 staging logic. Legal definitions and procedures vary by country, so our outcomes are harmonised proxies rather than legal defaults.

Controls and remaining unobserved factors. We control for key variables such as LTV, interest rate type, income, employment, property characteristics, and macroeconomic indicators. However, we lack data on local conditions and building-level details such as heating type, retrofit timing, or local shocks. If these omitted factors are correlated with both risk and performance, some residual bias may persist.

Measuring ratings and accounting for recency. We rely on agency rating bands and assign higher weight to more recent updates. Rating methodologies differ across agencies and are ordinal in nature, so we do not track small notch changes. This simplifies analysis and reduces the risk of overinterpreting minor adjustments.

Tranche loss simulation design. We use a simple loss allocation approach: based on observed default rates and a fixed recovery input, we estimate a total pool loss and distribute it across tranches according to subordination. We do not simulate cash-flow waterfalls, reserve accounts, coupon step-ups, or prepayment dynamics. This choice prioritises transparency and comparability across deals. A full engine would project monthly cash flows through the legal waterfall; our method applies a one-time loss and allocates it by seniority. See the section on stress-testing assumptions for details on recovery inputs.

Stress-testing assumptions. Stress scenarios depend on assumptions about recovery rates and the distribution of defaults within the pool. We report both moderate and severe settings to illustrate the range. Country-specific factors (e.g., foreclosure regulation and timelines) could shift the level of losses, but the relative performance of green versus non-green deals is more robust to these assumptions.

6.2.3 Limitations of Chapter 5

This chapter analyses the link between EPC efficiency and delinquency in securitised mortgages reported to EDW between 2021 and 2024. The main limitations are outlined below. Most of them increase measurement noise, which tends to push estimates toward zero. As such, the relationship between energy efficiency and credit performance should be interpreted as a conservative association, not a causal effect.

Representativeness of securitised mortgages. Securitised loans can differ from those held on banks' balance sheets in terms of origination, documentation, and seasoning. Our findings are most directly applicable to EU RMBS that meet ESMA reporting standards. They may not extend to unsold loans or non-EU markets.

Unobserved borrower traits and selection. Although we control for many observable factors, we cannot observe personal traits that may influence both EPC choices and repayment behaviour. For instance, risk-averse or conscientious borrowers may prefer energy-efficient homes and be less likely to fall into arrears. More risk-tolerant or less disciplined borrowers may accept lower efficiency and face higher credit risk. Traits such as time preference, financial discipline, or environmental concern are unobserved in our data, so selection on these characteristics may influence the results.

EPC reporting and harmonisation. EPC disclosure was optional during our sample period, and reporting practices vary across issuers. We address this using fixed effects and by harmonising label ranges into kilowatt-hour estimates per square metre per year, capped at [0,500]. Nonetheless, assessor variation, outdated certificates, and national differences may introduce error.

Energy inflation and cost pass-through. We use national energy CPI as a proxy for energy costs. However, it does not reflect household-specific contracts, regulated price caps, or hedging. These differences limit the precision of our inflation-efficiency interaction and suggest our estimates are a lower bound on the true effect.

Income and property value measurement. Income is reported in broad bands and property values may be imprecise. While efficiency is only weakly correlated with income or property value, some overlap remains. This could reduce the size of estimated efficiency effects once controls are included.

External validity and sample period. A large share of mortgages lack EPC information, and reporting banks may differ from non-reporters. Our sample focuses on a high-volatility period for energy prices. Caution is needed when generalising to bank-held loans, other regions, or more stable periods.

Other unobserved mechanisms. We do not observe actual energy bills, heating systems, usage patterns, or details of retrofits. This limits our ability to confirm the cash-flow channel directly. Our macro controls are broad, so we may miss local pricing shocks or support schemes. These gaps introduce noise and suggest our results should be seen as indicative rather than precise.

6.3 Policy and regulatory implications

The findings of this thesis have several implications for policy, regulation, and financial market practice. This section brings together the overarching insights that emerge in the thesis.

First, the results highlight the importance of credibility and verification in green finance. Chapter 3 shows that green bonds with external certification consistently enjoy stronger pricing benefits, especially in sectors with high environmental impact. This suggests that trusted verification frameworks play a key role in building market confidence and limiting greenwashing. Policymakers can support this by reinforcing standards for external reviews and encouraging their use across the green bond market, particularly in sectors where environmental claims are harder to verify. Over time, stronger certification requirements could improve transparency and help shift more capital towards truly sustainable investments.

Second, the findings support the idea that green securitisation can align financial stability and climate goals. Chapter 4 shows that Green RMBS are backed by loans with lower delinquency rates, and that these deals are more resilient under stress. This supports the direction taken by the EU Securitisation Regulation and the ESMA disclosure templates, which require granular information on the underlying loans, including EPC ratings. In practice, this kind of transparency appears to influence originators' behaviour, pushing them to include more energy-efficient properties. Regulators might consider building on this by gradually strengthening expectations around the energy performance of securitised pools, alongside clearer reporting rules.

Third, Chapter 5 shows that energy efficiency matters for household credit risk, especially when energy prices are high. Borrowers in inefficient homes are more likely to fall behind on payments—not because of the loan structure, but because their energy bills are higher and more volatile. This matters for lenders, who can improve risk management by including EPC data in affordability assessments, PD models, and stress testing. It also matters to policymakers: supporting home retrofits and improving EPC coverage can reduce household vulnerability and improve loan performance, especially in countries with higher energy insecurity.

Finally, the thesis highlights the role of climate policy credibility in shaping financial outcomes. In Chapter 3, investor behaviour changes in response to major policy announcements (like the Paris Agreement) or to shocks that increase the salience of climate risks (like natural disasters). These events influence how markets price green bonds. This suggests that predictable, time-consistent climate policy helps guide capital towards low-carbon assets. Uncertainty, on the other hand, can weaken incentives and reduce the pricing advantage of certified instruments.

Taken together, the results point to four areas where policy and regulation can work together to strengthen climate-aligned finance: i) support clear standards for verification and certification to improve trust and reduce greenwashing; ii) use transparency and disclosure, especially around energy efficiency, to improve risk pricing and portfolio construction; iii) recognise energy efficiency as financially material and integrate it into risk and underwriting tools; iv) maintain credible, consistent climate policy paths to guide investor expectations. These steps would not only improve the functioning of the green bond and RMBS markets, but also help link private capital more effectively to the EU's climate and energy goals, while strengthening financial resilience along the way.

6.4 Directions for future research

Chapter 3. Future research could improve the identification of greenium and certification effects in several ways. First, instead of mapping climate events and policies to the issuer's country of domicile, it would be more accurate to link them to the firm's actual geographic exposure, such as the location of revenues or assets. This would help separate true physical risk from investor attention effects. Second, the impact of certification could be studied using rule changes or shifts in reviewer practices, and by comparing bonds just before and after certification decisions. Third, the proxy for climate attention could be refined using investor-level data such as fund flows or portfolio holdings, along with higher-frequency bond price data to capture intramonth reactions. Fourth, extending the sample beyond 2022 and including other regions would allow testing for the stability of effects under different policy frameworks and interest rate environments. Finally, future work could link secondary-market pricing to primary-market behaviour to better understand how climate attention and certification influence both issuance and trading.

Chapter 4. There are several ways to build on the results for Green RMBS. First, the effect of the green label could be better isolated by comparing the same originators before and after they adopt the label, or by analysing closely matched deals with and without the label. Second, a more detailed treatment of deal structure (e.g., including cash-flow waterfalls) could complement the simple static loss allocation used here. Third, it would be useful to examine tranche pricing more directly, looking at spreads and secondary-market performance alongside ratings, to assess whether the market reflects the observed resilience in pricing. Fourth, external validity could be improved by including private or ineligible deals, and by comparing different legal systems with varying foreclosure and recovery processes. Finally, future research could track changes as EPC reporting becomes more widespread, to test whether better disclosure sharpens the link between energy efficiency and credit risk, and whether it influences how deals are structured.

Chapter 5. The chapter highlights avenues for future work. First, although previous studies (e.g., Bell et al., 2023) found limited evidence that financial institutions actively factor energy efficiency into lending, it would be useful to test whether banks are beginning to price household energy efficiency and transition risk into mortgage rates and fees. Second, future work could assess the added value of EPC information in credit risk models by testing whether it improves model performance in terms of discrimination, calibration, and stability across application and behavioural scores, as well as other parameters of IFRS 9 or IRB models such as Loss Given Default (LGD) and Exposure At Default (EAD). Out-of-sample validation, stress testing, and stability analysis during periods of high energy price volatility would help determine whether efficiency data can support more robust and forward-looking lending decisions.

Acronyms and Abbreviations

AA High credit rating (double-A)

AAA Highest credit rating (triple-A)

ABS Asset-Backed Securities

AR Autoregressive

avg average

BB Speculative-grade credit rating (double-B)

BBB Investment-grade credit rating (triple-B)

BIS Bank for International Settlements

bps basis points

CBI Climate Bonds Initiative

CCC Speculative-grade credit rating (triple-C)

COP Conference of the Parties (UN Climate Conference)

COVID-19 Coronavirus Disease 2019

CPI Consumer Price Index

CSR Corporate Social Responsibility

EAD Exposure at Default

ECB European Central Bank

EDW European DataWarehouse

EE Energy Efficiency

EEA European Economic Area

EIB European Investment Bank

EM-DAT Emergency Events Database (Guha-Sapir et al., 2009)

EPC Energy Performance Certificate

ESG Environmental, Social, and Governance

ESMA European Securities and Markets Authority

EU European Union

EuGB European Green Bond

EuGBS European Green Bond Standard

FE Fixed Effects

FMA Financial Market Authority

FSB Financial Stability Board

GHG Greenhouse Gas

HHI Herfindahl–Hirschman Index

HPI House Price Index

ICMA International Capital Market Association

ID Identifier

IFRS International Financial Reporting Standards

IMF International Monetary Fund

IRB Internal Ratings-Based Approach

LGD Loss Given Default

LTV Loan-to-Value ratio

MA Moving Average

MD Mahalanobis Distance

MSE Mean Squared Error

OECD Organisation for Economic Co-operation and Development

OLS Ordinary Least Squares

ONS Office for National Statistics

OPEC Organization of the Petroleum Exporting Countries

PCA Principal Component Analysis

PD Probability of Default

PDSI Palmer Drought Severity Index

RMBS Residential Mortgage-Backed Securities

ROA Return on Assets

S&P Standard and Poor's

SASB Sustainability Accounting Standards Board

SONIA Sterling Overnight Index Average

SSPE Securitisation Special Purpose Entity

STS Simple, Transparent and Standardised (securitisation)

UK United Kingdom

US United States

USD United States Dollar

YTM Yield to Maturity

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